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MODELLING THE AIRCRAFT MAINTENANCE ROUTING PROBLEM FOR FRACTIONAL FLEETS WITH THE INCLUSION OF PROGNOSTICS AND HEALTH MONITORING INFORMATION

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I dedicate this work to my loving wife,
mother, father and brother.

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"Logistics is simple, but not easy".

Joe Lynch

Resumo

Esta tese apresenta duas abordagens para modelar o problema de roteamento e manutenção de aeronaves (AMRP) para frotas compartilhadas incluindo informações de prognóstico de saúde das aeronaves: uma baseada em modelagem de risco e outra modelando estímulos para etapas de voo com oportunidades de manutenção. Estes modelos visam tratar o problema da potencial falta de efetividade sistêmica em resolver o AMRP sem considerar todos os recursos de suportabilidade e manutenção disponíveis em sistemas aeroespaciais complexos contemporâneos. Nesse sentido, o uso de dados de prognóstico pode ser incorporado no processo de planejamento de rotas e manutenção com o intuito de reduzir custos com manutenção e reduzir tempo de aeronaves paradas devido a falhas. As soluções propostas neste trabalho constroem as rotas e as atribui às aeronaves enquanto determina o melhor momento e base para se realizar as atividades de manutenção preventiva. Modelou-se com base em casos reais informações de um sistema de monitoramento e prognóstico de falhas críticas das aeronaves. Sendo que suas ocorrências causam a indisponibilidade da aeronave até que a manutenção corretiva seja realizada. A manutenção corretiva é tratada em poucos trabalhos anteriores, e diferentemente deles, esta tese usa uma abordagem proativa para fazer um planejamento de rotas flexível que evite disrupções devido à manutenção corretiva. Foram usados vários casos para testar os modelos desenvolvidos, dentre eles casos reais de uma operadora de frotas compartilhadas e outros casos de dimensões de modo a contemplar amostras mais significativas do problema. Os modelos desenvolvidos também foram testados para frotas heterogêneas visando a refletir alternativas reais de operações de frotas compartilhadas. As contribuições desta tese incluem uma modelagem mais flexível de manutenções preventivas, permitindo que seu planejamento se adeque melhor à demanda de voos e a inclusão de informações de prognóstico de falha para planejar as rotas de forma proativa considerando disrupções específicas. Os resultados obtidos aqui demonstram o possível ganho em eficiência das soluções de roteamento, reduzindo custos de manutenção sem aumentar significativamente horas de reposicionamento.

Abstract

This thesis presents two approaches to modeling the aircraft maintenance routing problem for fractional fleets including aircraft health prognostics information; one based on risk modeling and the other modeling stimuli for flights that present maintenance opportunities. These models approach the problem of a systemic lack of effectiveness in solving the AMRP without considering available maintenance and supportability resources of complex systems. In this sense, the use of prognostics information can be incorporated into the planning process of routes and maintenance with the purpose of reducing maintenance costs and grounded aircraft times due to failures. The solutions proposed in this work build routes and allocate them to aircraft while determining the best moment and base to perform preventive maintenance activities. Information from a monitoring and prognostics system of critical failures of the aircraft was modeled based on real data. Being that these failures, cause unavailability of the aircraft until the corrective maintenance repair is done. Corrective maintenance is treated in few works, and differently from them, this thesis uses a proactive approach to make a flexible route plan that avoids disruptions due to corrective maintenance. Various cases were used to test the developed models; among them were real cases from a fractional fleet operator and other cases with dimensions that contemplate significant samples of the problem. The developed models were also tested for heterogeneous fleets to reflect real alternatives of fractional fleet operations. The contributions of this thesis include a more flexible modeling of preventive maintenance and the inclusion of failure prognostics information to proactively plan routes for specific disruptions. The results obtained here show the possible gain in efficiency of the routing solutions, reducing maintenance costs without significantly increasing repositioning flight hours.

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List of Abbreviations

AMRP	Aircraft Maintenance Routing Problem
AOG	Aircraft-On-Ground
ATSP	Asymmetrical Traveling Salesman Problem
CAP	Crew Assignment Problem
IBAC	International Business Aviation Council
ICAO	International Civil Aviation Organization
IVHM	Integrated Vehicle Health Management
MILP	Mixed Integer Linear Programming
PHM	Prognostics and Health Monitoring
RUL	Remaining Useful Life
TAT	Turn Around Time
TSP	Traveling Salesman Problem
VRP	Vehicle Routing Problem

List of Symbols

F Set of demanded flights that must be accomplished

F' Set of demanded flights that must be accomplished including the origin bases of the aircraft

M Set of maintenance activities that need to be performed

A Set of demanded flights and maintenance activities, $F \cup M$.

A' Set of demanded flights including aircraft origin bases and maintenance activities, $F' \cup M$.

T Set of aircraft available in planning.

O Set of opportunistic demanded flights, whose destination is a maintenance base.

$F1$ Set of demanded flights specific to fleet of aircraft type 1

$F2$ Set of demanded flights specific to fleet of aircraft type 2

$T1$ Set of type 1 aircraft (smaller aircraft)

$T2$ Set of type 2 aircraft (larger aircraft)

c_{ijt} Flight time for aircraft t to connect from activity i to activity j.

dur_j Duration of flight j.

$C_{FH,t}$ Cost per flight hour of aircraft t.

C_c Cost per canceled flight.

N_{tot} Total number of demanded flights.

K_{ijt} Large value such that the constraint is not imposed unless $x_{ijt} = 1$.

a_j Lower bound of the time window for activity j.

b_j Upper bound of the time window for activity j.

$K2_{ijt}$ Large value such that the constraint is not imposed unless $x_{ijt} = 1$.

lim_t Flight hours limit for aircraft t before it has to stop for maintenance.

FH_t Initial accumulated flight hours for aircraft t.

α Tuning parameter to modify the influence of the risk index.

R_{ijt} Risk index associated to aircraft t operating flight i followed by flight j.

P_{ijt} Failure probability associated to aircraft t operating flight i followed by flight j.

C_{cor} Additional cost of out-of-base corrective maintenance.

f_{jt} Factor that encourages opportunistic flights j for aircraft t.

x_{ijt} Binary variable equal to 1 if flight j is flown after flight i by aircraft t and 0 otherwise.

N_c Integer variable indicating the number of canceled flights.

s_{it} Time window at which activity i is started by aircraft t.

y_{it} Accumulated flight hours of aircraft t after it finishes activity i.

δ_F Expected deadhead flight hours cost increase

δ_M Expected maintenance cost reduction

D Total demanded flight hours

ϕ Expected deadhead hours to demanded flight hours ratio

Contents

1 Introduction

The airline industry has been changing considerably in recent years. Aircraft are becoming more efficient, providing more data, and flight operators aim to reduce costs and work more efficiently as well (ELTOUKHY et al, 2017a). In this way, they may provide services with more competitive prices while maintaining a reasonable profit.

The aviation sector is divided, primarily, into three segments; military aviation, scheduled airlines, and general aviation. Any aircraft that is owned, operated, and maintained by military organizations are categorized in military aviation and regulated by their respective military organization. Commercial airlines, which are the most popular means of air transportation, make up the scheduled airlines segment. General aviation is described as any operation outside of the other two categories and is divided into other subdivisions such as experimental, sport, tourism, and business, among others. Business aviation is a subdivision of general aviation and is defined by the International Business Aviation Council (IBAC) as: “That sector of aviation which concerns the operation or use of aircraft by companies for the carriage of passengers or goods as an aid to the conduct of their business, flown for purposes generally considered not for public hire and piloted by individuals having, at the minimum, a valid commercial pilot license with an instrument rating.” (IBAC, 2002).

Business operators differ from commercial airlines not only in the size of aircraft operated but also in the legislation that they must follow. Albeit both are in the major category of civil aviation, commercial airlines are considered scheduled air transport while business aviation is categorized as general aviation in the definition adopted by the International Civil Aviation Organization (ICAO) (ICAO., 2009).

Up to now, the focus of the works done in the area of aircraft maintenance routing was in solving the problem for large airlines with predetermined operations to manage disruptions, maintenance, and crew planning (ELTOUKHY et al, 2017a).

In this context, the operations planning is done in four parts; flight scheduling, fleet assignment, tail assignment, and crew assignment. However, in the business aviation sector, flight scheduling and fleet assignment are in most part out of the planner's hands. This happens firstly because the scheduling of flights is done on client demand and not based on the prevision of market demand, as is the case of commercial aviation. Secondly, clients usually own a share of a specific type of aircraft, and therefore it is already known which type of aircraft will attend each flight beforehand.

Business aviation has three main models of shared operating; leasing, shared, and prepay. In the leasing regime, the operators lease the aircraft from lessors and fly them as they need, without the cost of acquiring the aircraft. This way, the operator has more flexibility in the contract and more responsibility when it comes to managing the aircraft. Depending on the contract between client and lessor, the operators may be responsible for maintenance and other aspects of operations, which may be more troublesome than expected (PAPERDUE, 2011).

For a shared regime, operators own a share of the aircraft and each shareholder uses the aircraft as needed depending on the percentage owned. In this regime, one partner's operations may be limited by that of the other shareholders. All operational duties befall on the shareholders as well, such as flight planning, maintenance responsibilities, and crew contracting. The focus of this work is on the last model of business aviation, prepay.

The prepay model considers both charter, fractional operations, and jet cards. Charter operations simply require that customers contact an operator who offers this type of service and request a determined flight leg. The operator may accept this request or not depending on their availability of aircraft. However, the costs per flight hour for the customer using this service tends to be higher than that of the fractional customer. The situation for jet cards is very similar to chartered flights, with the drawbacks of having to purchase a predetermined number of flight hours or make a deposit to be consumed as well as sometimes being limited during peak travel periods.

For the fractional aircraft regime, the customers buy a share of the aircraft and pay a monthly fee to the operator to have a certain usage of an aircraft in that period, depending on the size of their share. In this sort of contract, the client (owner) does not have the burden of managing an aircraft while still having one at their disposal. One of the most pronounced advantages here is that the client is not limited to the use of a single aircraft; rather they have a fleet of the same type of aircraft available to attend to their needs and may eventually fly in a higher category aircraft in the event of unavailability of the contracted aircraft type. Usually, shares of fractional ownership may be as small as 1/16th of an aircraft, which in general gives the owner the right to 50 flight hours per year. Although the initial investment may be higher than charter operations, the initial acquisition cost is lower than sole ownership of an aircraft. The cost per flight hour is normally lower than charter operations and it is a more convenient model in terms of managing aircraft and its operations when compared to shared and lease models (HICKS, et al., 2005; MARTIN, et al., 2003). The IBAC defines fractional operations as “The operation or use of aircraft operated by an entity for a group of owners who jointly hold minimum shares of aircraft operated by the entity. Fractional Ownership operations are normally non-commercial; however, the operation of the aircraft may be undertaken as a commercial operation in accordance with the AOC held by the entity.” (IBAC, 2002).

Figure 1 shows the growth of the fractional aircraft fleet from 2000 to 2019. The worldwide fractional business aviation fleet has been growing steadily in the past years, despite its decline in 2008, as can be seen in Figure 1 adapted from the 2019 annual report from the General Aviation Manufacturers Association. From 2018 to 2019, the fractional operator flight hours grew 5.9%. This represents 45,180 more flight hours and a total of 620,288 flight hours in 2019. With larger fleets, the prospects of higher revenues are promising, but an increase in operating volume and complexity is also expected. With this in mind, the peculiarities of business aviation operations need to be considered during the planning of the operations.

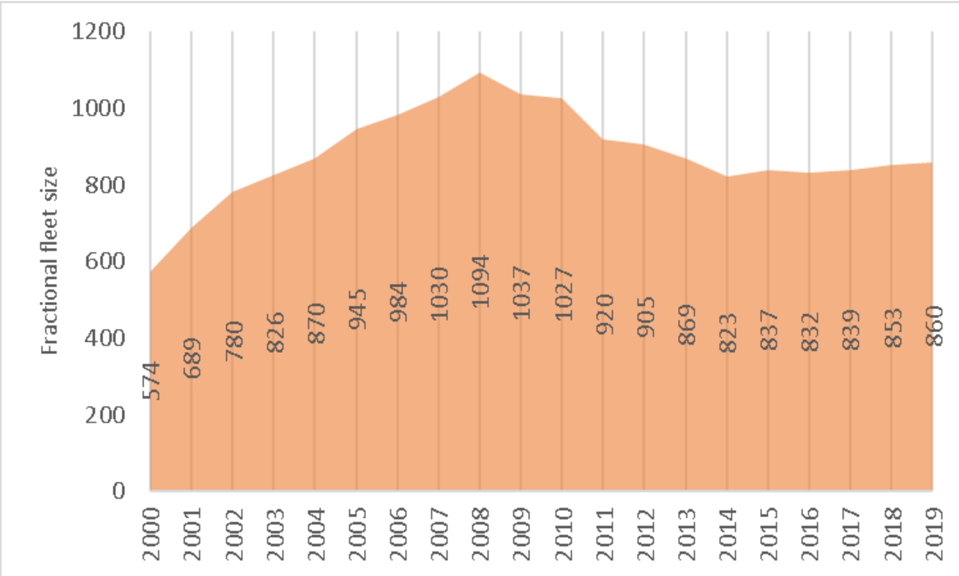


Figure 1 – Business fleet growth from 2000 to 2019. Adapted from GAMA, (2019)

Taking into account the ongoing pandemic that is still a large issue today, how the fractional fleet sector was affected must be analyzed. With the harsh initial restrictions set in place by most countries, all areas of air transport had large declines in operations, more so in commercial aviation. After the initial shock, the fractional fleet operations recovered from these effects in a few months. By the end of 2020, fractional fleet activity had almost returned to 2019 pre-pandemic levels (COPLEY, 2021a). Due to social distancing recommendations and fear of contracting the virus, flyers who usually opted for flying first-class commercial flights turned to business aviation. This increased interest in business aviation has caused hourly costs of chartered flights and jet cards to increase as well as some companies suspending new jet card sales (COPLEY, 2021b). This has also led to operators acquiring more aircraft to be delivered in the next years, (COPLEY, 2021b), indicating that the sector tends to grow in the years to come.

One of the main problems faced in this scenario is that conventional maintenance routing solutions do not adhere well to this highly variable demand, as is the case for fractional aircraft operations. This inefficiency may result in wasted flight hours and lower availability than necessary. In many cases, fractional owners do not fly round trips within a reasonable time to justify maintaining an aircraft waiting and since the costs of relocating aircraft are the responsibility of the company managing the fleet, this is a major aspect when aiming to improve operator efficiency.

There is a well-established consensus between many authors with respect to the phases of planning the operations of aircraft fleets. These phases consist of flight scheduling, fleet assignment, aircraft maintenance routing, and crew assignment (AL-THANI, et al., 2016; BASDERE & BILGE, 2014; DÍAZ-RAMÍREZ, et al., 2013; ELTOUKHY, et al., 2017a; ELTOUKHY, et al., 2017b; KHALED, et al., 2018b; KOHL, et al., 2007). Most works consider these phases as a linear sequence, some merging phases or considering them in parallel, due to the nature of commercial aviation. In the context of fractional operators, however, it makes more sense to approach these phases as a cycle depicted in Figure 2, due to the constantly changing demand.

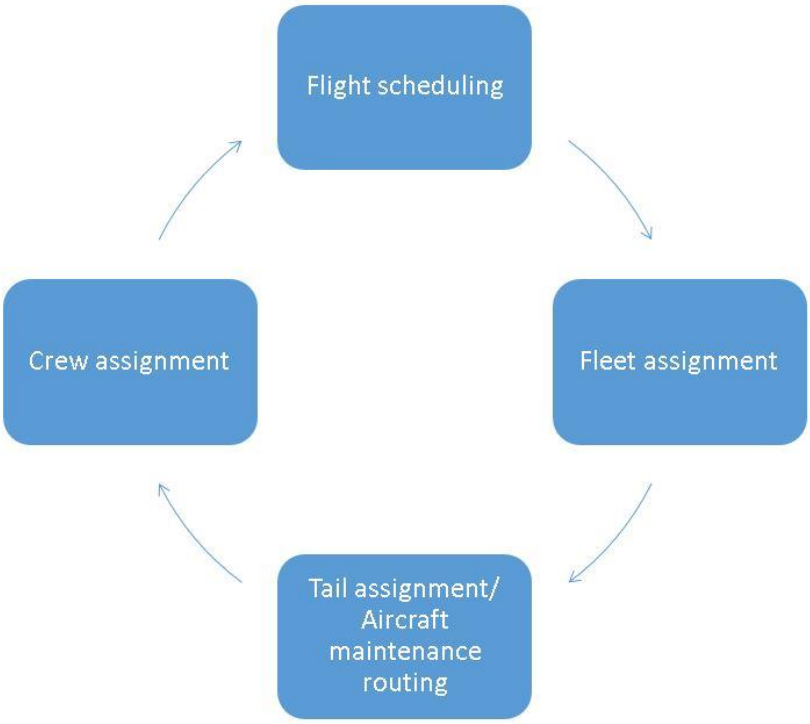


Figure 2 – Flight planning phases. Source: author, inspired by ELTOUKHY, et al., (2017a)

The flight scheduling problem is crucial for the profitability of large commercial airlines. Extensive market research is done in order to determine what flight routes should be offered and when they should be offered, to avoid flights with low demand and consequently low profitability. In most cases, the flight schedules must be ready months in advance.

Given that most airlines have more than one type of aircraft operating flights, the fleet assignment problem deals with the decision of which aircraft type is best suited for each flight. In the case of fractional operations, each partial owner has access to a fleet composed of aircraft of the same type. This is important because each aircraft type has a different capacity of passengers, flight range, crew limitations, and maintenance requirements to operate. Therefore, it is imperative that the fleet chosen for each flight maximize the profit for an airline.

Once the flight scheduling and the fleet assignment are done, the next step in planning is the aircraft maintenance routing. Here, the objective is to find the best feasible route for each individual aircraft where it has the possibility to perform all maintenance activities required with minimal cost. The routing problem is an important optimization problem that has been studied for many years, with some works testing and building new solution methods while others build new models to include different characteristics in each model (ELTOUKHY et al., 2017a). This is the focus of this work, the development of an innovative Aircraft Maintenance Routing Problem (AMRP) model.

To finish the planning, the last phase is the crew assignment problem (CAP). This phase deals with pairing crews to aircraft to create a roster for the employees. This involves organizing the activities considering different regulations for each country of operation, work hour limits, crew capacities along with other aspects. Figure 2 illustrates the phases involved in flight planning.

The focus here is on aircraft maintenance routing. Due to the nature of the AMRP, in business aviation, the demand comes directly from the clients, therefore, the flight scheduling problem is not in the operator's control if compared with airlines. The fleet assignment problem follows the same reasoning as the flight scheduling problem since in fractional operation each client owns a share of a specific aircraft type. So unless the possibility of upgrading clients is considered, most of the planning can be considered for homogeneous fleets. The crew assignment problem for a business aviation case is treated by MARTIN, et al., 2003; YAO, et al., 2005; YAO, et al., 2008 and is not the focus of this thesis.

While aircraft fleets and flight demands are still small enough to be managed more easily, decision-makers can plan operations and maintenance intuitively without losing much efficiency in operations. Nevertheless, as fleets and demand grow larger, the complexity of planning also grows, as is the nature of its combinatorial problems. In addition, maintenance activities add another level of complexity to the problem, considering the many ways to approach them during planning. After all, how much does maintenance affect route planning?

In the literature, much attention has been given to large commercial airline problems (ELTOUKHY, et al., 2017a; ELTOUKHY, et al., 2017b; HAOUARI, et al., 2011; KHALED, et al., 2018b; KOHL, et al., 2007; LIANG & CHAOVALITWONGSE, 2012; LIANG, et al., 2015; MAHER, et al., 2018; WARBURG, et al., 2008). This is due to the large number of flights and variety of fleets operated by such companies, which complicates the solution of the problem.

