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AN AGENT-BASED APPROACH FOR AIRCRAFT ASSIGNMENT PROBLEM

Ivo Paixão de Medeiros

Doctorate Thesis of the Graduate Course in Applied Computing, guided by Dr. Rafael Duarte Coelho dos Santos, approved in May 16, 2019.

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"God, grant me the serenity to accept things I cannot change, courage to change the things I can, and wisdom to know the difference".

Reinhold Niebuhr

I dedicate this work to my family that embraced this journey after me. A special mention has to be made of my wife Synara, my son Davi, my mother Madalena, my brother Igo and in memoriam of my father José.

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ABSTRACT

This thesis introduces agent-based modeling to solve aircraft assignment problem taking into consideration vehicle efficiency in terms of fuel consumption, aircraft health condition, and flight importance. The solution proposed in this thesis assigns aircraft to routes (set of flights), this thesis assumption is that an aircraft performance monitoring system provides information on fuel consumption efficiency and a prognostics and health monitoring system provides information on aircraft components health condition. Aircraft components health condition are aggregated at vehicle level employing a fault tree representation, which represents systems architecture and components interaction that could lead to aircraft unavailability. Such information is used to determine if a vehicle demands no maintenance, opportunistic or mandatory maintenance. In the proposed model, mandatory maintenance demands are hard constraints, and opportunistic maintenance demands are soft constraints. There are two types of agents in our multi-agent system framework, one representing aircraft assignment task and other representing aircraft itself and they interact by following an ascending biding auction procedure in order to perform a competitive equilibrium approach. Three different fleets and flight schedules were considered to simulate six scenarios aiming to validate our approach.

Keywords: Aircraft Assignment. Multi-agent Systems. Integrated Vehicle Health Management. Aircraft Performance Monitoring. Prognostics and Health Monitoring.

UMA ABORDAGEM BASEADA EM AGENTES PARA O PROBLEMA DE ALOCAÇÃO DE AERONAVES

RESUMO

Esta tese apresenta uma modelagem baseada em sistema multi-agentes para resolver o problema de alocação de aeronaves; levando em consideração o consumo de combustível da aeronave, a condição de saúde do veículo e a importância dos voos a serem executados. A solução proposta nessa tese atribui aeronaves a rotas (conjunto de voos); além disso, esse trabalho assumiu como premissa a existência de um sistema de monitoramento de desempenho da aeronave que estima a eficiência da aeronave em termos de consumo de combustível e que também existe um sistema de prognóstico e monitoramento de saúde que provê estimativa da condição de saúde dos equipamentos do veículo. A informação de saúde dos equipamentos da aeronave é agregada a nível de veículo através do uso de uma árvore de falha para representar arquitetura do sistema e a interação dos componentes que pode levar a indisponibilidade da aeronave. Essa informação sumarizada é utilizada para determinar se o veículo necessita de manutenção mandatória, preventiva ou não precisa de manutenção. As demandas de manutenção mandatórias são modeladas como restrições mandatórias e as de manutenção preventiva como restrições flexíveis. Na solução proposta, há dois tipos de agentes, um representando a atividade de alocação de aeronaves e outro representando as próprias aeronaves. Esses agentes interagem seguindo um protocolo baseado na abordagem de leilão com lances incrementais a fim de alcançar uma condição de equilíbrio competitivo. Três frotas e programações de voo são utilizadas para simular seis cenários para validar a solução proposta.

Palavras-chave: Alocação de aeronaves. Sistemas multi-agente. Gerenciamento Integrado de saúde de veículo. Monitoramento de desempenho de aeronave. Prognóstico e monitoramento de saúde.

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LIST OF ALGORITHMS

LIST OF ABBREVIATIONS

ABQ	–	Albuquerque International Sunport Airport (ABQ)
ABZ	–	Aberdeen Dyce Airport (ABZ)
ACFT	–	Aircraft Agent
Acft.	–	Aircraft
AES	–	Ålesund Airport (AES)
ALL	–	Villanova D'Albenga International Airport (ALL)
AMS	–	Agent Management System
AMS	–	Amsterdam Schiphol Airport (AMS)
AOCC	–	Airline Operations Control Centre
API	–	Application Programming Interface
APM	–	Aircraft Performance Monitoring
ATL	–	Hartsfield Jackson Atlanta International Airport (ATL)
BDL	–	Bradley International Airport (BDL)
BGO	–	Bergen, Flesland Airport (BGO)
BHX	–	Birmingham International Airport (BHX)
BIO	–	Bilbao Airport (BIO)
BLL	–	Billund Airport (BLL)
BLQ	–	Bologna / Borgo Panigale Airport (BLQ)
BNA	–	Nashville International Airport (BNA)
BOD	–	Bordeaux-Mérignac (BA 106) Airport (BOD)
BRE	–	Bremen Airport (BRE)
BRS	–	Bristol International Airport (BRS)
BRU	–	Brussels Airport (BRU)
BSB	–	Presidente Juscelino Kubistschek International Airport (BSB)
CBM	–	Condition-based maintenance
CFP	–	Computerised Flight Plan/ Call for Proposal
CHS	–	Charleston Air Force Base-International (CHS)
CLE	–	Cleveland Hopkins International Airport (CLE)
CMH	–	Port Columbus International Airport (CMH)
CWB	–	Afonso Pena Airport (CWB)
CWL	–	Cardiff International Airport (CWL)
CZM	–	Cozumel International Airport (CZM)
DCA	–	Ronald Reagan Washington National Airport (DCA)
DEN	–	Denver International Airport (DEN)
DF	–	Directory Facilitator
DTW	–	Detroit Metropolitan Wayne County Airport (DTW)
DUS	–	Düsseldorf International Airport (DUS)
ELP	–	El Paso International Airport (ELP)
EWR	–	Newark Liberty International Airport (EWR)
EYW	–	Key West International Airport (EYW)
FF	–	Fuel flow

FIPA	–	Foundation for Intelligent Physical Agents
FLN	–	Hercílio Luz International Airport (FLN)
FLR	–	Florence (Firenze / Peretola) Airport (FLR)
FMS	–	Flight Management System
FPO	–	Grand Bahama International Airport (FPO)
FRA	–	Frankfurt am Main International Airport (FRA)
FSM	–	Finite State Machine
FTA	–	Fault Tree Analysis
GGT	–	Exuma International Airport (GGT)
GIG	–	Rio Galeão – Tom Jobim International Airport (GIG)
GOT	–	Gothenburg-Landvetter Airport (GOT)
GRU	–	Guarulhos - Governador André Franco Montoro International Airport (GRU)
GSO	–	Piedmont Triad International Airport (GSO)
GVA	–	Geneva Cointrin International Airport (GVA)
HAM	–	Hamburg Airport (HAM)
HDN	–	Yampa Valley Airport (HDN)
IAH	–	George Bush Intercontinental Houston Airport (IAH)
IFHM	–	Integrated Fleet Health Management
IFP	–	In-Flight Performance
IND	–	Indianapolis International Airport (IND)
IVHM	–	Integrated Vehicle Health Management
JADE	–	Java Agent DEvelopment Framework
JAX	–	Jacksonville International Airport (JAX)
JFK	–	John F Kennedy International Airport (JFK)
KRK	–	John Paul II International Kraków-Balice Airport (KRK)
LGA	–	La Guardia Airport (LGA)
LIR	–	Daniel Oduber Quiros International Airport (LIR)
LPI	–	Linköping SAAB Airport (LPI)
LUX	–	Luxembourg-Findel International Airport (LUX)
LYS	–	Lyon Saint-Exupéry Airport (LYS)
MAN	–	Manchester Airport (MAN)
MAO	–	Eduardo Gomes International Airport (MAO)
MAS	–	Multi-agent systems
MEM	–	Memphis International Airport (MEM)
MHH	–	Marsh Harbour International Airport (MHH)
MIA	–	Miami International Airport (MIA)
MSP	–	Minneapolis-St Paul International/Wold-Chamberlain Airport (MSP)
MSY	–	Louis Armstrong New Orleans International Airport (MSY)
MTY	–	General Mariano Escobedo International Airport (MTY)
NAS	–	Lynden Pindling International Airport (NAS)
NASA	–	National Aeronautics and Space Administration
NCE	–	Nice-Côte d'Azur Airport (NCE)

NCL	–	Newcastle Airport (NCL)
NUE	–	Nuremberg Airport (NUE)
OEM	–	Original Equipment Manufacturer
ORD	–	Chicago O'Hare International Airport (ORD)
ORF	–	Norfolk International Airport (ORF)
OSL	–	Oslo Gardermoen Airport (OSL)
Perf.	–	Performance
PHL	–	Philadelphia International Airport (PHL)
PHM	–	Prognostics and Health Monitoring
PIT	–	Pittsburgh International Airport (PIT)
PLR	–	St Clair County Airport (PLR)
PLS	–	Providenciales Airport (PLS)
PNS	–	Pensacola Regional Airport (PNS)
POA	–	Salgado Filho Airport (POA)
PRG	–	Ruzyně International Airport (PRG)
Prob.	–	Probability
PVD	–	Theodore Francis Green State Airport (PVD)
RCM	–	Reliability centered maintenance
RDU	–	Raleigh Durham International Airport (RDU)
REC	–	Guararapes - Gilberto Freyre International Airport (REC)
RHTA	–	Receding Horizon Task Assignment
RIC	–	Richmond International Airport (RIC)
RSW	–	Southwest Florida International Airport (RSW)
RUL	–	Remaining Useful Life
SAT	–	San Antonio International Airport (SAT)
SDF	–	Louisville International Standiford Field Airport (SDF)
SEMOR	–	Self Evolving Maintenance and Operations Reasoning System
SRUL	–	System-Level Remaining Useful Life
SSA	–	Deputado Luiz Eduardo Magalhães International Airport (SSA)
STL	–	St Louis Lambert International Airport (STL)
STR	–	Stuttgart Airport (STR)
Sys	–	System
TAS	–	Tail Assignment Agents
TLS	–	Toulouse-Blagnac Airport (TLS)
TRD	–	Trondheim, Værnes Airport (TRD)
TRF	–	Sandefjord, Torp Airport (TRF)
TRN	–	Torino / Caselle International Airport (TRN)
TRO	–	Taree Airport (TRO)
UAV	–	Unmanned Aerial Vehicle
VLRS	–	Vehicle Level Reasoning System