When compared to the number of authors and works that have treated the commercial airline problems, there are few pieces of research concerning the business aviation model of operating. Some of these works include (MARTIN, et al., 2003; YAO, et al., 2005; YAO, et al., 2008).

Although works focusing on commercial aviation are more abundant, some aspects of business aviation differ greatly from them. The most prominent is the quantity of repositioning flights. Since business aviation does not typically have cyclical routes, much more repositioning is needed during business aviation operations, driving most works focused on this type of operation to try to minimize these empty flights. However, the shortest route approach is not necessarily always the best to accommodate maintenance activities and may result in unexpected cancelations and other disruptions, becoming more costly.

Seeing that fractional operators are from the private sector, their end objective is to generate profit. The problem being solved is the minimization of inefficiencies in aircraft maintenance routing. Such inefficiencies could lead to missed opportunities in planning and the inability to attend flyer demands. This, in turn, may lead to loss of clients and their trust, negatively affecting the fractional operator revenue.

In literature, there are some similar problems to the AMRP that can help in developing the formulation and solution methods. Among these problems are the traveling salesman (TSP) and vehicle routing problems (VRP), and their variations using capacity and time windows for example. All of these problems follow a structure of nodes and arcs, with the solution providing a route by which to connect all the nodes. Many works have varied how they treat nodes, arcs, and vehicles to better fit the specific cases.

The nodes in these problems represent a position or event that must be serviced. The service that is carried out at each node can be as simple as a delivery that requires little to no time or as complex as an event that takes hours to be completed. For this work, nodes are defined as demanded flights or maintenance activities. They have, therefore, an origin, destination, duration, departure time, and cost.

The arcs may present costs based on distance, time, or any other metric deemed fit for the specific problem. Some arcs can present different costs depending on the direction that the object travels, as is the case for the asymmetrical traveling salesman problem. The arcs in the formulation presented here are defined as deadhead connection flights between each demanded flight. These arcs have a duration, origin, and destination.

Lastly, there is the object or vehicle that services each node. Many characteristics can be attributed to them, such as the capacity of load that they can carry, the distance they can travel, or from where they can begin their route. Vehicles most commonly represent delivery trucks (CARIC, et al., 2008; EL HASSANI, et al., 2008; HSUEH, et al., 2008; KARA, et al., 2008; WATANABE & SAKAKIBARA, 2007). Since most problems treat supply delivery instances, it is common that vehicles originate and finish their routes at specific depots (BELFIORE, et al., 2008; CARIC, et al., 2008; EL HASSANI, et al., 2008; HSUEH, et al., 2008; KARA, et al., 2008; MURATA & ITAI, 2008; TAM & MA, 2008; WATANABE & SAKAKIBARA, 2007). In commercial airline operations, this is a very common characteristic since they usually operate a cyclic plan. The aircraft must return to its original position to repeat its cycle. This is not the case for fractional fleet operations. Here aircraft rarely have cyclical routes and may remain at a base until it is requested for another flight. For this reason, the vehicles, i.e. aircraft, do not have an origin to which they must return at the end of the route. They are spread out among different bases at the start of planning and can finish at any other position.

The first aspect mostly used in these types of works is time windows. By applying time windows to nodes, the space of feasible solutions is restricted. Although they do not specify the exact time windows used, (BELFIORE, et al., 2008; CARIC, et al., 2008; CUNEO, et al., 2018; EL HASSANI, et al., 2008; HSUEH, et al., 2008; TAM & MA, 2008) use time windows to service each node. These time windows are defined by a boundary of the earliest and latest times at which a node can be serviced. This is a result of when an establishment is open, a predefined delivery time, or a critical situation that requires urgency, such as disaster relief or a medical emergency. In the case of this work, strict and flexible time windows are used for different types of activities. The departure times for demanded flights are treated as strict time windows so that flights are not delayed. The maintenance events are treated more flexibly, calendar-based maintenance activities present a daily window to begin.

Another important trait commonly used in VRP is capacitated vehicles. This means that each vehicle has a limited load capacity. A very important aspect when treating delivery problems. This may decide if a certain vehicle is capable or better suited to serve a specific node, especially if dealing with heterogeneous fleets. BELFIORE, et al., (2008) treat a VRP that presents time windows and split deliveries. Each node can be serviced by more than one vehicle. This allows the service of nodes whose capacity exceeds that of the vehicles. Different from fractional fleets, commercial aviation depends on the capacity of the aircraft to determine how many seats can be offered for each flight, making it a crucial decision to optimize revenue.

There are many other variants of the VRP, like the pick-up and delivery problem, multi-depot VRP, and many others (ELSHAER & AWAD, 2020). Nevertheless, the one that most resembles the constraints used here is the cumulative VRP. This type of constraint restricts the accumulation of a resource. In KARA, et al., (2008), the accumulated travel time of each truck is limited to a specified time. This was because their objective was to minimize depot open hours and as long as all trucks were not back at the depot, it remained open. In our case, however, the cumulative constraint is set on the hours flown by each aircraft. Once the aircraft reached a certain amount of flight hours, they are required to stop for preventive maintenance.

Maintenance is referred to as any activity required to restore or maintain a system in operational condition. It is a necessary part of operating any complex system, since components in these systems are always worn down during utilization and sometimes when idle as well. In some cases, in operation due to lack of maintenance results only in extra costs, but other times there is a safety risk involved.

In the aviation sector, maintenance is highly regulated by ICAO and other air certification organizations. Therefore, since all aircraft require regular maintenance, it is a crucial part of operations planning.

The maintenance aspects of the AMRP considered in previous works vary greatly. Such characteristics used in these works are maintenance workshop capacity (LIANG, et al., 2015), the number of maintenance workshops, maintenance workshop location (ELTOUKHY, et al., 2017a), level of maintenance to be performed (CLARKE, et al., 1997) and resources available at the maintenance workshops (HAOUARI, et al., 2011). These aspects have a great influence when deciding where and when to stop an aircraft for maintenance.

The models in previous literature introduce maintenance requirements in various ways. Most works create mandatory flight legs in the demanded activities, which have the duration of the checks, and the origin and destination of the 'flight' are the same maintenance station.

Despite many works treating the problem of including maintenance activities in the planning process, few acknowledge the different types of preventive maintenance (KHALED, et al., 2018a; KHALED, et al., 2018b; MARTIN, et al., 2003) and the possibility of having flexibility in maintenance allocation (MUNARI & ALVAREZ, 2019).

For the AMRP, maintenance can be treated in two main ways; the first as a constraint to the planning, second as an objective to be optimized. Most works approach this aspect of planning as a hard constraint in the optimization of other problems, such as the CAP. The most common way this done is by adding a mandatory flight leg that is equivalent to the maintenance event (CAETANO & GUALDA, 2015; HICKS, et al., 2005; MARTIN, et al., 2003; MUNARI & ALVAREZ, 2019; YANG, et al., 2008; YAO, et al., 2005; YAO, et al., 2008). Some authors allow for some flexibility in the starting time of these maintenance events to better reflect real operations.

As for optimizing the maintenance aspect in the planning, this approach is more used when the objective is to maximize the utilization. AL-THANI, et al., (2016) and BASDERE & BILGE, (2014) minimize the remaining legal flying time before flight hour-based maintenance activities, deciding when to perform these activities. Since they use commercial aviation scenarios, with hub and spoke networks, there are more possibilities to perform maintenance than in fractional fleet operations.

Although preventive maintenance is considered a mandatory activity, the possibility to use maintenance events with more flexibility is modeled here. This is done by separating the time-triggered and flight hours maintenance activities and allowing a wider window to accomplish them as well as minimizing the transportation cost to do each maintenance.

All these maintenance considerations mentioned previously in this section refer to preventive or planned maintenance. BEN-DAYA, et al., (2009) describe three types of maintenance, preventive, corrective, and predictive. As can be seen from the previous works cited here, preventive maintenance is usually planned some time in advance and aims to perform repairs before failures occur. This way, unwanted delays due to system failures can be avoided.

Corrective maintenance is the most intuitive, after a failure occurs in the system, maintenance is done to correct whatever is wrong. Sometimes these failures are small and have few consequences for the planned operations. Other times, they may be critical, leaving the aircraft grounded for extended periods. When critical events like these happen outside of a maintenance base, the effects can be even more detrimental to planned operations.

Predictive maintenance is a concept where cost-effective tools are used to monitor the condition of critical equipment. Instead of relying on average life statistics, direct monitoring estimates the remaining useful life (RUL) of the parts (MOBLEY, 2002). Given the recent advances in sensors and data analysis, many more systems can be monitored cost-effectively in complex systems (BIGGIO & KASTANIS, 2020). This type of maintenance relies on some type of prognostics analysis.

Lastly, prescriptive maintenance expands on the concept of predictive maintenance. While predictive maintenance monitors degradation levels and uses data analysis to estimate the RUL of components of a complex system, Prescriptive maintenance goes beyond the system being monitored, the aircraft in this case, and takes into account the whole infrastructure necessary to maintain the aircraft. This includes ground resources, spare parts, logistics, and minimum downtime to repair the aircraft (MEISSNER, et al., 2021).

Given that many aircraft nowadays are equipped with sensors that provide information about the use and wear of components and these data can be processed by analysis software, they have the potential capability of using these data to provide useful information to the operations planner.

System monitoring and prognostics analyses are an integral part of modern industries. One of the most valuable information provided by these types of systems for operational planning is the remaining useful life (RUL) of components and sub-systems. This indicates an estimate of when a component will fail in the near future. Although it may not be completely accurate, it is better to have an idea of when something might fail than have it fail unexpectedly.

This information has the potential to improve not only operations, but also maintenance planning, resource allocation, and fault troubleshooting (RODRIGUES, et al., 2012).

Seeing that the use of failure prognostics information is relatively scarce in maintenance routing problems, an opportunity to improve operations may be missed in conventional routing solutions. Some out-of-base (maintenance capable base) failures could be averted if fault prognostics information is considered during the routing phase of planning, for example, possibly having a significant effect on maintenance costs.

Solution methods used in AMRP can be divided into two main categories; exact and approximate solutions. Approximate solution methods include various heuristics and metaheuristics. These works usually treat commercial aviation problems that are too large to be solved in reasonable time through exact methods (ELTOUKHY, et al., 2017b; ELTOUKHY, et al., 2018a; MAK & BOLAND, 2000). Other works use this type of problem to evaluate developed heuristics (KOZANIDIS, et al., 2014).

In business aviation, it is more common to see authors use exact approaches to solve the AMRP, mainly due to the reduced problem size when compared to commercial aviation. The first solution method used in this type of problem is column generation (HICKS, et al., 2005; LIANG & CHAOVALITWONGSE, 2012; MAHER, et al., 2018; YAO, et al., 2008). This method consists of breaking down the problem into a master problem and a subproblem. The master problem is where the used variables are considered and the subproblem is a new problem to identify new variables to enter the final solution. MARTIN, et al., 2003 and YAO, et al., 2005 both use CPLEX solver for business aviation cases, ELTOUKHY, et al., (2018a) also uses CPLEX for reduced instances. The CPLEX algorithm is based on the simplex method and branch and cut algorithm. This work will use the Gurobi solver for the presented instances. Like the CPLEX solver, Gurobi is also based on the simplex method and branch, price, and cut algorithms.

Gurobi solver is one of the fastest mathematical optimization software available. It is capable of solving a wide variety of problem types faster than competitors and performs well as problems increase in size and complexity. Gurobi uses a branch, price, and cut algorithm that solves linear programming sub-problems to solve the MILP problem.

As described in CARIC, et al., (2008); EL HASSANI, et al., (2008); EL-SHERBENY, (2010) and MURATA & ITAI, (2008), the AMRP is in the class of combinatorial problems and are consequently NP-Hard. However, as was stated during the qualification of this thesis, the problem sizes treated here, reflecting real-world operations, can still be solved through exact methods, such as the branch, price, and cut algorithm.

Branch and bound algorithms are designed to solve discrete and combinatorial optimization problems (RALPHS, et al., 2010). It consists of enumerating candidate solutions for a relaxed version of the original problem, allowing infeasible solutions. At each branch, the solutions with variables that do not obey certain restrictions, such as integrality restrictions, are branched out further until feasible solutions are obtained, thus forming a tree of solutions. Each branch is compared to upper and lower branches to obtain the best solution.

The efficiency of the branch and bound method depends on the tightness of the relaxation applied. In this context, the branch and cut algorithms provide a relaxed set of solutions that are closer to the feasible solution set than the simpler branch and bound strategy. By adding globally valid inequalities, the search space is reduced as they affect all branches of the solution tree (RALPHS, et al., 2010). One of the ways to generate these inequalities is to use Dantzig-Wolfe decomposition (DESROSIERS & LUBBECKE, 2010).

Branch and price is another method used to tighten the relaxation of the original problem. Here, this is done by column generation. This may result in a large number of variables in the formulation, therefore the initial relaxation starts with a small subset of variables (DESROSIERS & LUBBECKE, 2010; RALPHS, et al., 2010).

The combination of the two previous methods results in the branch, price, and cut algorithm. By using both strategies, the solution space is established more efficiently.

1.1 Problem

The problem definition for this thesis is the potential lack of systemic effectiveness in solving the AMRP problem without taking into account all the resources in terms of support and maintenance information that contemporary complex aerospace systems make available.

By considering preventive maintenance activities as fixed events, opportunities for a better maintenance plan are discarded, especially in the case of fractional fleet operators that have an erratic demand for their aircraft. If system monitoring prognostics information are ignored during operations planning, more efficient maintenance routing solutions can be missed and a valuable resource of modern complex aerospace systems will be wasted.

From the review of the works treating the AMRP and similar problems, and the identification of the research gaps, the following hypothesis is established. It is possible to improve routing solutions of the AMRP by incorporating PHM information into the routing model, reducing maintenance costs and repair times. In addition, by using more flexible preventive maintenance windows and multiple maintenance bases, shorter repositioning flights can be found to perform these maintenance events, thus having more efficient routing solutions.

1.2 Objective

The objective of this work is to develop an aircraft and maintenance routing model to treat the AMRP specifically for the fractional fleet model of operation, considering the individual characteristics of each aircraft, irregular demand, and failure prognostics information to reduce correspondent maintenance costs while still finding efficient routing solutions.

In order to analyze the model, real and synthetic data are used to make a dynamic aircraft maintenance routing plan that will adapt the routing to possible maintenance disruptions and consider failure prognostics information provided by modern aircraft systems proactively. Thus, the specific objectives are:

- Study the vehicle routing problem in general, with a greater focus on aircraft routing, especially fractional fleet operations, and the inclusion of prognostics information in these types of problems.
- Model fractional fleet operations incrementally, leading to a more realistic model, to optimize both maintenance and overall operational costs.
- Analyze the effectiveness of different approaches to including failure prognostics information in route and maintenance planning.
- Analyze the behavior of the models in heterogeneous fleet operations.
- Analyze the effects of variability in planning, brought on by the uncertainties in remaining useful life (RUL) estimates that are inherent to prognostics information.

1.3 Organization of this work

Chapter 1 presents the introduction of this work, including the identification, and definition of the problem, work objectives and organization of the text.

A review of the literature regarding the problem including the AMRP and derivatives as well as solution methods used to them, failure prognostics in routing problems, and related works is presented in chapter 2.

The methodology applied in the realization of this work is presented in chapter 3. The approaches used during this thesis are explained in further detail in this chapter. The model used in the present work is also detailed here.

In chapter 4 the application of the models is presented along with the results obtained during this work and a discussion of the results.

Chapter 5 is the conclusion and final remarks of this thesis.

2 Literature Review

This chapter presents a review of the literature relevant to the topic studied in this thesis. The focus is on the main aspects of the aircraft maintenance routing problem, fractional fleet operations planning and failure prognostics information. The works treating these problems and their variations are analyzed to identify if they use modern maintenance and supportability resources when approaching these topics.

2.1 Aircraft maintenance routing problem

When solving the aircraft maintenance routing problem there are many aspects that can be considered in the planning. These aspects can be of a maintenance-oriented or operational nature. These characteristics are introduced to make the model more realistic depending on the scenario used.

Considering the operational aspects of the AMRP that are just as important as the previous aspects of the final planning. Some examples treated in previous literature are aircraft capacity, homogeneous/heterogeneous fleets (CLARKE, et al., 1997), overnight location (ELTOUKHY, et al., 2017a; HICKS, et al., 2005), airport limitations to operate certain aircraft (KHALED, et al., 2018b), stochastic demand (BASDERE & BILGE, 2014; YAO, et al., 2005), conditional flights (Minimum Equipment List - MEL) (PAPAKOSTAS, et al., 2010), different costs of operation for different aircraft and disruption management (KOHL, et al., 2007).

The main aspects considered in this work are stochastic demand of flights, preventive maintenance plan, use of prognostic health management data, location of maintenance workshops, and corrective maintenance. For this study it is considered that the maintenance workshop capacities are infinite, allowing multiple aircraft to perform maintenance at the same time.

As seen in GRONKVIST, (2005), there are three types of operating networks in the airline industry, illustrated in Figure 3. The first is the linear network, which is the least used of them all in the aeronautical sector. Here, all the airports are connected by a single tour. In other words, there is a single flight path followed by all aircraft.

Next comes the point-to-point network. For this case, all airports are connected by a single flight. This type of network is mostly used by low-cost commercial airlines and business aviation operators, allowing the operators to bypass busy and expensive airports and have more flexibility.

The last type of network and most used by commercial airlines is the hub-and-spoke network. In this type of network, there is the main hub of operation that all flights arrive at or depart from. This model is the preferred method of large commercial airlines because it makes it easier to mitigate operation disruptions and permits operators to have a single maintenance station to service a large portion of their fleet.

Having a maintenance station at an airport where all flights go through minimizes logistics costs for maintaining aircraft operationally ready.

Most models that used real data from commercial airlines also use a hub-and-spoke network and the only ones to use a point-to-point network used data from business aviation, low-cost commercial airlines, or synthetically generated data.

In spite of the fact that operators rarely use pure point-to-point or hub-and-spoke networks, this work will focus on a point-to-point network model since it reflects more adequately the operation of the business aviation sector.

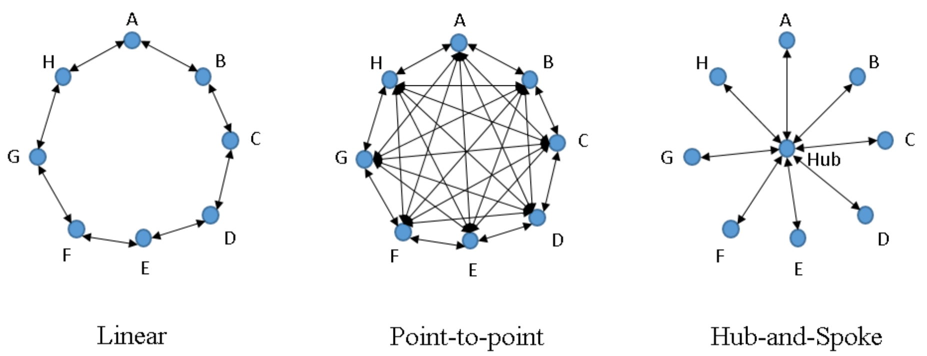


Figure 3 – Operating networks

As explained in ELTOUKHY, et al., (2017a) and MAHER, et al., (2018), there are many models by which to construct a routing solution for aircraft. Some authors used a string-based approach where the strings are a sequence of connected flights. For example, flights that have coinciding origins and destinations will typically be in the same string, as this provides a pairing with a low connection cost between flights. Generally, for the airline scenario, the strings begin and end at the same base. This method is usually formulated as a set partitioning problem and solved using a branch and price strategy. This method has one drawback which is the large number of strings generated which takes a large computational time to solve.

Another approach is the network-based method, which can be solved in a considerably smaller amount of time when compared to the string-based method (Eltoukhy et al., 2017a). The network model uses timelines for different stations, including airports and maintenance stations, to depict the flow of the aircraft as shown in LIANG & CHAOVALITWONGSE, (2012).