LIST OF SYMBOLS

N_1	–	Engine Rotation Speed
v_i	–	Bidder i demand valuation
p_m	–	Item m price
p_m^*	–	Item m non-negative price
T	–	Demand bundle
S	–	Demand bundle at price p_m
$U_{j=1}^n$	–	Set union
S_m^*	–	Demand bundle at price p_m^*
$p_i(S)$	–	Price for bundle S and agent i
$v_i(S)$	–	Valuation for bundle S and i
M	–	Items-set
$\wedge$	–	Conjunction logical operator
$\vee$	–	Disjunction logical operator
P_{OR}	–	Probability of the union
P_{AND}	–	Probability of the intersection
P_{Fi}	–	Probability of the event Fi
P_T	–	Top event probability
$P(e_i)$	–	Probability of the component failure event e_i
$P(c_i)$	–	Probability of the cut set c_i
N	–	Set of routes
X	–	Set of aircraft
W	–	Set of possible route-aircraft combination
$v(i,j)$	–	Assignment valuation function for agent i and route j pair
A	–	A possible assignment from W
$u(i,j)$	–	Assignment utility function for agent i and route j pair
ϵ	–	Positive value added to bidding increment
τ	–	Opportunistic maintenance threshold
ω	–	Mandatory maintenance threshold
σ_j	–	Opportunistic maintenance penalty
J	–	Assignment total utility value
$r(i)$	–	Required fuel for aircraft fly over route i
$f(j)$	–	Fuel consumption efficiency factor for aircraft j
C	–	Fuel price
w_k	–	Flight importance value

CONTENTS

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1 INTRODUCTION

This chapter introduces the aircraft assignment problem. It also presents related work, followed by the statement of the research question and this work contribution; and it outlines the remaining of this thesis.

1.1 Aircraft Assignment Problem

The aircraft assignment problem is one of the significant planning problems to be solved by commercial airlines regularly. Airlines face some of the most significant and most challenging planning problems known. For example, one major airline operates and plans about 1,400 flights per day to over 150 cities in 76 countries, using about 350 aircraft of 11 different types, and about 3,400 cockpits, 14,000 cabins, and 8,300 ground crew (GRONKVIST, 2005).

The most critical resources to plan for an airline operation are the aircraft and flight crew. Fuel consumption, other aircraft expenses and flight crew salaries typically represent the most substantial expenses for an airline. Using the best-suited aircraft on each flight is thus crucial to transport as many paying passengers as possible in order to maximize profits. Similarly, to reduce the crew costs, the crew must be utilized as efficiently as possible, without violating security and union regulations. Airlines also need to plan utilization of other resource types, e.g., ground crews and departure slots, but the planning of these is often less crucial (GRONKVIST, 2005).

The airline operations are composed of long and short-term phases. In the long-term phase, everything starts with publishing the flights' timetable for a specific period. After publishing the timetable, revenue management phase starts. Here the goal is to maximize the revenue obtained by selling tickets. At the same time, scheduling of the two most essential resources: aircraft and crew starts. Regarding the aircraft, the first step is a fleet assignment, that is to assign the aircraft type or aircraft fleet that will perform the flights. It is a crucial step because the aircraft type/fleet will define the number of available seats in each flight (CASTRO, 2013).

Nearer to the day of operations, short-time phase, i.e., the assignment of the specific aircraft to each flight is performed. This step is known as aircraft assignment or tail assignment[1]. During the same period, crew scheduling also takes place. The first step is crew pairing; in doing so, crew duty periods (pairings) that will be necessary

[1]The name tail assignment comes from the fact that their tail numbers identify aircraft, and that the aircraft assignment problem considers individual aircraft.

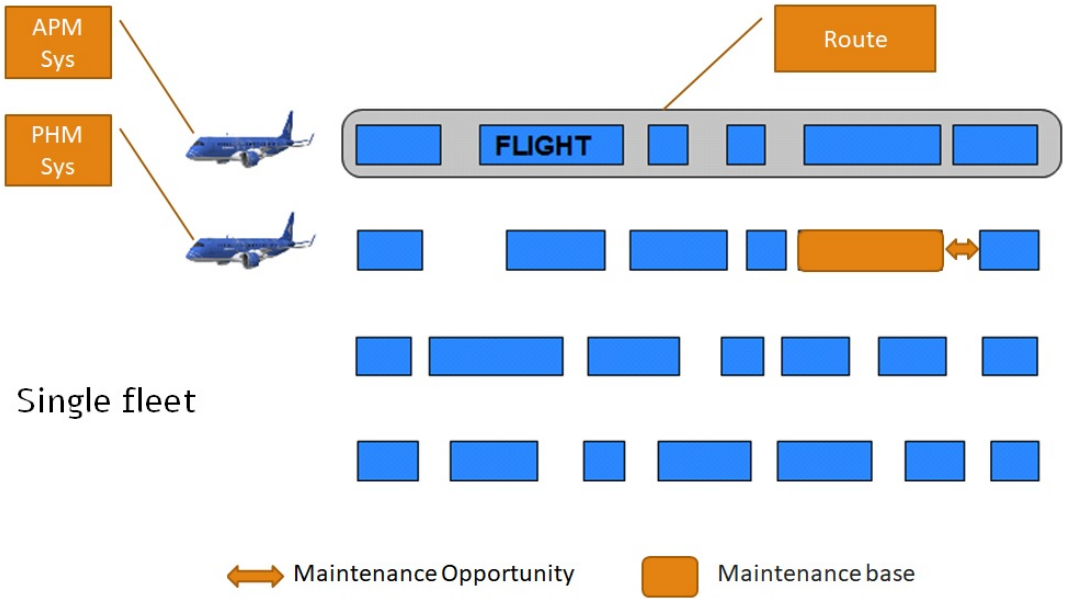
to cover scheduled flights is established. Following this, crew rostering step comes up that is to assign crew members to the pairings (CASTRO, 2013).