The third solution model is the big cycle approach, which includes the traveling salesman approach. Some authors associated the aircraft routing problem with the asymmetric traveling salesman problem (ATSP) due to the similarities between them (CLARKE, et al., 1997 and MAK & BOLAND, 2000). The first focused on finding feasible maintenance rotation problems by formulating the problem of aircraft maintenance routing problem (AMRP) as an ATSP and the second solving with meta-heuristics the AMRP formulated as an ATSP.

In commercial aviation, the planning horizon is a well-defined parameter when it comes to establishing operations. It is the operator who decides what flight legs are to be flown, from the flight scheduling problem. This way, the planning can be done in such a way as to create cyclical routes that repeat in periods of days, weeks, or even months. By doing this, the distribution of activities among aircraft can be more easily controlled. In commercial aviation, this is crucial due to the large number of flights and aircraft to manage.

However, for the business aviation operator, the flight scheduling problem is in most part out of the hands of the operator. Since the clients determine the flights, the demand can come from months in advance to as soon as hours from departure, making it difficult and complex to build a cyclical route plan.

This implies a greater difficulty in activity distribution, which may lead to more than one aircraft, grounded unnecessarily, affecting fleet availability. This erratic behavior is one of the challenges in on-demand routing due to the nature of the business aviation sector (YAO, et al., 2008; VAN Der ZWAN, et al., 2011; MUNARI & ALVAREZ, 2019).

Next, there are the maintenance aspects of the AMRP, there are three types of limitations for maintenance activities, flight hour, cycle, and time-triggered maintenance events. These limitations are applied to preventive maintenance plans. Most works do not consider all three maintenance limitations in planning (AL-THANI, et al., 2016; BASDERE & BILGE, 2014; DÍAZ-RAMÍREZ, et al., 2013; ELTOUKHY, et al., 2017b; KHALED, et al., 2018a; KHALED, et al., 2018b; MAK & BOLAND, 2000). A few authors, however, include all three limitations for a more realistic approach (ELTOUKHY, et al., 2019; MARTIN, et al., 2003).

Another part of the maintenance activity that few works incorporate into the planning model is the maintenance workshop characteristics. These include the number of aircraft that can be serviced simultaneously, the workshop location, and available crew and equipment for certain maintenance tasks. ELTOUKHY, et al., (2017b) and ELTOUKHY, et al., (2019) include workshop capacity in their works, but do not include the possibility of multiple maintenance bases being used during operations.

Flight hours and time-triggered preventive maintenance activities are applied since they are enough to test the maintenance planning. The aspect that differentiates this work from previous ones is the multiple maintenance bases for possible maintenance stops. Because fractional fleet operators tend to use networks that are closer to point-to-point networks rather than hub-and-spoke networks, it makes more sense that there be multiple maintenance base options as opposed to only one at the hubs. The capacity of these workshops as limited resources are not considered.

Different from the previous works mentioned, this thesis focuses on the fractional aviation model of operation and introduces failure prognostics information into route planning.

2.2 Fractional fleet operations

In works focused on fractional operations, the main aspect treated was the crew-scheduling problem. HICKS, et al., (2005); MARTIN, et al., (2003); YAO, et al., (2005); YAO, et al., (2008) and YANG, et al., (2008) all solved the crew scheduling problem using aircraft maintenance routing as a feasibility constraint, thus, not necessarily optimizing the maintenance routing.

The first published work for fractional fleet operations is by MARTIN, et al., (2003), who present an integrated system that provides routing solutions based on a mixed-integer linear programming model solved with CPLEX. The focus of MARTIN, et al., (2003) is primarily on crew scheduling, some simplifications are used to merge aircraft, and crew scheduling and preventive maintenance are treated as fixed stops in the planning.

Next HICKS, et al., 2005 focused on modeling constraints and cost factors for another integrated system used for fractional operations. To solve this model, they used GENCOL a software based on column generation developed by GERAD, an operations research center. This formulation allows 15- minute delays in planning.

YAO, et al., (2005) continue to study the effects of flexible time windows for departure times and was solved using CPLEX. This approach showed promising results when compared to heuristically determined routes used by the fractional operator. By using more flexible crew swapping strategies, departure times, and modifying demand, YAO, et al., (2008) are able to improve operating costs in their study. A column generation approach is used in this study and maintenance events are included in the planning as they occur and the problem is resolved after that.

Finally, MUNARI & ALVAREZ, (2019), continue to use flexible time windows for flight departures, anticipating or delaying flights, in planning. Their main contribution is allowing clients to be upgraded to a larger aircraft if the upgrade will result in a lower overall cost and allowing the anticipation or postponement of the beginning of flight and maintenance events within a given tolerance. Flight upgrades usually happen when no aircraft of the contracted category are available for a client, in this case, an aircraft of a higher category is made available even if its operating cost is higher.

A previous work by the authors of this thesis BARRETO, et al., (2021), presents the first work treating the AMRP for fractional fleets including failure prognostics information. Here the authors develop a model that uses this type of information in route planning. This model led to the development of the models presented in the following chapter.

2.3 Failure prognostics / E-maintenance

Most works develop robust models in an attempt to manage disruptions of the planned routes. The disadvantage of this method is that by making more robust routes, the decision-maker runs the risk of having less efficient routes with wasted flight hours and missed flight opportunities.

ELTOUKHY, et al., (2019) cite two approaches to dealing with disruptions, stability-oriented and flexibility-oriented. The work stated previously focuses on a stability-oriented approach by producing robust models to avoid changes to the built routes. This is better suited to large airline operations, whose operations are less flexible and must avoid delays. These robust approaches follow three lines, adding buffer times to the operations (LIANG, et al., 2015), allowing changes to the departure time of flights (AHMED, et al., 2017; WARBURG, et al., 2008; MUNARI & ALVAREZ, 2019; YAO, et al., 2005; YAO, et al., 2008) and scenario-based approach using simulation (ELTOUKHY, et al., 2018b; MARLA, 2018).

ELTOUKHY, et al., (2019) in particular uses the possibility of reducing turnaround time (TAT), the time necessary for an aircraft to be ready for take-off, by using more maintenance resources, assuming that the increase in maintenance costs is small compared to the propagated delay cost.

In this work, the focus is on a flexible approach to manage a specific type of disruption, corrective maintenance events. To do this a proactive approach is modeled that uses information from monitored systems to plan routes flexibly depending on predicted failure probabilities. This is a more viable approach when considering fractional fleet operations given its dynamic nature. The broader maintenance network and small time window for planning operations favor a more flexible replanning to account for changes in RUL of monitored systems.

Integrated Vehicle Health Management (IVHM) is an integrated view of a system of systems, monitoring the health of each system to assist in the decision-making process (JENNIONS, 2013). In this way, this approach provides the ability to recognize, evaluate, isolate and mitigate faults in the system (JIANG, et al., 2017). An important part of IVHM is prognostics and health management (PHM).

PHM provides an estimated RUL for components or systems based on collected data and estimated future usage. Modern aircraft provide more data than older models and thus an opportunity to improve operations and maintenance planning. It is divided into three main categories, model-based, experience-based, and data-driven prognostics (TOBON-MEJIA, et al., 2012). Each of these methods presents advantages and disadvantages amongst them.

Model-based prognostics use analytical models of systems to represent behavior and degradation during operations. These models provide the most precise prognostics results among the methods, given that they are algebraic equations based on the actual physical systems. Although the results are easily interpreted since it is modeled after the physical system, this tends to be the most costly method. This is due to the difficulty of building analytical models of complex systems (TOBON-MEJIA, et al., 2012).

On the other hand, the experience-based method is the least expensive to implement, but it is also the least precise in terms of RUL prediction. This method uses data from maintenance, operations, failure events, and other sources spanning a large period of time to adjust reliability parameters. As long as data is abundant, this method can be easily applied to a complex system (TOBON-MEJIA, et al., 2012).

The data-driven method is a middle ground in relation to the other two methods, both in terms of implementation costs and prognostics precision. As the name suggests, it is highly dependent on large amounts of data as well. Both the behavior and degradation models are derived from observed data. Statistical methods and artificial intelligence are used to obtain these models and predict the RUL of the components. One of the drawbacks of this method is the potentially long learning times of artificial intelligence algorithms (TOBON-MEJIA, et al., 2012).

In the last years, many works used PHM and IVHM to improve maintenance, design, and cost reduction. VIANNA, et al., (2015) used PHM to estimate aircraft on ground (AOG) events and better plan aircraft line maintenance. SCANFF, et al., (2007) researched the impact of PHM on life cycle cost for helicopter avionics. The RUL provided by PHM is also used in a system-level analysis to aid in the maintenance decision process regarding component replacement (RODRIGUES, et al., 2014).

Other works propose frameworks for IVHM (JENNIONS, 2013) and methodologies to integrate PHM and maintenance data (CAMCI, et al., 2007). The benefits of IVHM are analyzed even in the manufacturing stage of a system to reduce the overall cost of the product (JIANG, et al., 2017).

RODRIGUES, et al., (2012) study possible opportunities brought on by using PHM techniques for aircraft operators. The main aspects mentioned by them are inventory management optimization, scheduled maintenance planning, reduction of unscheduled maintenance tasks, improved troubleshooting, and intelligent aircraft allocation. The latter is the area of interest of this work. All of these topics also have potential benefits for personnel management, helping to isolate failure causes more rapidly and efficiently and planning appropriate workforce for each maintenance event beforehand. The two most prominent benefits cited are increased fleet availability and reduced operational costs, by placing technicians and parts closer to predicted maintenance events, reducing logistics costs and mean time to repair.

Although prognostics and forecasting are considered synonyms in most cases, here they are defined as follows. Prognostic is a prediction of future events based on the current condition of a system and future operational and environmental conditions, while forecasting is a prediction based on the extrapolation of past data. A small part of PHM is used here, in the form of failure prognostics information, in an attempt to improve aircraft routing and reduce maintenance costs.

As can be seen from BULA, et al., (2016), COUTINHO-RODRIGUES, et al., (2012) and CUNEO, et al., (2018), risk in routing problems can be defined as the probability of an event occurring versus its expected outcome. Most cases focusing on risk in routing are associated with transporting hazardous material (BULA, et al., 2016; CUNEO, et al., 2018), fuel being the most common. In these cases, the risk is measured by the probability of a spill and the density of population that will be affected, or the environmental damage that may be caused.

Another approach is the routing of evacuation routes during disasters. Some pathways may present higher risks for escapees depending on terrain or surrounding structures. COUTINHO-RODRIGUES, et al., (2012) used a mixed-integer linear programming (MILP) model to design evacuation routes in case of fires in a busy and densely populated city center. In this study, they propose primary and secondary evacuation routes based on risks associated with each route.

Although this work does not treat life-threatening cases such as these, a risk assessment of flight routes becomes important once failure prognostics information is added to the aircraft maintenance routing. From this information, some insight can be drawn from the risk associated with each connection, providing an opportunity to reduce maintenance costs by averting failures far from maintenance bases. A risk index is defined for each deadhead flight as the probability of failure occurrence and the added cost of performing maintenance outside of a maintenance base.

There are a few papers that are more adherent to the problem faced in this thesis. First, there are the ones treating fractional fleet operations (MARTIN, et al., 2003; HICKS, et al., 2005; YAO, et al., 2005; YAO, et al., 2008; YANG, et al., 2008; MUNARI & ALVAREZ, 2019). All of these authors consider fixed maintenance events that need to be carried out similar to demanded flights. Among them, YAO, et al., (2005); YAO, et al., (2008) and MUNARI & ALVAREZ, (2019) consider flexible departure times for flights and maintenance, but they do not consider the effects of aircraft usage and multiple maintenance bases for more flexible maintenance planning.

In terms of using PHM information in operational maintenance improvement, the following works are relevant to the problem treated here. Although they do not solve the routing problem of aircraft operations, PAPAKOSTAS, et al., (2010) are the first authors encountered here that use RUL to improve maintenance planning at an operational level. RODRIGUES, et al., (2012) first study the possibilities of improvements in aircraft operations due to the use of PHM techniques. Later, RODRIGUES, et al., (2014) use PHM information to optimize aircraft maintenance planning. None of these works, however, incorporate this into the aircraft maintenance routing problem.

Table I presents a summary of the most relevant works studied here.

Table I – Literature Review

Authors	Data type	Solution Method	Focus	Contribution
CLARKE et al., 1997	Commercial	Lagrangian relaxation	Model to maximize profit	Use of all connections for maintenance routing
MAK & BOLAND, 2000	Generated	Simulated annealing	Solution method to minimize total cost	Use of meta-heuristics to solve ATSP with replenishment arcs
MARTIN et al., 2003	Business	CPLEX	Model that minimizes operating costs considering maintenance and crew restrictions	Merge crew schedule and aircraft schedule by using crew and maintenance restrictions in preprocessing of feasible routes
GRONKVIST, 2005	Commercial	Constraint programming	Integrating solution methods	Use of CP in aircraft assignment, integration of CP and CG and tests on real data.
HICKS et al., 2005	Business	Column generation	Model that minimizes connections costs by allowing flexible departure times	Constraint and cost factor modelling
YAO et al., 2005	Business	CPLEX	Finding optimal crew and aircraft pairings	Use of set partitioning to optimize crew and aircraft pairings
YANG et al., 2008	Business	CPLEX, Heuristic	Model that minimizes empty flight hours	Development of a module for a decision support tool
YAO et al., 2008	Business	Column generation	Model that minimizes operating costs considering maintenance and crew restrictions and non-owner flights	Considering demands from customers that are not fractional owners and unscheduled maintenance.
PAPAKOSTAS et al., 2010	Commercial	Multi-criteria evaluation	Model that minimizes cost and flight delay focusing on short-term decision making and line maintenance	Model that improves line maintenance based on health assessment, flight delays, costs and operational risks.
LIANG & CHAOVALITWONGSE, 2012	Commercial	MILP	Model that minimizes connection costs focusing on weekly schedules and integrating fleet assignment	Novel weekly rotation-tour network representation.

DIAZ-RAMÍREZ et al., 2013	Low-cost commercial	Greedy and longest path heuristics	Model that maximizes profit and merges flight scheduling and aircraft routing	Simultaneous solution of the flight scheduling and AMRP.
BASDERE & BILGE, 2014	Commercial	B&B and compressed annealing	Model that maximizes utilization of remaining flying time	Agile methodology to find maintenance feasible routes.
KOZANIDIS et al., 2014	Generated	Developed heuristic	Solution method to minimize number of aircraft and residual flight times	Development of heuristic algorithms to solve the AMRP.
GAVRANIS & KOZANIDIS, 2015	Generated/ Military	MILP	Solution method to maximize available flight hours of a fleet	Development of exact algorithm to solve AMRP.
LIANG et al., 2015	Commercial	Column generation	Model that minimizes expected propagated delay	Model complex and nonlinear cost functions and accurate calculation of expected delays.
AL-THANI et al., 2016	Commercial	MILP	Model that minimizes remaining flying time of aircraft	Exact mixed-integer model with graph reduction procedure and variable neighborhood search algorithm to solve AMRP.
ELTOUKHY et al., 2017b	Commercial	Metaheuristics (ACO, GA, SA)	Model that maximizes profit	Maintenance restrictions with work force availability considerations and development of novel algorithm.
SAFAEI & JARDINE, 2017	Commercial	Branch and bound	Model that minimizes maintenance misalignment	Novel decision approach to minimize maintenance misalignment.
ELTOUKHY et al., 2018a	Commercial	MILP	Model that maximizes profit minus penalties for exceeding maintenance workshop capacity	Develop model and solution algorithm considering all operational maintenance requirements.
ELTOUKHY et al., 2018b	Commercial	Metaheuristics (ACO)	Model that minimizes propagated delay and maintenance workforce	Scenario-based approach to deal with uncertainties in propagated delay and merge the AMRP with the maintenance staffing problem
MAHER et al., 2018	Commercial	Column generation	Solution approaches for the one-day-TAP	Development of an iterative algorithm that reduces the computational effort for one-day TAP.

MARLA et al., 2018	Commercial	CPLEX	Model that minimizes delay propagation	Develop and compare uncertainty models in robust aircraft routing
MUNARI & ALVAREZ, 2019	Business	CPLEX	Model that minimizes connection costs by anticipating/postponing flights and maintenance events	Inclusion of service upgrade possibility and anticipating/postponing flights and maintenance events
ELTOUKHY et al., 2019	Commercial	Metaheuristics (ACO)	Model that reduces propagated delay by reducing TAT	Novel model that considers TAT reductions to reduce propagated delay
This work	Business	GUROBI	Minimize deadhead connection flights while reducing maintenance costs.	Flexible time windows for preventive maintenance, allowing an active planning of preventive maintenance, and the incorporation of PHM information in route planning

3 Methodology and Modelling

Given the problem scenario described in the introduction and literature review presented in chapter two, a routing model is developed, such that it takes into consideration specific points of fractional fleet operations and relevant maintenance issues to plan efficient aircraft maintenance routing solutions.

Ideally, there would be no deadhead connection flights between requests in the final planning, as is the case for most commercial airline operations. This is not, however, a realistic assumption for fractional operators as flight origins and destinations rarely coincide in a convenient time window. Thus, our main objective is to minimize the connection flights in our formulation, while simultaneously finding better maintenance opportunities.

One of the most common considerations in previous works, especially the ones treating commercial aviation cases, is the need to return to a home base. From the literature, this characteristic aids operators in building cyclical routes and use overnight maintenance to their advantage. For fractional fleet operations, however, this would add another repositioning flight to the schedule without any benefit, since there is no guarantee that a flight will be requested from that maintenance base and overnight maintenance is not a critical aspect of this type of operation.

By treating flight hour-based and calendar-based preventive maintenance separately, greater flexibility in maintenance planning is possible. Although the preventive maintenance cost itself cannot be avoided, the maintenance location can be chosen so that repositioning costs can be reduced by choosing more convenient maintenance bases at a better time. This also helps improve the utilization of aircraft since they will only stop for maintenance once they are close to their utilization limits, avoiding unused flight hours in the case of flight hour-based maintenance.

Another cost driver in fractional operations is corrective maintenance. This happens because these maintenance situations usually cannot be accurately predicted and therefore have a greater repair cost if a maintenance team, equipment, and parts need to be transported outside of a maintenance base. Most authors do not touch upon this topic in previous works, with the exception of (Yao, et al., 2008). They generate corrective maintenance events during operation and resolve the routing problem considering the consequences of the maintenance events. Instead of this type of reactive approach, a more proactive way of dealing with corrective maintenance events is proposed. Since modern aircraft provide more data that can be used in failure prognostics information, a new opportunity to improve operational cost reduction is presented.

After analyzing and testing exact and metaheuristic approaches to solving the AMRP, it was decided that an exact solution was viable for the proposed instances and thus, more beneficial for this work. Therefore, it was decided that the approximate methods would not be used in the remainder of this work.This is in line with the works featured in the literature review, where all works treating business aviation tend to use exact methods. The works that use approximate solution methods are focused on commercial aviation that usually presents much larger cases. A flowchart of the thesis is presented in List 1, with a brief overview of each chapter.

Introduction – The overall aircraft routing scenario is studied and the research problem is identified.
Literature Review – An analysis of relevant works was done to determine what has already been done and how previous authors approached the AMRP and other topics, explicating the research problem as a real gap to be treated in this work..
Methodology – The methodological approach is explained along with the model presentation and experiment designs.
Methodology Application – Experiments are done as specified in the previous stage in order to analyze the proposed model.
Conclusion – The conclusion of the work is presented, pinpointing the relevant findings.

List 1 – Structural flowchart of this work

The third part of List 1 is further expanded upon in List 2. This chapter follows the points cited in this list, explaining how the problem is formulated, the process to develop the model and the tests. The application of the model and the tests are then detailed.

Problem modelling – The AMRP is adapted for the specific case of fractional fleet operations, expliciting the details that set it apart from commercial aviation operations.
Problem Solution and Model Development – The reasoning behind solution method and model design are presented.
Experiment design – The experiments used to test the proposed hypothesis are detailed, and explained how they do this.
Model aplication and Scope – The assumptions and limitations of the model are presented with the mathematical formulation, detailing how the model was applied to each case.