Airline operation is composed of the previous phases and steps, and its objective is to maximize airline operating profit. In this thesis, we are focusing on aircraft assignment, subject to vehicle health condition restrictions and fuel consumption efficiency. As mentioned, the aircraft is one of the most critical resources to plan for an airline. Fuel consumption typically represents the top most significant expense for an airline, so that using the best-suited aircraft, in terms of fuel consumption efficiency on each flight, is essential for profitability purposes.

The objective of the airline assignment and scheduling process is to maximize profit and reduce operational costs. Considering that aircraft assignment is part of this effort, this thesis aims to obtain a solution that minimizes fuel consumption while considering flight priority (e.g., prioritizing the most profitable flights).

As presented in Figure 1.1, this work assumes the existence of an aircraft performance monitoring (APM) system that provides information on aircraft fuel consumption efficiency. However, this assignment is subject to predictive maintenance constraints obtained from a prognostics and health monitoring (PHM) system. Figure 1.1 also shows that there are predefined routes (a subset of flights), so that the algorithm assigns aircraft to routes. Besides that, this thesis considers that not all bases (aerodromes) are capable of providing maintenance. In doing so, once plane demands maintenance tasks; only routes that contain aerodromes that contains maintenance capability are eligible for assignment.

Figure 1.1 - Aircraft assignment problem big picture.



As mentioned in previous paragraphs this thesis takes into consideration predictive maintenance constraints. For aircraft allocation end, those predictive constraints should be computed at the vehicle level. Next section presents vehicle level reasoning concept that takes advantage of PHM at component level and aggregates it at vehicle level.

1.2 Related Work

The aircraft assignment problem has been solved mainly by deploying operational research techniques such as linear programming. Gronkvist (2005), one of the most cited works for the topic, developed a hybrid algorithm that is a combination of column generation, constraint programming, and local search; an approach to aircraft assignment which captures operational constraints, including minimum connection times, airport curfews, maintenance, preassigned activities and can model various types of objective functions. In a more recent work, Hottenrott (2015) adopted an adaptive large neighborhood search algorithm for the aircraft assignment problem of airlines to also capture maintenance requirements and operational restrictions such as minimum turn times, curfews and maintenance capacities. The work developed by Lapp and Wikenhauser (2012) is another work taking advantage of linear programming modeling to solve the aircraft assignment problem.

Agent-based approaches brought insight on how to model the aircraft assignment problem as a multi-agent system, throughout the perspective of distributed artificial intelligence[2]. We can cite among the works taking advantage of agent-based approach the ones presented in (CASTRO, 2013) to solve disruption management problem; Kalina (2014) to solve vehicle routing problem; Shoham and Leyton-Brown (2008) that introduces an agent-based assignment algorithm and Wu (2015) presenting an agent-based approach as the implementation of game theory applied to emergency management.

Valenti et al. (2007) presents an application of Integrated Vehicle Health Management (IVHM) concept in the field of mission planning. It is an algorithm to assign a group of Unmanned Aerial Vehicle (UAV) to accomplish a set of tasks considering Prognostics and Health Monitoring (PHM) information. This work focused on the Remaining Useful Life (RUL) of single components separately, without considering that those components are part of a complex system composed by multiple interacting components.

In Tang et al. (2006) work, SEMOR (Self Evolving Maintenance and Operations Reasoning System) is developed based on model-based reasoning, case-based reasoning, and reinforcement learning. This approach takes advantage of PHM reasoning through a model-based reasoning module as well as realizes the benefits of case-based reasoning as a PHM knowledge base grows. Besides that, reinforcement learning is employed to evolve a maintenance model. Intelligent agents are deployed to negotiate decisions regarding database adaptation, maintenance, and logistics actions before the human review.

Camci et al. (2007) designed an architecture to integrate available PHM information from a variety of different sources into the maintenance and logistics infrastructure. It presented a multi-agent technology to integrate maintenance and PHM data to provide more effective maintenance identification (maintenance recommendation) and scheduling. In Camci et al. (2007) work, PHM systems update themselves based on feedback obtained from the maintenance systems.

In the domain of flight operations decision making, Castro (2013) proposed a multi-agent system (MAS), as an integrated solution to the disruption management problem, whose agents represent the roles, functionalities and competencies existing in a typical AOCC (Airline Operations Control Centre), the airline entity responsible for managing the impact of irregular events on planned operations. This MAS produces

[2] An approach to solving in a distributed manner complex learning, planning, and decision-making problems.

intelligent solutions in the sense that its outcomes are the result of an autonomous reaction and adaption to changes in the environment, solving partial problems simultaneously. This thesis does not tackle the disruption management problem, but this work brought insights on how to develop a protocol that is responsible for the negotiation among decision domains, making distributed optimization possible.

Rodrigues et al. (2015) introduced how to take advantage of PHM information and system architecture for maintenance planning based on the estimation of an overall system-level RUL (SRUL). This thesis devised a solution that takes advantage of the concept presented by Rodrigues et al. (2015) for maintenance recommendation and integrates it to distributed aircraft assignment algorithm.

Medeiros et al. (2014) developed a preliminary vehicle assignment algorithm that takes advantage of vehicle health information, where multi-UAV task assignment based on UAV health condition (probability of failure information), mission time and tasks priorities using a modified version of the Receding Horizon Task Assignment (RHTA) algorithm proposed by Alighanbari (2004).

Hess and Fila (2002) presented the Joint Strike Fighter Autonomic Logistics system, a new supportability concept, which consists of the automation of the logistics environment such that little human intervention is needed to engage the logistics cycle; that automation would include actions such as maintenance scheduling, flight scheduling and ordering spare parts. That work also places the importance of PHM as the foundation to that concept, and it proposes a hierarchical approach where data begins at the sensor level, and it is transported up to area reasoners that turn the data into information about a particular subsystem. From such area reasoner, the information is then passed up to a top-level "Air Vehicle Reasoner" where subsystem information is then fused to assess the health of the entire air vehicle. Hess and Fila (2002) brought up two main contributions to our research: 1) It sheds light on the application and relevance of a system similar to our solution and 2) It corroborates hierarchical approach, that we adopted as an assumption to integrate vehicle components health estimative to our solution.

Keller et al. (2001) was suggestive of new perspectives to our research when introduced the integration of signal processing, condition monitoring, health assessment and prognostic capabilities from outside suppliers with the major focus on the integration of prognostic algorithms and model based reasoning and the goal of providing an indication of the relative likelihood the system can complete a particular mission.

Other works we found corroborative of the approaches underlying this thesis proposed solution are Qiang et al. (2009), Xinwei and Wenjin (2011), Zhi-yong and Li-qing (2011) and Feng et al. (2012) that present systems to synthesize equipment fault detection, fault diagnosis, and maintenance management into a whole to establish an integrative maintenance management and support platform based on information of UAV system via multi-agent architecture, and ultimately perform autonomous logistics support.

This thesis was also influenced by Walker (2010), who states a proposal for health management design applied to UAV. It showed how the concepts of Reliability Centered Maintenance[3] could be applied to the specification of PHM system requirements and model-based reasoning methodologies for the implementation of PHM systems. This thesis research considers on Condition Based Maintenance[4] philosophy to give a practical approach to the integration of PHM information to aircraft assignment.

1.3 Research Question

Given aircraft characteristics:

- Fuel consumption performance;
- Components health condition;
- System architecture.

Given flight characteristics:

- Flight importance (e.g. revenue);
- Fuel quantity required.

Given aerodrome characteristics:

[3] Reliability-centered maintenance (RCM) is a systematic approach to develop a focused, effective, and cost-efficient preventive maintenance program and control plan for a product or process. This technique is best initiated during the initial system design process and evolves as the system design, development, and deployment activities progress. The technique, however, can also be used to evaluate preventive maintenance programs for existing systems with the objective of continuous improvement (BLANCHARD et al., 1995).

[4] Condition-based maintenance (CBM) is the use of machinery run-time data to determine the machinery condition and hence its current fault/failure condition, which can be used to schedule required repair and maintenance prior to breakdown (VACHTSEVANOS et al., 2006).

- If it is a maintenance base or not.

This thesis research question is:

> How to efficiently assign aircraft to routes (subset of flights), considering above mentioned aircraft and flight characteristics?

1.4 Hypothesis

This thesis hypothesis is that taking advantage of an agent-based approach; it would benefit an aircraft assignment from the computational burden due to distributed modeling. Additionally, this thesis hypothesis is that such a framework would allow integrating aircraft fuel consumption performance, aircraft components health condition, aircraft systems architecture, flight importance, flight fuel quantity required and aerodrome maintenance capability to generate; as a result, an efficient aircraft allocation that fits operational demand and fleet health management.

1.5 Contribution

This thesis contribution is a distributed aircraft assignment algorithm that optimizes fuel consumption by taking advantage of an aircraft performance monitoring system, subject to predictive health constraints. Health constraints come from a technique called SRUL (System-Level Remaining Useful Life) (FERRI et al., 2013) that puts together aircraft components prognostics and aircraft architecture information to provide a vehicle level health information. This thesis proposed solution also takes into consideration flight importance and aerodromes capability of providing maintenance.

Such an approach can be generalized for resource allocation applications that need to integrate available resources and operational demand; subject to asset health restrictions that come from a PHM system.

1.6 Outline

In the remainder of this thesis, Chapter 2 describes the theoretical background and introduces aircraft performance monitoring, prognostics and health monitoring, integrated vehicle health management, vehicle level reasoning system, multi-agent system, competitive equilibrium, ascending auctions, fault tree analysis and system level remaining useful life concepts. The following chapters focus on aircraft assignment agent-based model description at Chapter 3; scenarios rationale and simulation at Chapter 4; Chapter 5 discusses results generated during simulation and Chapters 6 and 7 concludes the thesis by presenting final remarks and future work suggestions, respectively.

2 BACKGROUND

In Chapter 2, this thesis presents the concepts that the proposed solution assumes as existent, such as aircraft performance monitoring and prognostics and health monitoring; theories on techniques this thesis takes advantage of, namely, multi-agent systems, competitive equilibrium, ascending auctions, fault tree analysis, and system level remaining useful life estimation. Besides that, Chapter 2 introduces the conceptual approach on vehicle level reasoning system and integrated vehicle health management.