List 2 – Methodology flowchart

Rolling time windows is an efficient strategy, presented in the literature, to simulate operations in a longer period of time, especially for a scenario as dynamic as fractional fleet operations. The rolling time windows also perform well given the considerations of evolving system conditions.

The failure probabilities used in this study come from a classification and regression tree machine-learning algorithm. This algorithm uses historical data from a central maintenance computer as well as failure occurrences from pilot reports and maintenance reports to estimate the failure probabilities. A simplified diagram of the process used to obtain the prognostics information is presented in Figure 4. This method was based on the solution proposed in (Baptista, et al., 2016). The probabilities were updated after new data was collected in real operations.

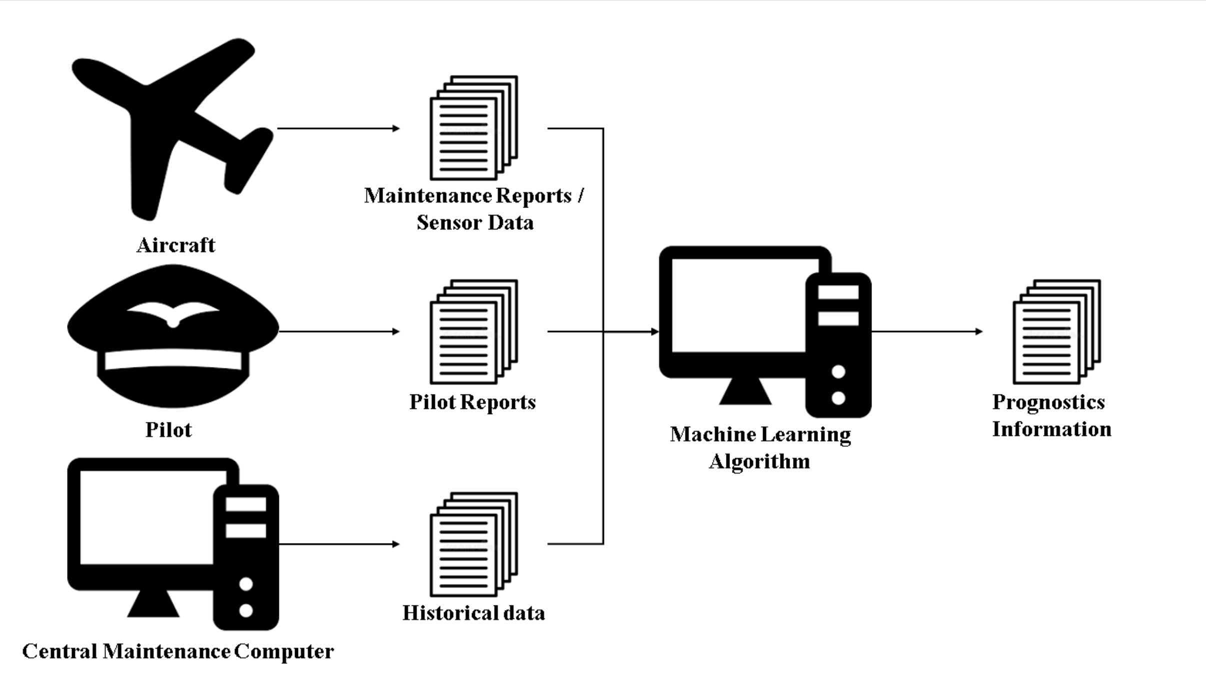


Figure 4 – Diagram of how prognostics information is obtained

Since the messages generated by the actual aircraft cannot be simulated in this study, an evolution of the failure probabilities after each completed mission is considered. This was the chosen criteria because it better adheres to this situation, rather than considering the evolution of failure probabilities with time.

This type of PHM information is relatively new in the airline industry and therefore, many other methods can be used to evaluate RUL. However, as stated before, RUL calculations are not exact and the inherent uncertainties of this type of information result in probability distributions similar to the ones presented in the next chapter. Thus, this information input can be modified to fit available information provided by various PHM systems.

The parameters used to compare the solutions of the proposed models are overall operating costs, maintenance costs, and deadhead flight hours. With these metrics, the benefits of prioritizing maintenance costs over relocation costs can be analyzed efficiently.

The following pseudo-code explains the process used to solve the AMRP.

```
General pseudo-code

Import input data (demand list, aircraft status, maintenance information)
Define initial parameters
For i in RollingTimeWindow:
    Define preventive maintenance activities and opportunistic flights
    Build connection cost matrix
```

Build objective function vector

Build contraint vectors and matrices

Build the model

Solve the model

Save flights from day of planning

Save maintenance activities performed

Verify fault occurences and canceled flights

Update aircraft status

Save planned day in global variable

Update PHM information

End for

Print and save results

3.1 Homogeneous fleet

The first experiment focuses on the most likely mode of fractional fleet operations, homogeneous fleets. As explained previously, flyers will usually have access to a fleet of a certain model or type of aircraft that is treated as a homogeneous fleet. Four aircraft routing models are used to solve the real and generated instances tested here. First, there is the shortest path heuristic, where the flights are planned according to their departure dates and are sequentially allocated to the aircraft that is nearest to the origin of each flight. For simplicity, we denominate this approach as a naïve model that simulates intuitive planning that may be required of an operation planner without many resources. Next comes the standard model that optimizes the routing solution considering preventive maintenance restrictions.

The last two models use different strategies to incorporate PHM information into the route and maintenance planning. The model defined in equations 15 and 16 will be referred to as the risk-based model, while and the one defined in equation 17 will be referred to as the preferential model. The risk model results will be referred to in the next section by their α values and the preferential model as “max” and “safe”, depending on the strategy used. The α values indicate the tuning parameter of how strongly the risk factor is taken into account during planning. Preferential max is the case when the critical date of the failure is the most probable failure date of the RUL distribution and preferential safe is the conservative approach when the critical date is the first date that presents a failure probability in the RUL distribution. The $\alpha =$

0 cases presented indicate the results from the standard formulation represented by equations 1 to 14. This is the nomenclature maintained throughout all of the experiments.

The results focus on the total cost, maintenance cost, deadhead hours, and processing time of the solutions of each method. Given a large amount of data, a statistical analysis of the instances is done. This allows to see if these models are consistent throughout the different flight configurations. By doing this, the performance of each model can be analyzed and a comparative study will show which one better adheres to the fractional fleet cases. From the maintenance costs and deadhead hours of the results, the maintenance opportunities found in each of the models can be observed as well as the extended flight hours needed to use them.

3.2 Heterogeneous fleets

Although fractional fleet operations tend to be more analogous to homogeneous fleets, there are some cases where a heterogeneous fleet approach is more advantageous. The option of upgrading clients to larger and more expensive aircraft may lead to a less costly routing solution. In cases where one of these larger aircraft will already be at the origin of a demanded flight and the contracted aircraft type is not able to service that client or the repositioning costs become greater than flying the more costly aircraft.

The next experiment explores this aspect of fractional fleet operations. Here, one of the conditions usually provided by fractional fleet operators is evaluated, the possibility of upgrading clients to larger aircraft in the event that a contracted model is not available or it is a cost-effective choice for the operator. To model this more realistic case and verify the effectiveness of the models in handling mixed fleets, the alternative to upgrade flyers to a larger aircraft is tested. In this scenario, two aircraft, of a different type, are added to the fleet along with a list of flights exclusive to them. Because these aircraft are larger than the ones in the rest of the fleet, they cost more to operate and the flights associated with them cannot be flown by the rest of the fleet. However, these aircraft may operate any of the other flights when allowing client upgrades. In other words, while some flyers may be upgraded to larger aircraft, downgrading from a larger aircraft to a smaller one is not allowed, as is usually the case in fractional fleet operations. The upgrading possibility is then tested against treating each fleet separately.

In the case where the fleet of larger aircraft presents maintenance needs, it is intuitive that by opening more flight options for these aircraft, by allowing upgrades, their maintenance costs may reduce. The contrary, however, is not true. Therefore, this condition can be studied; if it is worthwhile to allow upgrading at the cost of losing maintenance opportunities for the fleet of smaller aircraft.

Like the previous experiments, the naïve, standard, preferential, and risk-based models are tested in this new scenario. The total cost, maintenance cost, deadhead hours, and processing time provide information about the tendencies of allowing or not upgrades at the cost of losing maintenance opportunities.

3.3 Uncertainty analysis

As was stated previously, the RUL of a monitored system of the aircraft is not an exact science, but a calculated prediction of system behavior given the data of previous operations and expected future usage. Because of this, the time at which failure will occur cannot be assured, so it is important to understand the models' behavior in this uncertain scenario. The behavior of the models with the failure occurring at different dates according to the expected RUL is analyzed. The naïve routing model is not included in this analysis since it does not provide efficient routing solutions. For the risk-based solution model, only the two best performing values of α from the previous tests are used.

The preferential model and risk-based model results are then compared to the standard model to verify the variance that including PHM information brings in costs and flight hours. From this, the effects of the uncertainty of the estimated RUL distribution can be measured and the relevance of the changes in routing solutions can be analyzed.

3.4 Sensitivity analysis

The cost-benefit nature of the approach studied in this work will always leave one question in mind: is it worth spending more money on flying hours to save money on maintenance costs? In order to analyze this, a sensitivity analysis is performed on the tested cases. First, the relation between the possible cost reduction in corrective maintenance and the deadhead cost increase based on the flight hour cost is studied. This provides a clearer image of when it would be more or less effective to focus on maintenance efficient routing. However, the cost of the flight hour is not the only factor that needs to be taken into consideration in cases like these. Some operators may tend to fly more hours in general, which will result in flight hour costs having a greater impact on overall costs, while others may have more limited maintenance infrastructure or more costly aircraft to maintain, leading to maintenance costs having more influence on total costs.

To tackle this limitation, some of these variables are parameterized in relation to the duration of contracted flight hours in the planning period. The only two variables in this planning scenario that can be easily estimated are the possible savings in maintenance cost, via the comparison of in-base and out-of-base maintenance, and contracted flight duration, from the demand list. From here, an expected increase in deadhead cost can be determined. The operations profile of the various scenarios are analyzed and a ratio of deadhead hours to contracted hours is determined. From the previous experiment, an average cost variance for both deadhead hours and corrective maintenance for the real-world operator's mission profile is established. Given that this generalization depends on parameters specific to the case at hand, to expand this analysis to other operators, a study of their operating profiles must be carried out to tune the analysis to each case, including the analysis for a fleet of different aircraft.

3.5 Scope

In order to limit the scope of this work and establish a clear operating scenario of the AMRP, some assumptions and limitations are used and presented below:

Assumptions:

- The position and schedule of each aircraft is known at the moment of planning;
- Customer requests can be accepted as soon as six hours prior to departure;
- The flight time between each base is known;
- After a constant TAT, the aircraft will be ready for take-off;
- Connection between every base is permitted;
- Only one aircraft can attend each flight;
- Failure probabilities for each aircraft are updated on each day of planning depending on usage.

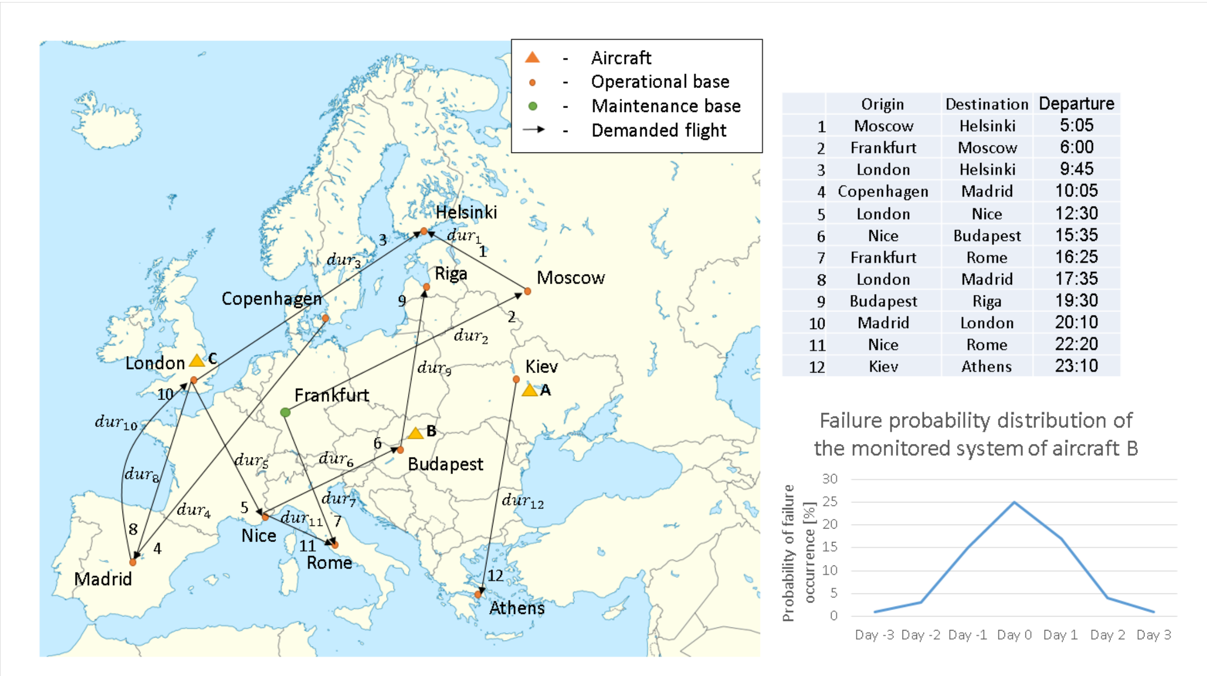
Limitations:

- The inability to attend a flight will incur a cancellation fee for the operator;
- The fleet is composed of only one type of aircraft in the basic cases and two types of aircraft in the extended cases;
- Routes are planned for a three-day time window;

- A rolling time window is used in planning;
- Only one failure occurs at a time;
- Maintenance activities are performed in sequence;
- Monitored failure occurrences result in aircraft-on-ground (AOG) events, being the aircraft able to arrive at its destination but unable to take-off until maintenance is done;
- Costs are constant for maintenance events and canceled flights;

3.6 Problem representation and mathematical formulation

To better explain the problem treated in this thesis, Figure 5 to Figure 8 detail a simple operation example comprised of three aircraft and twelve flights during one day. In Figure 5, the flights are shown on the map through the black arrows. The operation-only bases are represented by orange circles and maintenance /operation bases by green circles. The triangles represent the starting base of each aircraft at the beginning of planning. On the right side of the figure, next to the map is the demand list with origin, destination and departure times for each flight, and a graph showing the expected RUL distribution provided by the monitoring system of aircraft B. On the expected RUL distribution graph day 0 represents the current being planned.



	Origin	Destination	Departure
1	Moscow	Helsinki	5:05
2	Frankfurt	Moscow	6:00
3	London	Helsinki	9:45
4	Copenhagen	Madrid	10:05
5	London	Nice	12:30
6	Nice	Budapest	15:35
7	Frankfurt	Rome	16:25
8	London	Madrid	17:35
9	Budapest	Riga	19:30
10	Madrid	London	20:10
11	Nice	Rome	22:20
12	Kiev	Athens	23:10

Figure 5 – Example of demanded flights and expected RUL distribution

The following figures show possible solutions for the routing and aircraft allocation in this scenario, using naïve, shortest route optimized, and maintenance-optimized approaches. In addition to the graph elements stated before, the deadhead repositioning flights are identified by the orange, green and blue arrows, associated with aircraft A, B, and C, respectively. Canceled flights are identified by red arrows and the aircraft failure by a yellow star. Next to the graphs are a table indicating the flight routes of each aircraft, information regarding the solution, and a Gannt chart of each of the aircraft activities. The solution information includes the deadhead repositioning time, and cost, failure moment and corrective maintenance cost as well as the total cost of the routing solutions. The Gannt charts show the aircraft activities through the planned day, where the gray blocks represent the demanded flights and the orange, green and blue blocks represent the deadhead reposition flights for aircraft A, B, and C, respectively. Similar to the charts, the yellow blocks represent the failure and lead-time to fix the error and the red blocks represent canceled flights.

Starting with the naïve approach in Figure 6, there is a possibility of flights being canceled simply due to inefficient planning. Better routing alternatives can be missed by not looking ahead while planning and identifying shorter connection flights. This reflects on the total deadhead hours of this approach when compared to the other two. Additionally, by not considering the possibility of failure identified by the aircraft's monitoring system, there is an AOG event outside of a maintenance base resulting in higher maintenance costs. Overall, the costs of this approach are significantly higher than the other two exemplified here.

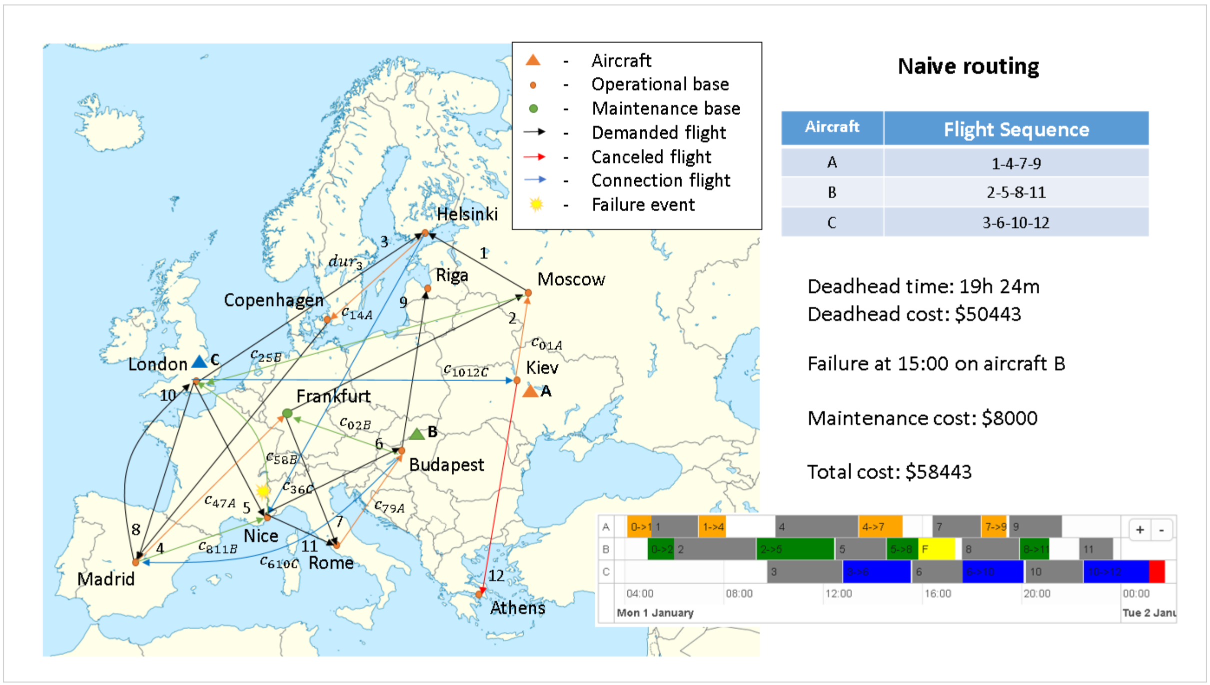


Figure 6 – Naïve routing solution

Figure 7, on the other hand, presents an approach optimized for the route with the shortest connections. Compared to the other two approaches, it has the least deadhead time, resulting in much less deadhead cost. However, by overlooking the possible failure, signaled for aircraft B, this aircraft had the largest flight load to carry out. In this case, the failure occurred during daily operation and resulted in a canceled flight. Apart from the canceled flight, the aircraft was also outside of a maintenance base leading to a more costly and longer repair.

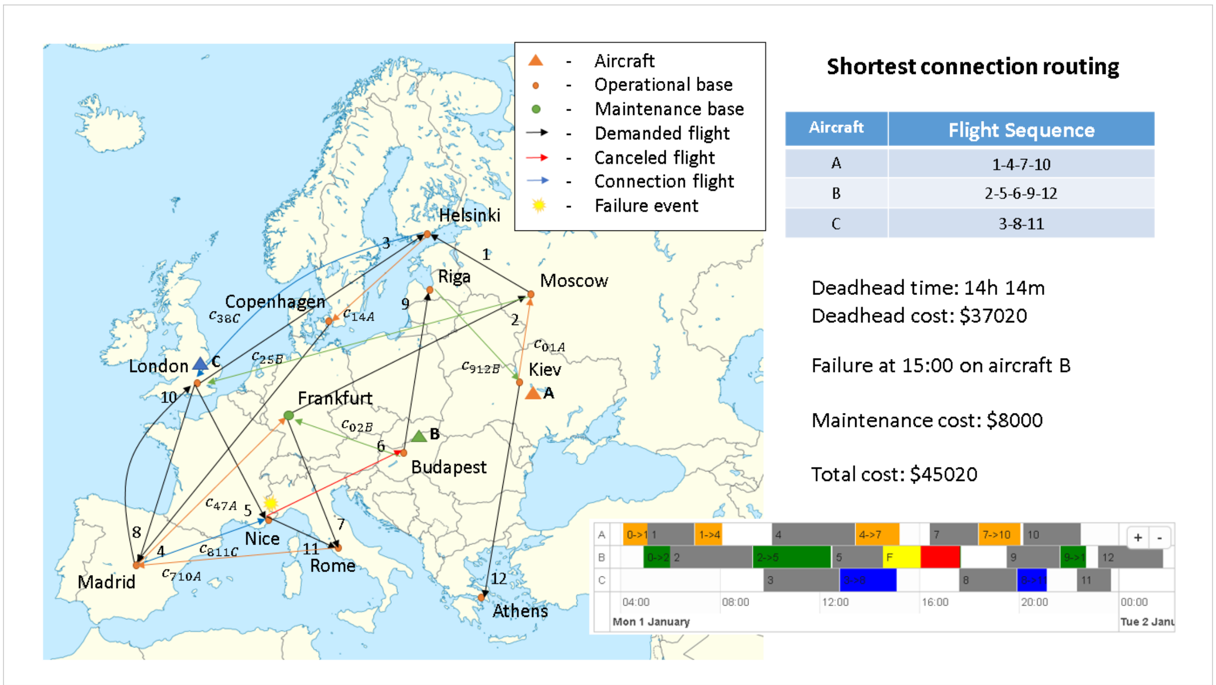


Figure 7 – Shortest connection routing solution

Following the hypothesis presented previously, Figure 8 shows a maintenance optimized routing solution. This approach sacrifices the shortest route to find better opportunities for maintenance activities. Given the knowledge supplied by the aircraft monitoring system, this approach uses flight passing through maintenance bases as opportunities in anticipation of possible corrective maintenances. In finding such an opportunity in this case, the repair cost and time are reduced albeit at the cost of more deadhead time. Although the planes flew more, the savings in maintenance costs resulted in an overall less expensive solution when compared to the other approaches.

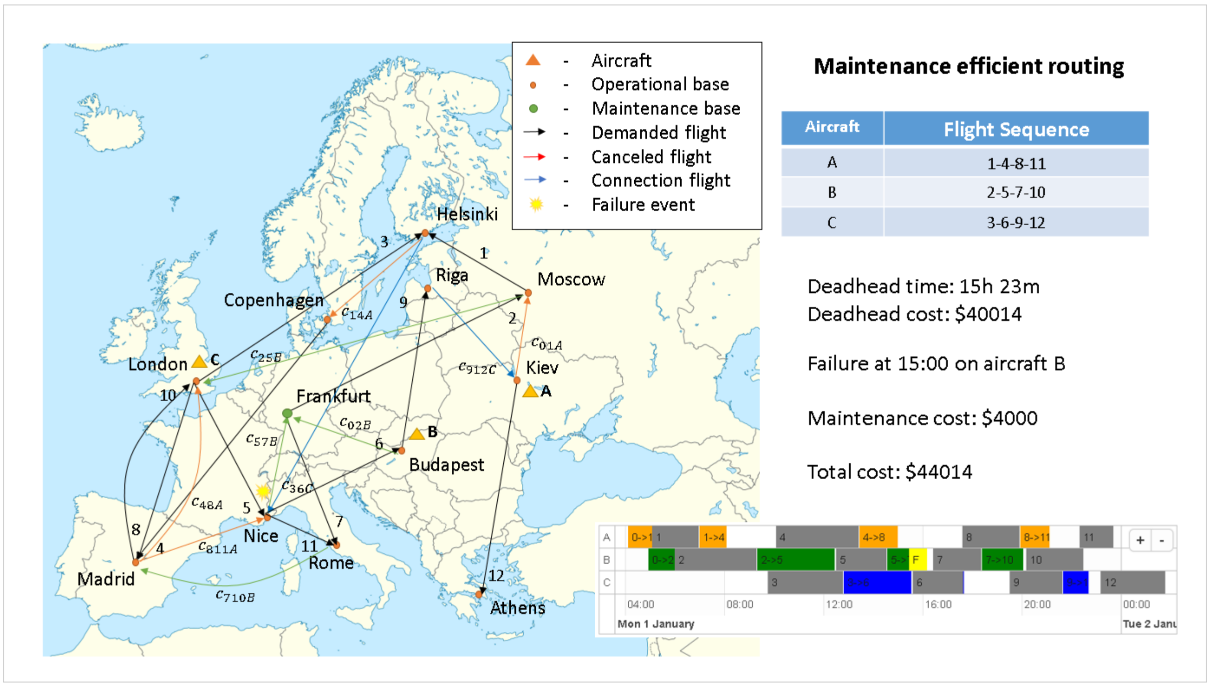


Figure 8 – Maintenance efficient routing solution

In order to explain the mathematical formulation, the parameters are presented below divided in sets, parameters, and decision variables.

Sets:

F Set of demanded flights that must be accomplished

F' Set of demanded flights that must be accomplished including the origin bases of the aircraft

M Set of maintenance activities that need to be performed

A Set of demanded flights and maintenance activities, $F \cup M$.

A' Set of demanded flights including aircraft origin bases and maintenance activities, $F' \cup M$.

T Set of aircraft available in planning.

O Set of opportunistic demanded flights, whose destination is a maintenance base.

$F1$ Set of demanded flights specific to fleet of aircraft type 1

$F2$ Set of demanded flights specific to fleet of aircraft type 2

$T1$ Set of type 1 aircraft (smaller aircraft)

$T2$ Set of type 2 aircraft (larger aircraft)

Parameters:

c_{ijt} Flight time for aircraft t to connect from activity i to activity j.

dur_j Duration of flight j.

$C_{FH,t}$ Cost per flight hour of aircraft t.

C_c Cost per canceled flight.

N_{tot} Total number of demanded flights.

K_{ijt} Large value such that the constraint is not imposed unless $x_{ijt} = 1$.

a_j Lower bound of the time window for activity j.

b_j Upper bound of the time window for activity j.

$K2_{ijt}$ Large value such that the constraint is not imposed unless $x_{ijt} = 1$.

lim_t Flight hours limit for aircraft t before it has to stop for maintenance.

FH_t Initial accumulated flight hours for aircraft t.

α Tuning parameter to modify the influence of the risk index.

R_{ijt} Risk index associated to aircraft t operating flight i followed by flight j.

P_{ijt} Failure probability associated to aircraft t operating flight i followed by flight j.

C_{cor} Additional cost of out-of-base corrective maintenance.

f_{jt} Factor that encourages opportunistic flights j for aircraft t.

Decision variables

x_{ijt} Binary variable equal to 1 if flight j is flown after flight i by aircraft t and 0 otherwise.

N_c Integer variable indicating the number of canceled flights.

s_{it} Time window at which activity i is started by aircraft t.

y_{it} Accumulated flight hours of aircraft t after it finishes activity i.

The mathematical formulation is described below starting with the objective function, Equation 1. This objective function aims to minimize the total costs of connections between flights and canceled flights. In the formulation,

$$min \sum_{t \in T} \sum_{i \in F\prime} \sum_{j \in F} (C_{FH,t}\big(c_{ijt} + dur_j\big)x_{ijt}) + N_c\, C_c \tag{1}$$

where, x_{ijt} is a binary variable equal to 1 if aircraft t operates flight i followed by flight j and zero otherwise. The flight hours to connect from flight i to flight j and the duration of flight j are represented by c_{ijt} and dur_j, respectively. The number of canceled flights is determined by the variable N_c. C_{FH} is the cost per flight hour and C_c is the cost for a canceled flight. T is the set of aircraft available to fly. F is the set of flights and F' is the set of flights including the origin of each aircraft.

Constraints 2 are restrictions that guarantee that each flight is flown once and by only one aircraft.

$$\sum_{t \in T} \sum_{i \in F\prime} x_{ijt} = 1, \quad \forall j \in F \tag{2}$$

The continuity constraints defined by Constraints 3 ensure that an aircraft connecting to a given flight also connects from it.

$$\sum_{j \in F} x_{ijt} - \sum_{j \in F} x_{jit} \geq 0, \quad \forall i \in F', \forall t \in T \tag{3}$$

Constraints 4 makes it so that each aircraft departs from its position at the beginning of the planning period.

$$\sum_{j \in F} x_{ijt} \leq 1, \quad i = 0, \ \forall t \in T \tag{4}$$

Constraint 5 identifies the number of canceled flights by making the sum of canceled flights, N_c, and operated flights, x_{ijt}, are equal to the total number of flights, N_{tot}.

$$N_c + \sum_{t \in T} \sum_{i \in F\prime} \sum_{j \in F} x_{ijt} = N_{tot} \tag{5}$$

To establish that each maintenance activity will only be performed once and at a single maintenance base there are Constraints 6.

$$\sum_{j\in M} x_{ijt} \leq 1, \quad \forall i \in F', \forall t \in T \tag{6}$$

where The connections to maintenance bases are given in set M.

Constraints 7 set the time windows for each flight while Constraints 8 and 9 set the respective lower and upper bounds of the time windows.

$$s_{it} + c_{ijt} + dur_i + K_{ijt}(x_{ijt} - 1) - s_{jt} \leq 0, \\ \forall i \in A', \forall j \in A, \forall t \in T \tag{7}$$

$$a_j \sum_{i\in A'} x_{ijt} \leq s_{jt}, \quad \forall j \in A, \forall t \in T \tag{8}$$

$$b_j \sum_{j\in F} x_{ijt} \geq s_{jt}, \quad \forall j \in A, \forall t \in T \tag{9}$$

where A and A' represent the union of M with F and F', respectively. In these equations s_{it} and s_{jt} are the time windows at which aircraft t starts flight i and j, respectively. The duration of flight i is expressed as dur_i. K_{ijt} is a large enough number such that Constraints 7 is deactivated when $x_{ijt} = 0$ and is given by $K_{ijt} = c_{ijt} + dur_i + a_i + s_i$.

The initial time windows are fixed by Constraints 10.

$$s_{0t} = 0, \ \forall t \in T \tag{10}$$

Constraints 11 determines the flight hours accumulated by each aircraft given the allocated flights.

$$y_{it} + c_{ijt} + dur_i + K2_{ijt}(x_{ijt} - 1) - y_{jt} \leq 0, \\ \forall i \in A', \forall j \in A, \forall t \in T \tag{11}$$

where, y_{it} indicates the previously accumulated flight hours since completing flight i and y_{jt} the accumulated flight hours after completing flight j for aircraft t. Analogous to K_{ijt}, $K2_{ijt} = y_{it} + c_{ijt} + dur_i + lim_t$.

Constraints 12 prohibit the accumulated flight hours from exceeding the utilization limit of each aircraft, where lim_t is the maximum flight hours each aircraft t is allowed to fly before needing preventive maintenance.

$$lim_t \sum_{i \in A} x_{ijt} \geq y_{jt}, \quad \forall j \in A, \, \forall t \in T \tag{12}$$

The accumulated flight hours of each aircraft at the start of planning is set in Constraints 13, FH_t is the known accumulated flight hours of each aircraft t.

$$y_{0t} = FH_t, \;\; \forall t \in T \tag{13}$$

Constraints 6 to 13 also set this model apart from previous works as they distinguish calendar and flight hour-based preventive maintenance giving each a distinct window to be accomplished based on aircraft usage and date. In previous works, such as MUNARI & ALVAREZ, (2019), the maintenance restrictions do not consider the available lfight hours available to each aircraft, but use a predetermined limit for maintance events. This allows for greater flexibility in maintenance planning and also permits that aircraft return to service after maintenance is completed.

Equations 14 set the decision variables x_{ijt} as binary.

$$x_{ijt} \in \{0,1\}, \quad \forall i \in F', \, \forall j \in F, \, \forall t \in T \tag{14}$$

Equations 1 to 14 define the standard planning model stated in the next chapter. Although the maintenance constraints, equations 6 to 13, differ from models previously developed by other authors, this formulation does not consider failure prognostics information in the planning process.

In order to introduce this innovative characteristic into the model, the objective function is modified by introducing a third term including a risk index associated to each flight leg, based on the approach presented by CUNEO et al., (2018). The objective function in Equation 1 is then replaced by Equation 15, setting the proposed model apart from previous works that do not consider failure prognostics information.

$$min \sum_{t \in T} \sum_{i \in F'} \sum_{j \in F} (C_{FH,t}\left(c_{ijt} + dur_j\right) x_{ijt}) + N_c \, C_c \; + \sum_{t \in T} \sum_{i \in F'} \sum_{j \in F} \alpha R_{ijt} x_{ijt} \tag{15}$$

The risk index R_{ijt} is defined in Equation 16 as the probability of a failure occurrence, P_{ijt}, times its expected additional cost, C_{cor}, and α is a tuning parameter to vary the importance of the risk index in each solution. The expected additional cost, C_{cor}, is the difference between the in-base repair costs of an AOG event and the out-of-base repair cost of the same event.

$$R_{ijt} = P_{ijt}C_{cor} \tag{16}$$

A second approach developed by the author is the use of prioritizing opportunistic flight legs in an attempt to reduce maintenance costs. To do this, the objective function, Equation 1 is replaced with Equation 17.

$$\begin{aligned} \boldsymbol{min} \sum_{t\in T} \sum_{i\in F'} \sum_{j\in F} (\boldsymbol{C_{FH,t}}(\boldsymbol{c_{ijt}} + \boldsymbol{dur_j})\boldsymbol{x_{ijt}}) + \boldsymbol{N_c}\, \boldsymbol{C_c} \\ - \sum_{t\in T_O} \sum_{i\in F'} \sum_{j\in O} (\boldsymbol{C_{FH,t}}(\boldsymbol{c_{ijt}} + \boldsymbol{dur_j})\boldsymbol{f_{jt}}\, \boldsymbol{x_{ijt}}) \end{aligned} \tag{17}$$

where, O is a subset of F containing flights whose destination coincides with a maintenance base such that $O \subset F$, in other words, opportunistic flight legs. Similarly, T_O is a subset of $T_O \subset T$, containing the aircraft that present failure estimations in the planning period. f_{jt} is a factor by which the costs of flight x_{ijt} is reduced proportionally to its proximity to the expected failure event. These opportunistic flights are considered the flights before a predefined critical date.

Two corrective maintenance events are considered in order to verify the effectiveness of associating risk indexes to the routes. These events are relative to flap failures, which do not force the aircraft to perform an emergency landing but once on the ground, the aircraft cannot take off until the failure is fixed. This activity can be done at any base, however, in a maintenance base, the cost and lead-time for repair are significantly lower.

To analyze the effects of the risk associated with each path, α varied from 0 to 1 in intervals of 0.2. An α of zero represents the baseline for comparison, or a model without the influence of associated risks, while a value of one represents a strong influence of associated risk in the overall solution.

The rolling time windows mentioned previously can be defined as a fixed planning period that shifts after each day has passed. A planning horizon of three days is considered in this study. This is to help simulate real-world operations, where each day the flights for the following three days are determined.

The failure probability information is updated after each mission flown by aircraft, considering that the usage of the aircraft affects the failure prediction. This assumption is made because it is normal to collect flight data from the aircraft after each flight and thus, with new data, the failure prognostics algorithm is updated.

When considering heterogeneous fleets, the set of demanded flights, F, is split into two different sets, $F1$ and $F2$. In the case of this work, a fleet with two different types of aircraft, each one associated with a specific demand set is considered. Since F is equivalent to $F1 \cup F2$, set A is therefore defined as $F1 \cup F2 \cup M$. Analogously, sets F' and A' follow the same reasoning. Furthermore, set T is also split into subsets $T1$ and $T2$.

Although these changes do not affect the previous formulation of the standard, preferential, and risk-based models, another set of constraints to control whether client upgrades are allowed or not in the planning must be included. First, to allow upgrades in planning, Constraints 18 and 19 are included in the previous formulation. Second, to prevent upgrades, Constraints 18 to 21 are included in the previous formulation.

$$\sum_{j \in F2} \sum_{t \in T1} x_{0jt} = 0 \tag{18}$$

$$\sum_{i \in F1} \sum_{j \in F2} \sum_{t \in T1} x_{ijt} = 0 \tag{19}$$

$$\sum_{j \in F1} \sum_{t \in T2} x_{0jt} = 0 \tag{20}$$

$$\sum_{i \in F2} \sum_{j \in F1} \sum_{t \in T2} x_{ijt} = 0 \tag{21}$$

Table II provides a brief summary of the mathematical formulation.

Table II – Description of equations

Eq	Description
1	OF: Minimize total cost of connection flights and canceled flights
2	All flights are operated by only one aircraft
3	Connection flights connect to and from each assigned flight
4	All aircraft initially depart from their origin base at the beginning of the planning period
5	Verify the number of canceled flights

6	All maintenance activities will be performed only once and only at one maintenance base
7	Sets the time window for flights and maintenance events
8	Sets the lower bound of each time window
9	Sets the upper bound of each time window
10	Set the starting time window for each aircraft
11	Sum the accumulated flight hours for each aircraft
12	Prevents aircraft from exceeding flight hours limits
13	Set the initial FH for each aircraft
14	Defines the decision variable as binary
15	Modified OF for the risk-based approach
16	Defines the risk index associated to flight legs
17	Modified OF for the preferential approach
18	Prevents fleet 1 from operating flights specific to fleet 2 from origin base
19	Prevents fleet 1 from operating flights specific to fleet 2
20	Prevents fleet 2 from operating flights specific to fleet 1 from origin base
21	Prevents fleet 2 from operating flights specific to fleet 1

4 Results and Discussion

The numerical implementation was done using field data collected from a fractional fleet operator and generated instances, comprised of 13 instances. Each instance is composed of a set of demanded flights varying from 117 to 119 flights. These flights are then routed and distributed among 10 aircraft. The generated instances are of similar proportions to the real data case.

The case for mixed fleets and upgrading possibility includes 12 flights and two aircraft to each instance. These flights have a longer duration compared to those in the original instances and the new aircraft are more costly to operate since they are considered to be larger.

Each flight leg demanded has an origin, a destination, a departure time, and a duration. Turnaround time (TAT) after landing is assumed 45 minutes, and the flight time between the cities involved is also known. At the initial planning period, the position of each aircraft is known, as well as its accumulated flight hours.

The cost and repair time for corrective maintenance events in a maintenance base are 15000 monetary units and 5 hours while outside of maintenance bases they are 30000 monetary units and 12 hours, respectively.

The tests presented here were implemented and run in RStudio version 1.0.143 using an Intel Xeon 2.70 GHz desktop with 64 GB RAM, running Windows 7 Professional 64 bit operating system. Gurobi optimizer 8.1.1 was used to solve the real data and generated instances.