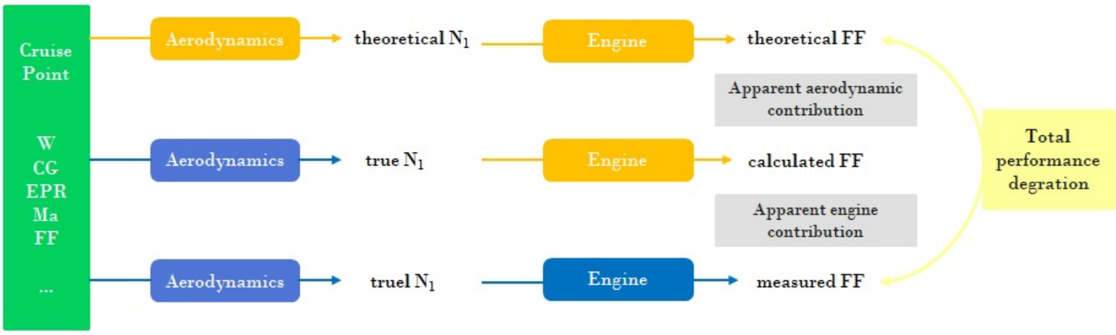
2.1 Aircraft Performance Monitoring

Aircraft Performance monitoring (APM) is a procedure to compute the actual performance level of each aircraft in a fleet versus the manufacturer's book level through the analysis of data gathered in operation. Book level is a reference established by aircraft manufacturer as a result of theoretical analysis and test flights.

A baseline level is a reference established during entry into service of an individual aircraft during the acceptance flight or delivery flight. It can be above or below book level. So that, performance levels are measured over time; in doing so, trends are built up, and the baseline level is the starting point of such trend monitoring (BARKER, 2013).

APM is also used for "apparent" distinction of the engine and aerodynamic performance influence. Figure 2.1 shows the schematic operating principle of APM method. Orange boxes present a theoretical model and blue boxes true aircraft flight data. Measured flight variables, such as weight (W), center of gravity (CG), engine pressure ratio (EPR), mach speed (Ma) and fuel flow (FF) are used as input data for In-Flight Performance (IFP) software that outputs analytical performance, or theoretical engine rotation speed N_1 and theoretical fuel flow FF. Difference between values of calculated and theoretical fuel flow represents the deviation of FF due to apparent aircraft airframe degradation, i.e., aerodynamic contribution. Conversely, if engine performance is degraded, calculated FF will differ from actual (measured) FF (KRAJCEK et al., 2015).

Figure 2.1 - Schematic APM cruise performance method representation.



Source: Krajcek et al. (2015).

According to Barker (2013), APM main objectives are:

- To adjust the performance factor of the computerized flight plan;
- To adjust the Flight Management System (FMS) predictions;
- To monitor the aircraft condition periodically in order to analyze fuel consumption trend of a given tail number or a whole fleet;
- To identify any degraded aircraft within the fleet and take the necessary corrective actions (maintenance actions, operational recommendations).

In order to compare the theoretical and actual performances of the aircraft, there are three different methods recommended by (AIRBUS, 2002):

- **Fuel used method**: this method compares, during cruise flight phase, actual fuel consumption and estimated fuel consumption according to flight manual or IFP software;
- **Trip fuel burn-off method**: The second method analyses discrepancy between actual overall fuel consumption and fuel required for same flight route according to flight planning software. Fuel calculated from flight planning software is adjusted considering the difference between true and predicted flight profile;
- **Specific range method**: it uses mathematical methods and flight mechanic equations from data collected in stabilized conditions during the cruise. It is the most accurate one among those three methods presented.

Additionally, according to (BARKER, 2013), it is also important to mention the main implications of not having previous knowledge of aircraft performance monitoring relating to:

- **Flight planning**: Deteriorated aircraft will burn more trip fuel than planned if Computerised Flight Plan (CFP) takes as reference a new aircraft performance and reserve fuel will also be optimistic;
- **Flight operations**: The FMS fuel prediction function will initially show values close to CFP, but these values will decrease as the flight continues;
- **Crew confidence**: If dispatch level takes no action, the crew will lose confidence in the fuel planning and will start adding their reserves;
- **Perception**: Operators with no previous knowledge of aircraft monitoring are often surprised by deterioration, and believe that there is a problem with the aircraft;
- **Operations**: Extra fuel due to aircraft deterioration may impact payload, and in the worst case make some routes not viable for some tail numbers;
- **Operating costs**: As fuel is a significant component of costs, any increase significantly affects the overall operating costs. Besides, overcompensation of reserves also increases fuel burn and costs.

Considering that APM results could potentially detect aerodynamic or engine system irregularities; significant improvements are difficult without an engine change. However, (BARKER, 2013) cites procedures such as regular engine core wash to reduce deposits, keeping aircraft clean in order to keep engine systems functioning with acceptable performance.

APM is the first step towards the identification of aircraft degradation; it helps monitor shift on the aircraft performance level. So, an airline could pay particular attention to degraded aircraft within the fleet and airlines could use the APM's results to take into consideration during aircraft assignment procedure, for instance.

2.2 Prognostics and Health Monitoring

Prognostics and Health Monitoring (PHM) is the ability to assess the health state, predicting impending failures and forecasting the expected RUL (Remaining Useful

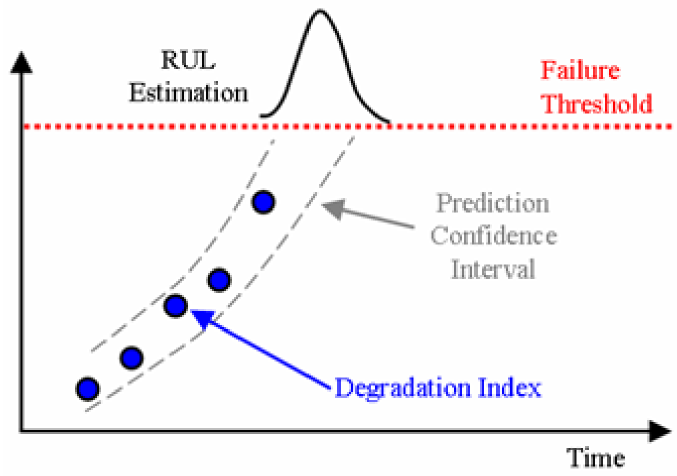
Life) of a component or system based on a set of measurements collected from the systems (VACHTSEVANOS et al., 2006). It comprises a set of techniques, which use analysis of measurements to assess the health condition and predict impending failures of monitored component or systems.

The main goal of a PHM system is to estimate the health state of the monitored component and forecast when a failure is expected to occur (ROEMER et al., 2005). In order to accomplish this task, it is necessary to collect a set of data from the component, data that will be recorded as defined on the basis of the type of component to be monitored (hydraulic, electronic, mechanic, etc.) and failure modes that are intended to be covered by the PHM system. A health monitoring algorithm must be developed for each monitored component. Each algorithm processes the relevant data and generates a degradation index that indicates how degraded the monitored component is.

For this purpose of estimating RUL and the health state of components/systems, a priori probability distributions and actual measurements are used to assess health state and predict impending failures of onboard equipment. The literature on PHM solutions comprises a wide range of applications such as the monitoring of valves (MOREIRA; NASCIMENTO JUNIOR, 2012), pumps (GOMES et al., 2012), engines (BABBAR et al., 2009) and electronic devices (SANDBORN, 2005).

In many cases, it is possible to establish a threshold that defines the system failure. When the failure threshold is known, it is possible to extrapolate the curve generated by the evolution of the degradation index over time and estimate a time interval in which the failure is likely to occur (LEAO et al., 2008), (KACPRZYNSKI et al., 2002). This estimation is usually represented as a probability density function, as illustrated in Figure 2.2. Figure 2.2 also shows that there is a confidence level associated with such predicted time interval.

Figure 2.2 - Degradation index evolution and remaining useful life estimation.



Source: Rodrigues and Yoneyama (2012).

PHM tools transform data into valuable information to manage the maintenance of the vehicles and to keep vehicle operation safe. It enables efficient maintenance management and logistics, optimizing usage of components, tools, and personnel by predicting future failures.

2.3 Vehicle Level Reasoning System

A Vehicle Level Reasoning System (VLRS) summarizes overall system health, consisting of several sub-systems with varying levels of dedicated health monitoring. The primary VLRS concern is to ensure vehicle safety, and it does this by detecting and predicting faults and failures at the vehicle level. A VLRS could receive health information in real time (onboard) or after a flight (in a ground station) from individual subsystems and fuses the information through a reasoning framework to derive an overall health state for the vehicle. Assessing the health state at vehicle level encompasses the following functional elements, according to Jennions (2013):

a) **Measure**: associated with sensing, measuring or reading data;

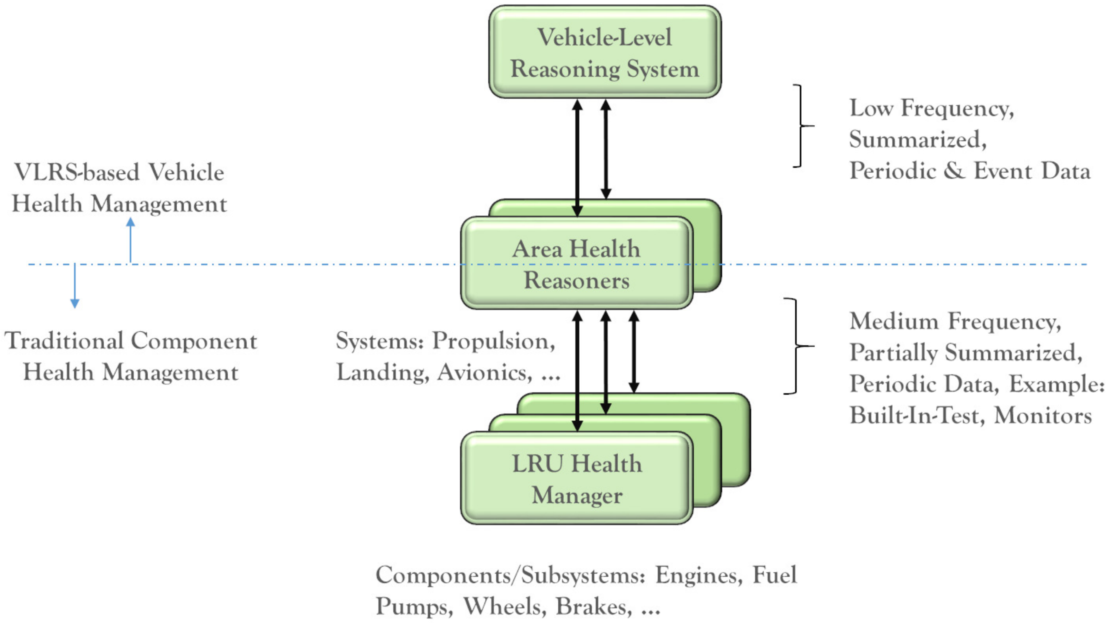
b) **Inference**: associated with extracting the evidential information from the data provided, and estimating the current and future health of the asset(s);

c) **System Model**: encodes the designer's knowledge of how the system/asset behaves under different conditions and operating modes;

d) **Human Machine Interface**: functions for displaying health data and status (text and graphics), displaying documents, controlling indicator lights and gauges, and also receiving commands and data inputs from the user.