Table III presents the results obtained in one of the instances tested during the experiments of this thesis. Each line of the table represents one of the different methods tested here for the case of homogeneous fleets. The first column shows the number of canceled flights, next is the processing time for each method. The third and fourth columns are the deadhead flight hours and demanded flight hours, respectively. These values are coherent to what is stated by (Yao, et al., 2008), that up to 35% or more of the total operating flight hours are comprised of deadhead connection flights in the case of on-demand air travel. Finally, the last two columns are the maintenance cost and total cost of each solution.

Table III – Test results from an individual case

	Canceled flights	Processing time	Deadhead flight hours	Demanded flight hours	Maintenance Cost	Total Cost
Naïve	0	21.16	114.28	224.54	60000	937e3
Preferential max	0	52.87	97.51	224.54	45000	878e3
Preferential safe	0	46.7	100.39	224.54	45000	885e3
Standard	0	50.08	97.37	224.54	60000	886e3
$\alpha = 0.2$	0	50.61	97.67	224.54	30000	865e3
$\alpha = 0.4$	0	47.08	96.9	224.54	30000	856e3
$\alpha = 0.6$	0	54.14	96.65	224.54	60000	892e3
$\alpha = 0.8$	0	59.5	96.55	224.54	30000	862e3
$\alpha = 1$	0	60.78	97.85	224.54	30000	864e3

In this specific case shown here, the naïve and standard methods have the highest maintenance costs. This is because they fail to find maintenance opportunities to avoid out-of-base maintenance events. On the other hand, both the preferential model and the risk-based model found better maintenance opportunities, given the lower maintenance costs. These reduced maintenance costs allowed for a lower overall operating cost, as can be seen in the total costs in the table.

Table IV and Table V present the flight allocation of the results shown previously. Each of the columns is relative to one of the methods stated before. The lines indicate which flights were allocated to each aircraft, A to J, in each method. These flight lists follow the order in which each aircraft services the demanded flights.

The naïve method stands out from the rest of the solutions, as the allocation of flights to aircraft is very different from the optimized methods, especially the initially demanded flights. The other methods have many subsets of flight sequences in common, identifying efficient flight pairings. There are small differences among the allocation of the optimized methods, and these small changes are where the maintenance opportunities arise.

Table IV – Routing solutions for the tests shown in Table III

Aircraft	Naïve	Preferential max	Preferential safe	Standard
A	8-10-21-36-42-47-52-57-59-63-93-96-104-124-105-119	11-17-33-35-43-55-59-72-76-80-90-101-125	11-17-33-35-43-61-68-77-90-101-125	11-17-33-35-43-49-51-64-79-83-87-107-125
B	6-16-18-23-26-28-32-38-48-64-70-78-81-84-108-110-112	6-16-26-28-32-47-52-57-63-73-86-108-111-118	6-16-26-28-32-47-52-57-72-76-80-96-106-113-118	6-16-26-28-32-47-55-59-74-93-96-101-117
C	20-27-39-49-51-54-55-56-69-71-79-82-87-95	13-15-23-38-49-51-64-79-88-105-119	13-15-23-38-49-51-64-79-88-110-112	7-38-48-67-71-81-89-108-111-118
D	1-4-13-15-17-45-58-66-72-80-83-85-90-97-99-101-115	1-4-20-27-42-60-62-65-69-84-102-109-115	1-4-20-27-42-60-62-65-122-67-71-81-89-99-104-109-115	1-4-20-27-42-60-62-65-69-84-122-95-100-103-106-113-116
E	11-40-73-76-86-102-107	3-18-40-46-66-87-107	3-18-40-45-53-75-82-91-94-107	3-18-40-45-53-75-85-90-99-104-110-115
F	9-14-30-34-60-62-65-67-74-92-114	9-14-22-24-29-31-41-44-54-56-70-78-83-85-92	9-14-22-24-29-31-41-44-54-56-70-78-83-85-92-114	9-14-22-24-29-31-41-44-54-56-76-97-105-119
G	25-37-100-103-106-111-118	5-12-19-25-37-45-53-75-82-91-94-98-117	5-12-19-25-37-46-66-87-95-98-117	13-15-23-30-34-39-61-68-77-92-114
H	2-33-35-43-61-68-77-98-117	2-8-10-50-58-74-93-121-95-100-103-106-113-116	2-8-10-50-121-69-84-102-116	2-8-10-50-58-72-80-82-91-94-98
I	3-7-22-24-29-31-41-44-89-91-94-109-113-116	21-36-48-67-71-81-89-97-99-104-114	21-36-48-58-74-93-100-103-108-111	21-36-66-70-78-88
J	5-12-19-46-50-53-75-88	7-30-34-39-61-68-77-96-110-112	7-30-34-39-55-59-63-73-86-97-105-119	5-12-19-25-37-46-52-57-63-73-86-102-109-112

Table V – Routing solutions for the tests shown in Table III (cont.)

Aircraft	$\alpha = 0.2$	$\alpha = 0.4$	$\alpha = 0.6$	$\alpha = 0.8$	$\alpha = 1$
A	11-17-33-35-43-49-51-54-56-70-78-81-89-101-124-113-116	11-17-33-35-43-49-51-64-79-83-91-94-98-125	11-17-33-35-43-49-51-64-79-83-90-101-124-113-116	11-17-33-35-43-49-51-64-79-83-97-124-109-115	11-17-33-35-43-49-51-54-56-70-78-91-94-98-124-109
B	6-16-26-28-32-47-55-59-74-93-96-110-112	6-16-26-28-32-47-55-59-74-93-96-110-112	6-16-26-28-32-47-55-59-74-93-95-100-103-106	6-16-26-28-32-47-55-59-74-93-96-112	6-16-26-28-32-47-55-59-74-93-96-110-112
C	7-38-48-67-77-90-97-99-104-114	7-38-48-67-77-90-108-111-118	7-38-48-67-77-92-105-119	7-38-48-67-77-90-99-104-110-114	7-38-48-67-77-90-97-99-104-115
D	1-4-20-27-42-60-62-65-69-84-102-109-115	1-4-20-27-42-60-62-65-69-84-122-95-100-103-106-113-116	1-4-20-27-42-60-62-65-69-84-102-109-115	1-4-20-27-42-60-62-65-69-84-102-116	1-4-20-27-42-60-62-65-69-84-102-116
E	3-18-40-45-53-75-80-85-92-105-119	3-18-40-45-53-75-85-92-105-119	3-18-40-45-53-75-80-85-96-110-112	3-18-40-45-53-75-76-85-92-105-119	3-18-40-45-53-75-80-85-92-105-119
F	9-14-22-24-29-31-41-44-64-88	9-14-22-24-29-31-41-44-54-56-70-78-97-99-104-114	9-14-22-24-29-31-41-44-54-56-70-78-91-94-98-117	9-14-22-24-29-31-41-44-54-56-70-78-87-95-100-103-106	9-14-22-24-29-31-41-44-64-79-83-95-100-103-106
G	13-15-23-30-34-39-61-68-71-79-83-95-100-103-106	13-15-23-30-34-39-61-68-71-81-89-101-117	13-15-23-30-34-39-61-68-71-81-89-97-99-104-114	13-15-23-30-34-39-61-68-71-81-89-101-107-117	13-15-23-30-34-39-61-68-71-81-89-101-117
H	2-8-10-50-58-72-76-120-82-108-111-118	2-8-10-50-58-72-76-120-80-82-88	2-8-10-50-58-72-76-82-88	2-8-10-50-58-72-120-80-82-91-94-98	2-8-10-50-58-72-76-120-82-87-107
I	21-36-66-87-107	21-36-66-87-107	21-36-66-87-107	21-36-66-88	21-36-66-88-114
J	5-12-19-25-37-46-52-57-63-73-86-91-94-98-117	5-12-19-25-37-46-52-57-63-73-86-102-109-115	5-12-19-25-37-46-52-57-63-73-86-108-111-118	5-12-19-25-37-46-52-57-63-73-86-108-111-113-118	5-12-19-25-37-46-52-57-63-73-86-108-111-113-118

First, it is clear from the results in all cases that any strategic planning performs better than a naïve approach. Each column in Figure 9 to Figure 12 represents the average results from all tested cases and the error bars are the standard deviation of those averages. In terms of cost, the naïve approach performed the worst, having the largest total cost and failing to find opportunities to reduce maintenance costs. As for the standard planning model, because it optimizes the deadhead repositioning flights, it presents a better total cost than the naïve approach, but it still fails to find opportunities to reduce maintenance costs. This failure to find maintenance opportunities can be seen in Figure 10 where there is no dispersion in maintenance costs for both naïve and standard models, meaning that in all cases, all corrective maintenances were performed out-of-base.

Figure 9 and Figure 10 show that both proposed approaches provide better solutions than the standard planning model on average. More specifically, the preferential formulation finds the same maintenance opportunities independent of the critical date approach. The conservative approach, although very close to the maximum probability date approach, presents an average of more costly solutions. As mentioned previously, although one of these approaches is referred to as conservative, none of these models breach maintenance requirements by extending maintenance activities past their limits.

As for the risk-based model, most solutions provide better results when compared to the standard planning model, especially for higher values of α. These results also tend to be better than those of the preferential model, partially due to the fact that more maintenance opportunities are found. The average improvement in maintenance cost is better and has less dispersion for an α value of 1 when compared to the preferential approach.

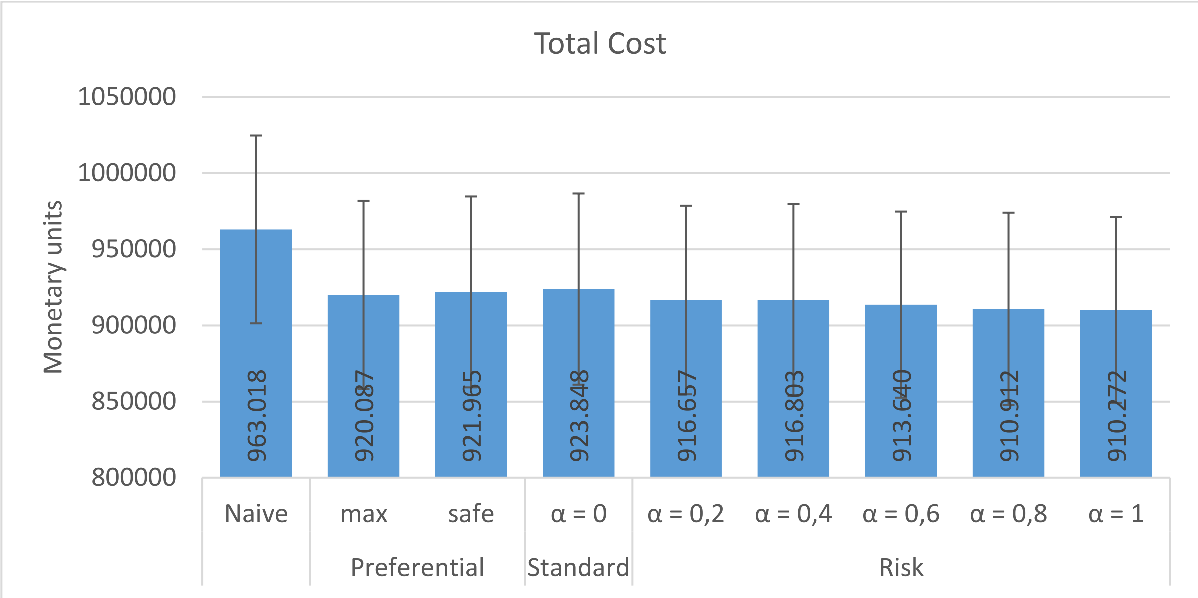


Figure 9 – Average total cost for basic cases

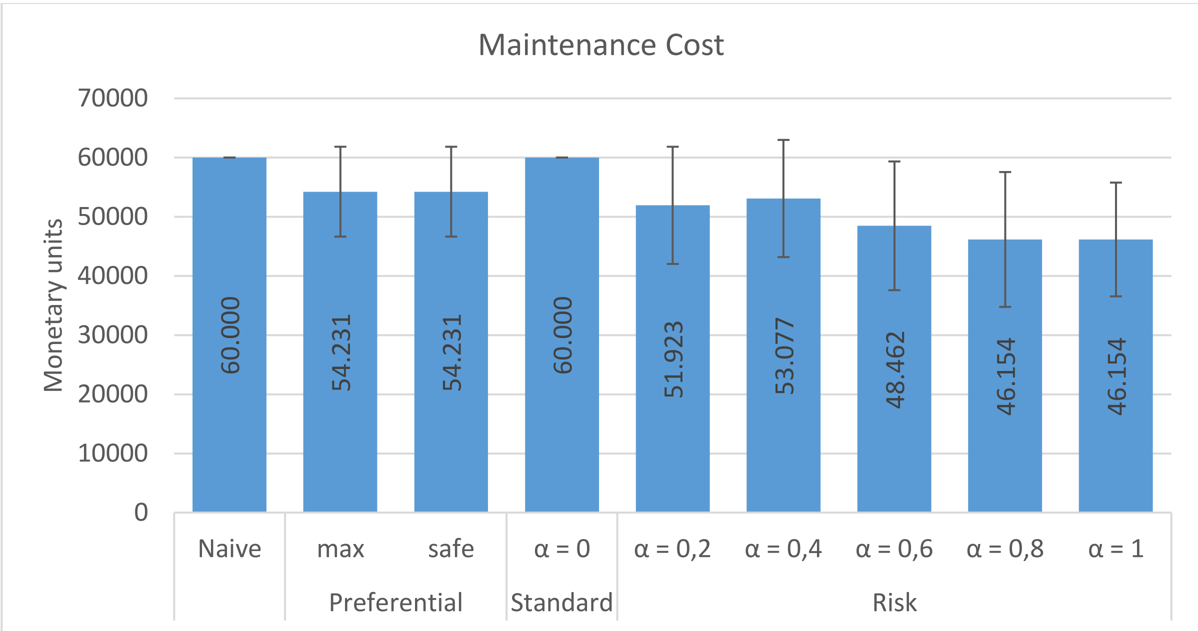


Figure 10 – Average maintenance cost for basic cases

Similar to the previous graphs, the bars in Figure 11 and Figure 12 present the average deadhead hours and processing time of the cases solved by each model, with the error bars representing the standard deviation of each average. As expected, Figure 11 shows that the proposed models tend to have longer connection flights when compared to the standard model given that these longer routes open opportunities for in-base maintenance events, but are still, significantly shorter than a naïve approach. Albeit, this is compensated by the reductions in maintenance costs presented previously. This is because the standard model is only focused on finding the shortest connection routes, regardless of corrective maintenance opportunities. In a few cases, the proposed models even found solutions with lower deadhead hours because of the rolling time windows, some connection choices opened shorter options later in the routing.

Figure 12 presents the processing time required by the models in each case. Although the naïve approach takes half the time of the other models, its results are significantly worse and the other models are well within a reasonable timeframe for agile planning required by fractional fleet operators.

Aside from the costs and flown hours from each method presented previously, all cases have a flexible approach to preventive maintenance. This characteristic of the model allows each solution to choose the best moment in each plan to perform the preventive maintenance. In some cases because of the utilization of specific aircraft, the preventive maintenance limits are not reached, and therefore these maintenance activities are not planned. The tables in Appendix A – Variability in preventive maintenance execution present the specific alterations in preventive maintenance planning. This suggestion of maintenance allocation encompasses some aspects of prescriptive maintenance by using prognostics information to determine the best maintenance base and time for each activity.

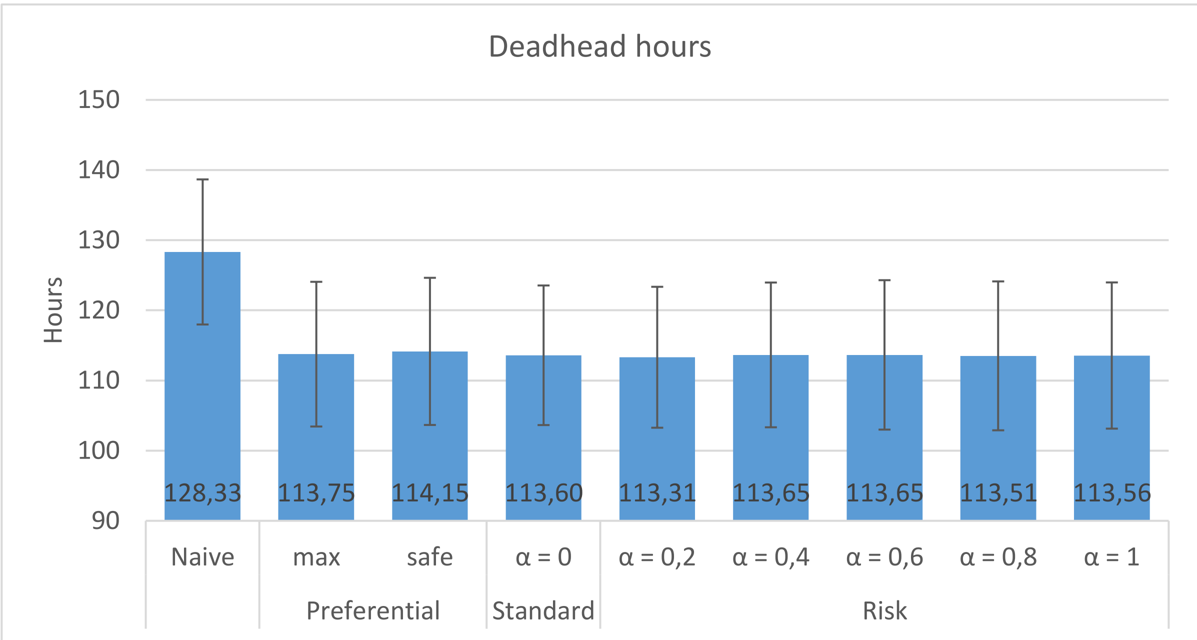


Figure 11 – Average deadhead connection hours for basic cases

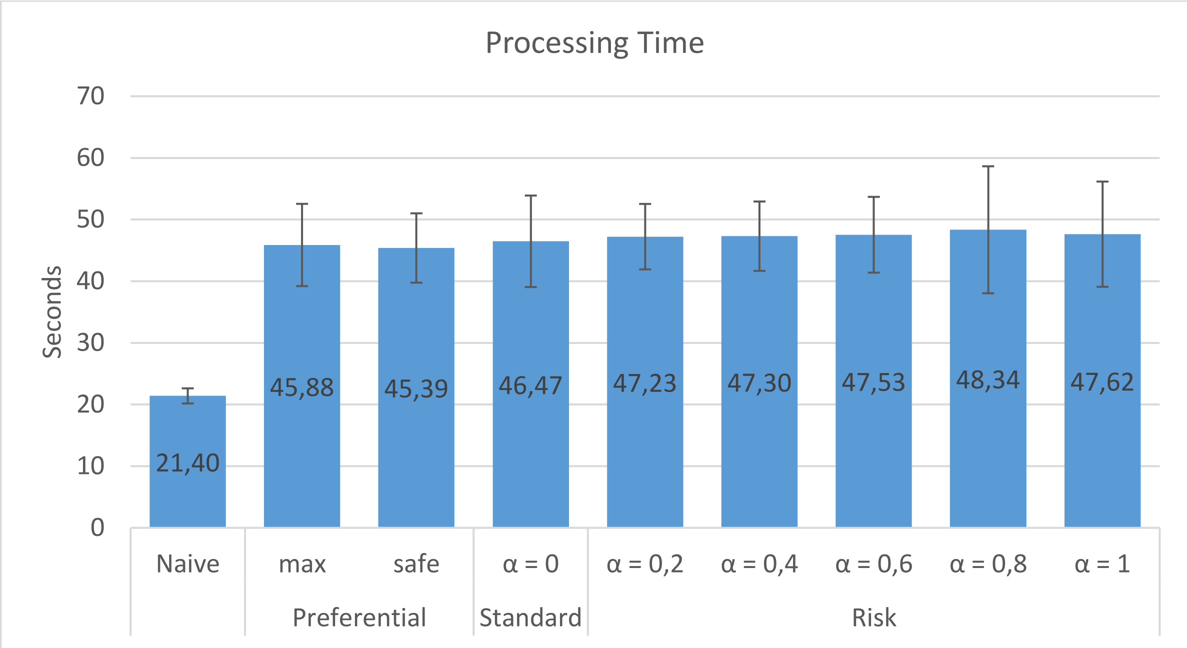


Figure 12 – Average processing time for basic cases

From 13 to Figure 16, the comparison between planning with and without upgrades is presented. Starting from Figure 13, it can be seen that by using a mixed fleet and allowing upgrades of certain flyers, the overall costs of operations can be reduced in some cases. Again, the naïve method proves more costly than all the other approaches. The preferential methods have a worse performance when allowing upgrades, both compared to the standard method and planning with no upgrades. This occurs because when upgrades are allowed, more flight legs that are opportune for maintenance activities can be allocated to a fleet of different aircraft.

On the other hand, the risk model performs better in most values of α by allowing upgrades. The biggest difference is for an α value of 1, presenting the lowest average cost of all. The most likely reason behind this is that the larger influence of the risk index in $\alpha = 1$ made the routing solution more driven to finding maintenance efficient routes rather than reducing deadhead connection costs for the more costly fleet of larger aircraft.

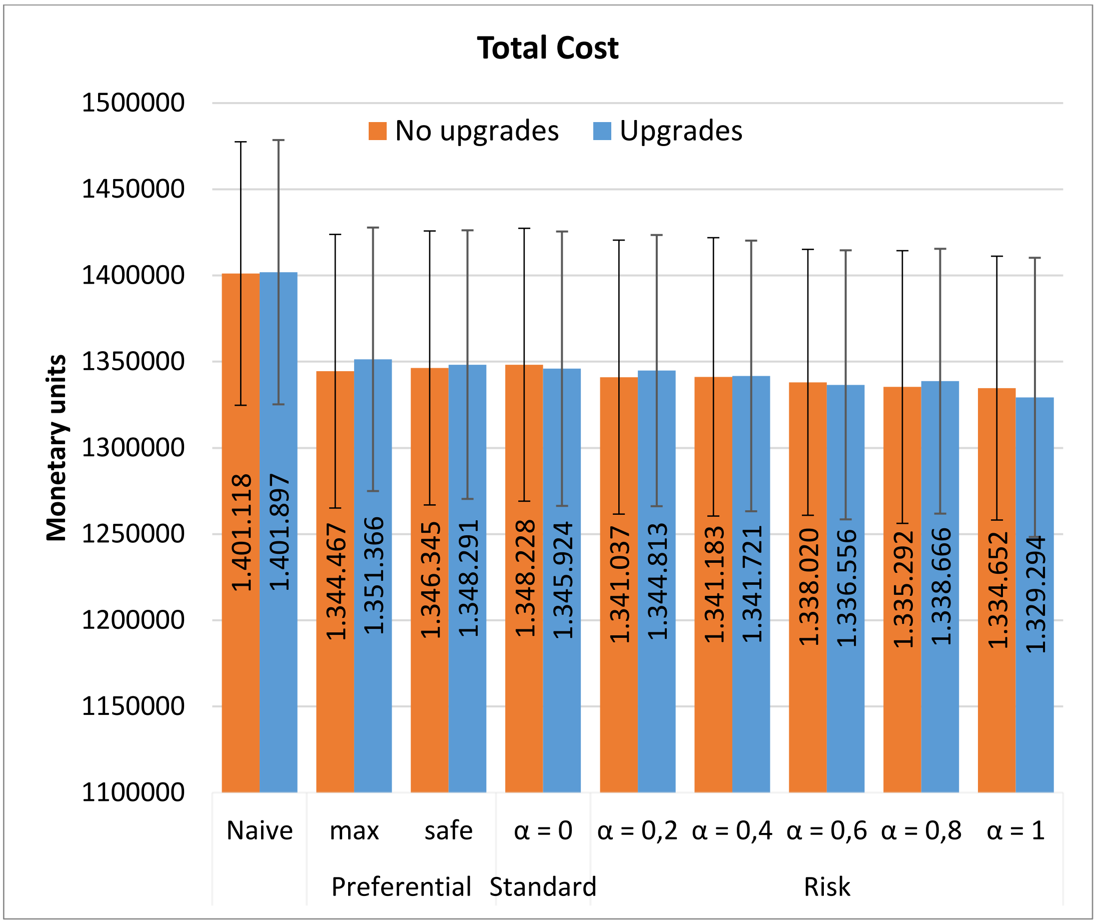


Figure 13 – Average cost comparison for mixed fleets not allowing versus allowing upgrades

Since the greatest contributors to the cost presented previously are the deadhead hour and maintenance costs, Figure 14 and Figure 15 can better explain the differences in allowing or not to upgrade. Figure 14 shows that allowing upgrades, mostly has a negative effect on maintenance cost reduction, finding less maintenance efficient routes. On average, the total deadhead hours all reduce when allowing upgrade, as seen in Figure 15. When having more flights and consequently more probable deadhead hours, it appears to be more advantageous to prioritize flight hours reduction over maintenance cost.

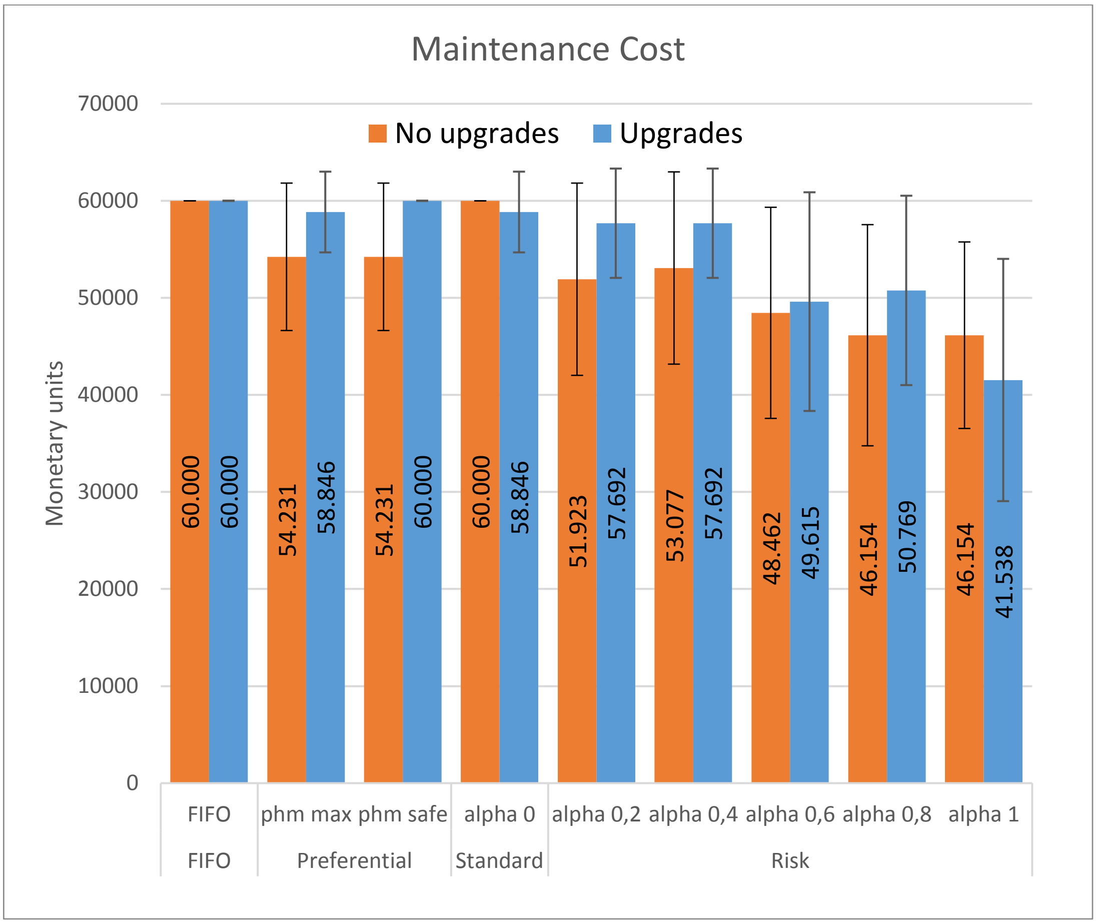


Figure 14 – Average maintenance cost comparison for mixed fleets not allowing versus allowing upgrades

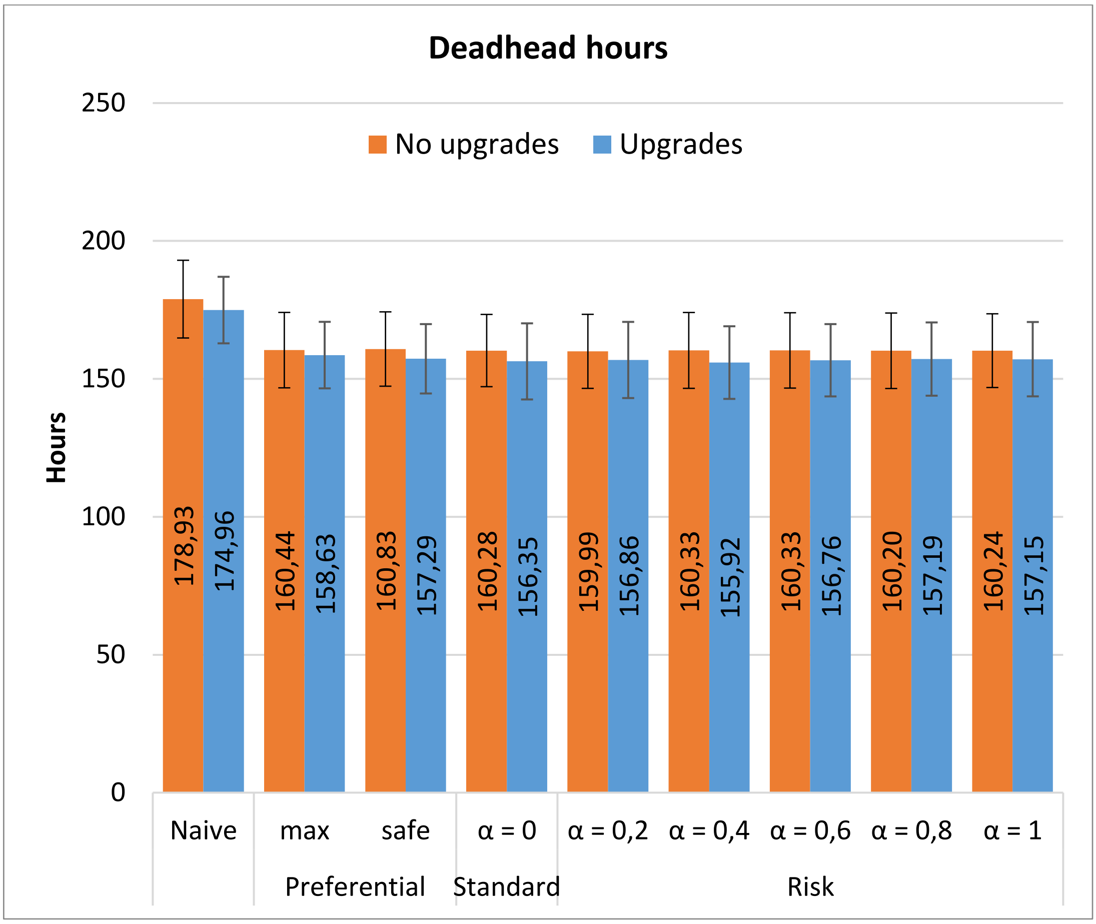


Figure 15 – Deadhead hour comparison for mixed fleets not allowing versus allowing upgrades

In regards to processing time, Figure 16 shows that due to the added complexity, there is a consistent increase when considering the upgrade possibility. This, however, is not a restrictive situation since these processing times remain small when compared to the requirement of agile planning, needing to be solved within a few hours. One important mention is the cases allowing upgrades for $\alpha = 1$, where the processing time is significantly lower than the no upgrades cases. Given that all tests were run identically, it can be inferred that this model encountered problems that were more easily solved when allowing upgrades.

Despite the differences in the contributing factors to the cost, the same tendency remains from the homogenous fleet cases. Higher values of α in the risk formulation, 0.8 and 1, continue to present the best results consistently.

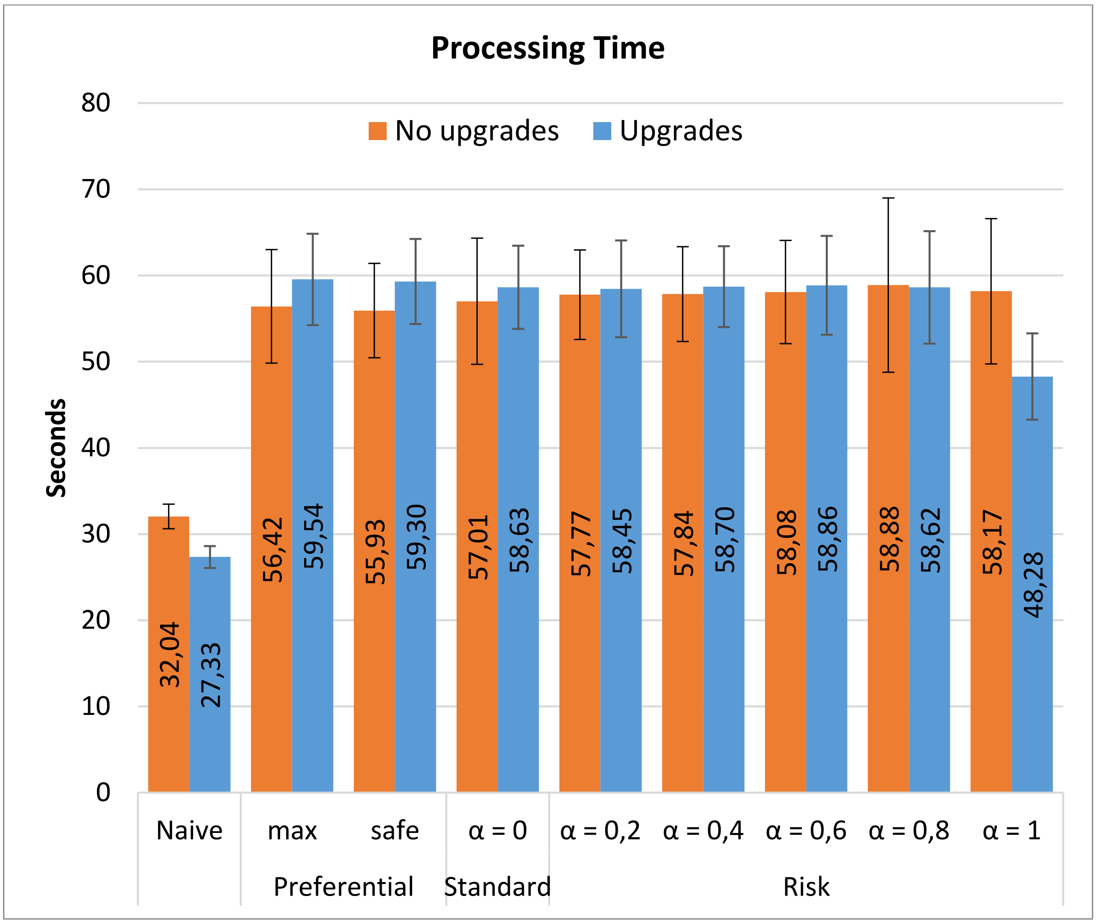


Figure 16 – Processing time comparison for mixed fleets not allowing versus allowing upgrades

Failure prognostics is a prediction, and therefore not always accurate to the specific time of the failure. To further study the effectiveness of using prognostics information in flight and maintenance planning, various simulations were performed with the monitored failure occurring at different points in time. In the cases presented in the sequence, prognostics information is provided for two critical failures. Figure 17 presents the expected RUL as it would be provided by a prognostics system. This shows how far away from the planning day that these faults are expected to occur and the calculated probability of them occurring.

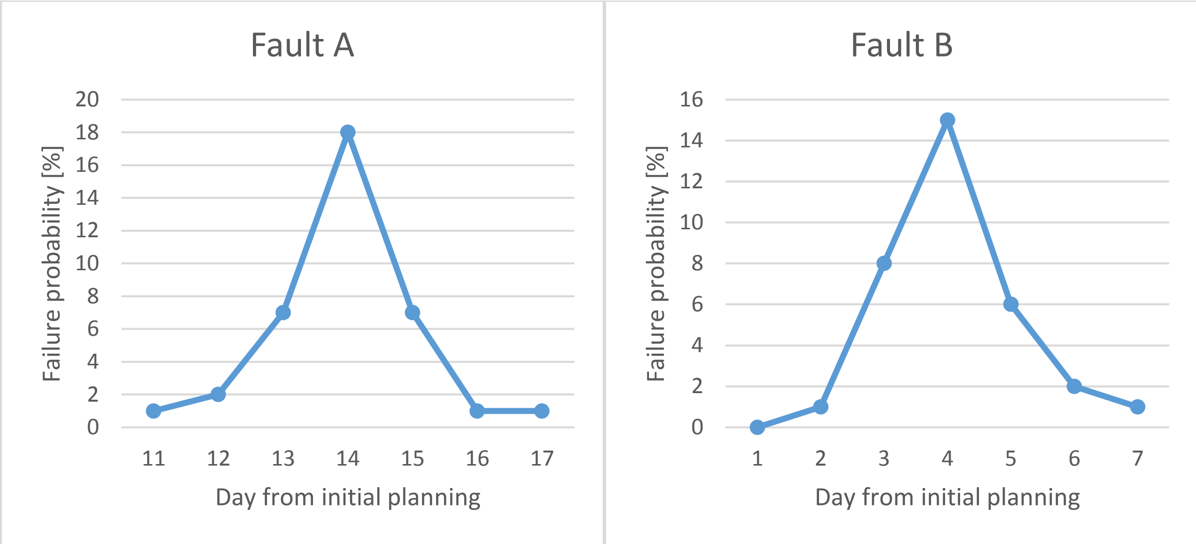


Figure 17 – Expected RUL of fault A (left) and fault B (right)

Considering all the possible dates at which these faults may happen, the behavior of the preferential method and the risk-based method for an α of 0.8 and 1, the best performing values, are simulated under these uncertainties. From Table VI, Table VII, and Table VIII, there is consistent improvement in both maintenance cost and total cost for most methods. The tables above represent the percentage of cases with a reduction and increase in total cost, maintenance cost, and deadhead hours of each model compared to the standard model. The first column of each table shows the percentage range of reduction and increase in each respective aspect. The following columns present the percentage amount of cases that showed an increase or reduction of each aspect within the stated range for their respective methods.

With the exception of the $\alpha = 0.8$, the other models present mostly a reduction in total cost up to 0.7%, while the rest of the cases that presented higher total cost also remained under 0.7%.

In terms of the maintenance cost, there are still very few cases with increased maintenance costs in comparison to the standard model. Even the model with $\alpha = 0.8$ that has the worst results considering the variability from the uncertainties provides consistent reduction in maintenance cost, up to 4.8%, while the other methods reach reductions of up to 8.2% with a higher frequency.

As for the deadhead hours, all the models present the expected behavior of increasing empty connection flights. This change remains mostly up to 1.3%, with the $\alpha = 0.8$ exceeding this limit in a few cases.

Although the risk-based model presented better results in previous tests, that had the failures happen on the most likely date of failure occurrence, the preferential model is more consistent in reducing total and maintenance costs considering the variability of the failure prognostic information. The difference in the margin of maintenance cost reduction, from 4.8% to 8.2%, and deadhead hour increase, up to 1.3%, shows that it can be advantageous to use the proposed models instead of traditional models. Despite the uncertainty involved in the prognostic process, the proposed models are still effective in reducing maintenance costs while maintaining similar deadhead hours.

Table VI – Total cost variance due to prognostics uncertainties

Total cost				
Variance range	Δ Pref max	Δ Pref safe	Δ $\alpha = 0.8$	Δ $\alpha = 1$
-0,7% - 0%	53%	61%	14%	59%
0% - 0,7%	47%	39%	71%	41%
0,7% - 1,4%	0%	0%	0%	0%
1,4% - 2,1%	0%	0%	0%	0%
2,1% - 2,8%	0%	0%	14%	0%

Table VII – Maintenance cost variance due to prognostics uncertainties

Maintenance cost				
Variance range	Δ Pref max	Δ Pref safe	Δ $\alpha = 0.8$	Δ $\alpha = 1$
-11,6% - -8,2%	2%	4%	0%	0%
-8,2% - -4,8%	51%	47%	2%	16%
-4,8% - 0%	37%	35%	80%	65%
0% - 2,6%	2%	6%	18%	18%
2,6% - 5,2%	8%	8%	0%	0%

Table VIII – Deadhead hour variance due to prognostics uncertainties

Deadhead hours				
Variance range	Δ Pref max	Δ Pref safe	Δ $\alpha = 0.8$	Δ $\alpha = 1$
-0,3% - 0%	0%	2%	0%	0%
0% - 0,7%	49%	59%	35%	47%
0,7% - 1,3%	49%	39%	51%	51%
1,3% - 1,9%	2%	0%	0%	2%
1,9% - 7,6%	0%	0%	14%	0%

To test the viability of these models, a sensitivity test considering the average increase in deadhead hours and reduction in maintenance cost is performed. In this sense, a more generalized approach to this sensitivity analysis would be a more useful tool for decision-makers. As the deadhead hours can only be determined after a routing solution is presented, it doesn't serve as a good parameter for generalization, although it is the object of the optimization, therefore a better parameter is the total demanded flight hours, D. By further analyzing all of the case studies presented previously, the expected deadhead to active flight ratio, ϕ, can be found for the operational profile of each fleet, which for the cases in this work is around 51.5%. This way, the active flight hours demanded by clients can be used to estimate the expected deadhead hours of future solutions and from there a better estimate can be found of how much the added cost of flights will be when using the proposed models focusing on finding maintenance opportunities.

The quantity of deadhead hours is not the only factor to balance in this scenario though. The flight hour cost is also a big influence in this comparison. Therefore, in order to effectively generalize this analysis, an expected deadhead hour cost based on the expected deadhead hours and flight hour cost for the aircraft of the operator is used. In summary, the expected cost increase in deadhead flight hour cost is a function of the total demanded flight hours, the deadhead to active flight hours ratio, and flight hour cost, $\delta_F(D, \phi, C_{FH,t})$.

The expected maintenance cost reduction, δ_M, is only a function of the additional cost of out-of-base maintenance events for the systems being monitored, C_{cor}.

Figure 18 shows the generalized sensitivity analysis for the homogeneous fleet cases. This analysis is based on the parameters extracted from the cases used here. These parameters can be updated to better suit specific operator scenarios and types of fleets by altering flight costs as needed and extracting flight hours relations from operators' flight profiles. The estimated maintenance cost reduction must also be altered depending on prognostic information derived from the systems being operated and added maintenance costs from out-of-base AOG situations.

In this example, point A identifies a situation close to the tested cases where the demanded flight hours are approximately 220 hours. With this value of demanded flight hours, the analysis indicates that the savings with maintenance costs will be higher than the added deadhead flight hour cost, point A being below the δ_M threshold. Point B shows the break-even point in terms of costs saved with maintenance and costs added with longer flight hours. In terms of cost variance, both the standard and proposed models will perform equally, but the proposed models have an advantage when it comes to lead times for repairs. Since the proposed models tend to have more in-base maintenance repairs, the amount of time that aircraft will be grounded will be smaller, increasing the availability of the aircraft. Lastly, point C indicates a situation where the amount demanded flight hours results in the proposed models having solutions where the added cost of longer routes surpasses the estimated savings in maintenance. This does not, however, make the planning with PHM information unviable, since these solutions still reduce maintenance costs as well as repair times. The decision-maker can then decide to spend slightly more money on flight hours to have a higher availability of the fleet.

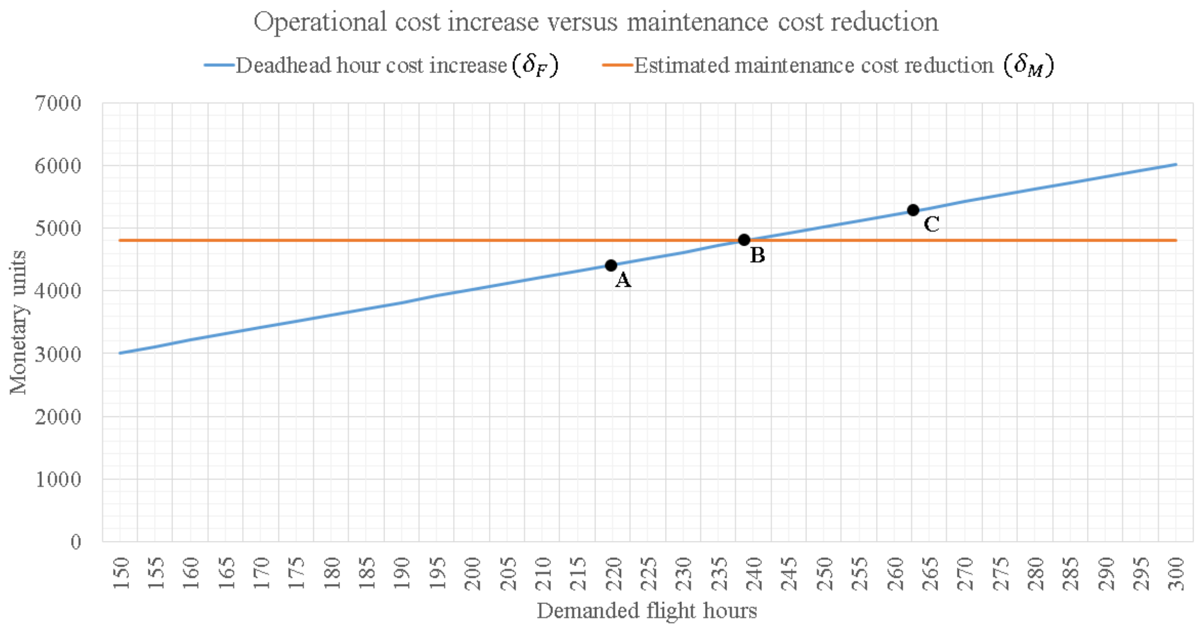


Figure 18 – Generalized sensitivity analysis

5 Conclusion

From the research done here relative to the AMRP, many works treated this problem in various ways, focusing on different aspects of the problem and how to solve it. This review presented a gap in these works in terms of using prognostics information to improve maintenance routing planning.

The contributions made in this thesis are as follows:

- A different approach to flexibilize preventive maintenance, considering not only the anticipation or postponement of planned activities but tracking when and where these activities would be best allocated.
- The inclusion of PHM information in route planning to plan proactively for specific disruptions, focusing on flexibility of planned solutions.

Two planning models for the AMRP that make use of failure prognostics information are developed in chapter 3. The first uses a risk parameter associated with each flight leg to penalize connections that could lead to out-of-base maintenance events. The second favors flight connections that could lead to in-base maintenance events. Both models are tested against a naïve approach and a standard model, comparable to those present in other works.

From the previous section, both models using failure prognostics information proposed in this study outperform both naïve and standard planning in a majority of cases. The two models find routes with lower overall costs and more in-base maintenance events. Between these two models, the risk-based one stands out as the more consistent of the two for the various cases tested. When applying a strong influence of the risk factor, more maintenance opportunities are found, along with better overall solutions, although the deadhead flight hours are slightly more than the standard model.

Both models, dynamically arranging these activities to best suit each routing solution, exploit the flexible time windows for preventive maintenance. By doing this, the maintenance schedule is also actively planned during the routing.

When considering the possibility of upgrading flyers with a mixed fleet, the models behaved similarly to the homogeneous fleet cases with the risk models performing better more consistently. By allowing upgrades, more efficient routes are encountered, despite fewer maintenance opportunities being found. The gains in cost reduction come mainly from fewer deadhead hours, especially for the fleet of larger aircraft. Therefore, depending on the flight hour cost of each aircraft and the possible gains in maintenance costs, it may not be worth allowing upgrades.

From this, fault prognostics information in planning is worthwhile using, allowing upgrades or not, for heterogeneous fleets, despite the drawbacks of not always finding the best maintenance opportunities. This comes with the caveat that allowing upgrades is better if flight hour costs such as fuel become more significant in relation to maintenance costs or if there is prognostic information indicating possible failures in the larger aircraft fleet.

In terms of the uncertainties inherent to prognostics information, it is shown that both models still provide better overall solutions compared to the standard model. These improvements are strongly related to the reduction in maintenance costs, the relative gains in maintenance being much greater than the relative loss due to added deadhead hours. Given the uncertainties, the preferential model is more consistent in presenting improvements than the risk-based model.

Addressing the concern of volatile fuel costs and other operating costs as well as specific maintenance situations, the generalized sensitivity analysis provided in this work presents a starting point to develop a tool that can provide valuable information to decision-makers. By tuning parameters and using data mining for specific scenarios, this type of analysis can give decision-makers a clearer view of operations planning.

It can, therefore, be concluded that there are possible gains to be had from the use of failure prognostics in AMRP. The presented models show that there are many alternatives to using this type of information in route planning. As condition monitoring becomes more frequent and less expensive in aircraft, the potential gains in maintenance costs tend to increase along with the growth of fractional fleets. By using prognostics information in route and maintenance planning, the output of such an algorithm can serve as input for prescriptive maintenance. This approach may also benefit other on-demand transportation models such as recent electric vertical take-off and landing urban mobility solutions.

5.1 Future Works

While developing this thesis, some aspects that can be improved, expanded upon, and tested differently arose:

- Addition of more maintenance events to verify the effects of the proportion of potential maintenance cost gains compared deadhead hour costs.
- The use of more detailed prognostics and artificial intelligence information, such as evolving flight hour costs.

- Using stochastic optimization to effectively model risks and simulate scenarios with uncertain travel times.
- Include crew planning, and maintenance restrictions such as maintenance base capacities and limited resources.
- Demand forecasting based on historical data to help optimization of routes.
- The in-depth development of a cost-effectiveness model for this type of planning.

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Appendix A – Variability in preventive maintenance execution

The following tables detail the differences in preventive maintenance planning given the flexibility allowed in the model. Each table shows the hour from the initial planning time at which the maintenance is performed and the maintenance base where it is performed. M1 and M2 are flight hour based maintenances and M3 and M4 are time-triggered maintenances. B1 and B2 represent the two maintenance bases that can be used.

Table IX – Maintenance allocations for case 1

Case 01								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	—	—	—	—	—	408
Pref safe	—	—	—	—	—	—	—	408
standard	301	—	—	—	—	—	—	408
$\alpha = 0.2$	301	—	—	—	—	—	—	408
$\alpha = 0.4$	301	—	112	—	—	—	408	—
$\alpha = 0.6$	—	—	187	—	—	—	—	408
$\alpha = 0.8$	301	—	187	—	—	—	408	—
$\alpha = 1$	—	—	187	—	—	—	—	408

Table X– Maintenance allocations for case 2

Case 02								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	17	—	341	—	408	—
Pref safe	—	—	17	—	336	—	—	408
standard	—	—	—	—	—	360	—	408
$\alpha = 0.2$	—	152	—	—	—	360	408	—
$\alpha = 0.4$	—	—	—	—	—	360	—	408
$\alpha = 0.6$	—	204	—	—	341	—	—	384
$\alpha = 0.8$	—	—	—	—	336	—	408	—
$\alpha = 1$	280	—	—	—	—	360	—	408

Table XI – Maintenance allocations for case 3

Case 03								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	—	—	349	—	—	—
Pref safe	—	—	226	—	341	—	—	—
standard	—	—	—	322	—	360	—	—
$\alpha = 0.2$	—	—	—	—	336	—	—	—
$\alpha = 0.4$	—	—	—	—	336	—	—	—
$\alpha = 0.6$	—	—	—	343	337	—	—	—
$\alpha = 0.8$	248	—	—	—	—	360	—	—
$\alpha = 1$	—	—	—	—	336	—	—	—

Table XII – Maintenance allocations for case 4

Case 04								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	164	—	—	344	—	408	—
Pref safe	194	—	273	—	344	—	—	408
standard	—	—	248	—	344	—	—	408
$\alpha = 0.2$	—	—	—	—	336	—	408	—
$\alpha = 0.4$	—	222	—	—	—	360	408	—
$\alpha = 0.6$	—	—	71	—	344	—	—	408
$\alpha = 0.8$	—	—	71	—	336	—	408	—
$\alpha = 1$	—	—	71	—	344	—	408	—

Table XIII – Maintenance allocations for case 5

Case 05								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	195	—	337	—	—	408
Pref safe	—	—	195	—	337	—	—	408
standard	—	—	34	—	337	—	408	—
$\alpha = 0.2$	—	—	—	—	336	—	408	—
$\alpha = 0.4$	204	—	—	—	336	—	408	—
$\alpha = 0.6$	—	—	—	—	336	—	408	—
$\alpha = 0.8$	—	—	34	—	337	—	—	408
$\alpha = 1$	—	—	34	—	336	—	408	—

Table XIV – Maintenance allocations for case 6

Case 06								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	—	—	—	360	—	—
Pref safe	—	—	—	—	—	360	—	—
standard	—	—	—	—	360	—	—	—
$\alpha = 0.2$	—	—	—	—	—	360	—	—
$\alpha = 0.4$	—	—	—	306	360	—	—	—
$\alpha = 0.6$	—	—	—	—	—	360	—	—
$\alpha = 0.8$	—	—	—	—	347	—	—	—
$\alpha = 1$	—	—	—	—	358	—	—	—

Table XV – Maintenance allocations for case 7

Case 07								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	222	—	336	—	—	408
Pref safe	—	—	—	—	336	—	—	408
standard	—	—	—	—	—	358	—	408
$\alpha = 0.2$	—	—	178	—	—	360	—	408
$\alpha = 0.4$	—	—	—	—	—	360	—	408
$\alpha = 0.6$	—	—	178	—	—	358	—	408
$\alpha = 0.8$	—	—	—	—	336	—	—	408
$\alpha = 1$	—	—	178	—	—	358	—	408

Table XVI – Maintenance allocations for case 8

Case 08								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	—	—	—	360	—	408
Pref safe	—	—	—	—	—	360	—	408
standard	—	—	—	—	—	345	—	408
$\alpha = 0.2$	—	—	—	—	—	357	—	408
$\alpha = 0.4$	—	—	—	—	—	345	—	408
$\alpha = 0.6$	—	—	—	—	—	360	—	408
$\alpha = 0.8$	229	—	—	299	340	—	—	408
$\alpha = 1$	245	—	—	—	340	—	—	408

Table XVII – Maintenance allocations for case 9

Case 09								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	—	—	352	—	408	—
Pref safe	—	—	—	—	336	—	408	—
standard	—	—	75	—	336	—	—	408
$\alpha = 0.2$	—	—	56	—	336	—	—	408
$\alpha = 0.4$	—	—	—	—	352	—	—	408
$\alpha = 0.6$	260	—	154	—	336	—	408	—
$\alpha = 0.8$	—	—	178	—	336	—	—	408
$\alpha = 1$	—	—	—	—	336	—	—	408

Table XVIII – Maintenance allocations for case 10

Case 10								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	193	—	—	360	—	384
Pref safe	—	—	193	—	—	360	—	384
standard	—	—	192	—	—	360	—	384
$\alpha = 0.2$	—	—	193	—	—	360	—	384
$\alpha = 0.4$	—	—	—	—	—	360	—	384
$\alpha = 0.6$	—	—	—	—	—	360	384	—
$\alpha = 0.8$	—	—	—	—	—	360	—	384
$\alpha = 1$	—	—	—	327	—	360	—	384

Table XIV – Maintenance allocations for case 11

Case 11								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	—	—	—	359	—	408
Pref safe	—	—	—	—	—	343	—	408
standard	214	—	—	—	—	343	—	408
$\alpha = 0.2$	211	—	—	—	—	351	—	408
$\alpha = 0.4$	211	—	—	—	357	—	—	408
$\alpha = 0.6$	211	—	—	—	—	351	—	408
$\alpha = 0.8$	211	—	—	—	—	351	—	408
$\alpha = 1$	211	—	—	—	352	—	—	408

Table XX – Maintenance allocations for case 12

Case 12								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	—	—	360	—	408	—
Pref safe	—	—	—	—	342	—	408	—
standard	—	—	—	—	338	—	408	—
$\alpha = 0.2$	—	—	—	—	338	—	408	—
$\alpha = 0.4$	—	—	—	—	338	—	408	—
$\alpha = 0.6$	—	—	—	—	360	—	408	—
$\alpha = 0.8$	—	—	—	—	355	—	408	—
$\alpha = 1$	—	—	—	—	355	—	408	—

Table XXI – Maintenance allocations for case 13

Case 13								
	M1B1	M1B2	M2B1	M2B2	M3B1	M3B2	M4B1	M4B2
Pref max	—	—	—	—	—	360	—	408
Pref safe	—	—	—	—	—	360	—	408
standard	—	—	—	—	—	360	—	408
$\alpha = 0.2$	—	301	—	—	—	360	—	408
$\alpha = 0.4$	209	—	—	353	—	360	—	408
$\alpha = 0.6$	—	—	—	—	—	360	408	—
$\alpha = 0.8$	—	—	—	379	—	360	—	408
$\alpha = 1$	—	—	—	—	—	360	408	—

FOLHA DE REGISTRO DO DOCUMENTO

1. CLASSIFICAÇÃO/TIPO	2. DATA	3. REGISTRO N°	4. N° DE PÁGINAS
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5. TÍTULO E SUBTÍTULO:

Modelling the aircraft maintenance routing problem for fractional fleets with the inclusion of prognostics and health monitoring information.

6. AUTOR(ES):

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7. INSTITUIÇÃO(ÕES)/ÓRGÃO(S) INTERNO(S)/DIVISÃO(ÕES):

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8. PALAVRAS-CHAVE SUGERIDAS PELO AUTOR:

1. Aircraft maintenance routing problem. 2. PHM information. 3. Maintenance planning

9.PALAVRAS-CHAVE RESULTANTES DE INDEXAÇÃO:

Manutenção de aeronaves; Monitoramento da saúde de sistemas; Análise de falhas; Manutenção preventiva; Controle de processos; Redução de custos; Engenharia aeronáutica.

10. APRESENTAÇÃO: **(X) Nacional ( ) Internacional**

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11. RESUMO:

This thesis presents two approaches to modeling the aircraft maintenance routing problem for fractional fleets including aircraft health prognostics information; one based on risk modeling and the other modeling stimuli for flights that present maintenance opportunities. These models approach the problem of a systemic lack of effectiveness in solving the AMRP without considering available maintenance and supportability resources of complex systems. In this sense, the use of prognostics information can be incorporated into the planning process of routes and maintenance with the purpose of reducing maintenance costs and grounded aircraft times due to failures. The solutions proposed in this work build routes and allocate them to aircraft while determining the best moment and base to perform preventive maintenance activities. Information from a monitoring and prognostics system of critical failures of the aircraft was modeled based on real data. Being that these failures, cause unavailability of the aircraft until the corrective maintenance repair is done. Corrective maintenance is treated in few works, and differently from them, this thesis uses a proactive approach to make a flexible route plan that avoids disruptions due to corrective maintenance. Various cases were used to test the developed models; among them were real cases from a fractional fleet operator and other cases with dimensions that contemplate significant samples of the problem. The developed models were also tested for heterogeneous fleets to reflect real alternatives of fractional fleet operations. The contributions of this thesis include a more flexible modeling of preventive maintenance and the inclusion of failure prognostics information to proactively plan routes for specific disruptions. The results obtained here show the possible gain in efficiency of the routing solutions, reducing maintenance costs without significantly increasing repositioning flight hours.

12. GRAU DE SIGILO:

(X) OSTENSIVO ( ) RESERVADO ( ) SECRETO