Figure 2.3 shows the hierarchical oriented vehicle-level health management approach adopted in this thesis. In such approach, area-level reasoners aggregate the subsystem-level health information such as the status of the built-in tests and the monitors. The hierarchical VLRS approach used to aggregate the information is primarily dependent on the available knowledge of the system and the subsystem architecture and dependencies.

Figure 2.3 - Hierarchical view of component, area/system, and vehicle-level health management.



Source: Jennions (2013).

2.4 Integrated Vehicle Health Management

Integrated Vehicle Health Management (IVHM) is a concept developed by the National Aeronautics and Space Administration (NASA), which requires the highest standards of maintenance for vehicles operating in space. Its natural focus may be on single vehicles, as there is only a limited number of vehicles Original Equipment Manufacturer (OEM). Additionally, the IVHM concept may also be understood as an Integrated Fleet Health Management (IFHM) concept that takes advantage of advances in PHM area. IVHM is the unified capability of systems to assess the current or future states of the system health and integrate that picture of system health within a framework of available resources and operational demand (JENNIONS, 2011).

PHM is an enabler to implement the IVHM concept, that means taking advantage of the existence of the health condition assessment and RUL predictions in order to support decision-making processes.

Methods for decision support using RUL information have also been reported in the IVHM and PHM literature. Previous investigations, such as (RODRIGUES et al., 2010), (SANDBORN; WILKINSON, 2007) and (VIANNA; YONEYAMA, 2017) that presented examples of decision support methods that use PHM information to improve maintenance planning. Rodrigues and Yoneyama (2012) presented an inventory optimization method based on RUL information. Valenti et al. (2007) and Medeiros et al. (2014) introduced a task assignment algorithm based on PHM information and Medeiros et al. (2015) extended such concept to an integrated task assignment and maintenance recommendation algorithm based on PHM information.

2.5 Multi-Agent Systems

Before defining Multi-Agent Systems (MAS), it is essential to define what an agent is. An agent is a computational entity such as a computational program, or a robot that is in some environment and that to some extent can act autonomously in order to achieve its design objectives (WEISS, 2013). In other words, it can be a physical entity or virtual entity that takes input from the environment and produces output actions that affect the environment to achieve a goal.

The term agent has been applied in the fields of computer science and artificial intelligence in many ways such as the typical "electronic assistant" or "virtual assistant" that autonomously acts on behalf of its user, i.e, they are delegated to solve a problem through negotiation and/or cooperation toward joint goals, considering their environment local views. Then they distribute resources and share knowledge about the problem and developing a solution.

There are different types of agents. Considering their behavior, agents can be reactive (perceive the environment and react to some change in it), pro-active (exhibiting goal-direct behavior by taking the initiative to satisfy their design goals) or social (interact with other agents in order to satisfy their goals).

Agents may have the following characteristics, according to Wu (2015):

- Capacity for playing a role in an environment;
- Communicate directly or indirectly with other agents;
- Maximize their payoff and optimize satisfaction/survival function depending on individual objectives;
- Possess useful resources in the environment;
- Perceive their environment;
- Have only partial responsibility of agents' environment (and perhaps none at all).

Given this agent definition, MAS are systems composed of multiple interacting intelligent agents. Therefore, considering the previous explanation on agents, MAS are those systems that include multiple autonomous entities with either diverging information or diverging interests, or both (SHOHAM; LEYTON-BROWN, 2008). In MAS, an agent is a self-directed software object with its value system and the means to communicate to other agents (BAKER, 1998), while the MAS architecture is a loosely coupled network of problem solvers that work together to solve problems that are beyond the individual capabilities or knowledge of each problem solver (DURFEE, 1988).

A MAS has distributed computation entities such as connected networks. In that computing, entities are distributed, large, open, and heterogeneous; granting interoperability, interconnectivity and distributed management. This analogy enables the construction and analysis of interacting models.

According to Ferber (1998), a MAS is based on the following assumptions:

- An environment;
- A set of objects eventually used for multiple agents;
- Any agent can perceive, create, destroy and modify their objects;
- An assembly of agents have specific objects;
- An assembly of relations links objects (and thus agents) to each other;
- An assembly of operations which are performed by agents in order to perceive, produce, consume, transform and manipulate their objects.

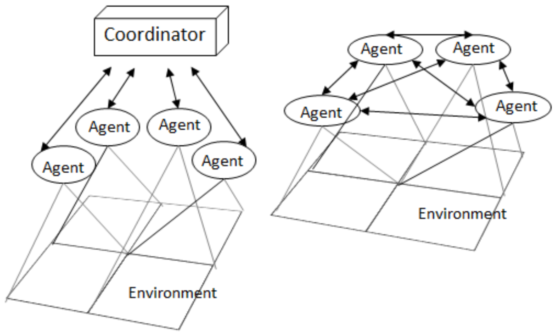
Based on this MAS definition, Weiss (2013) mentions the following challenging issues when developing systems based on agent approach:

- When, how and which agents should interact with, cooperate, and compete to achieve human beings' designed missions or objectives successfully;
- How to enable agents to describe and present the state of agents' interaction processes;
- How to enable agents to comprehend whether agents have achieved progress and objects in their coordination efforts;
- How to enable agents to improve their coordination and to work together consecutively.

In a MAS, for the agents to interact it is necessary to have an infrastructure that specifies a communication language, a domain language, and an interaction protocol. In doing so, language facilitates the communication in agent's interactions; domain language makes agents able to refer and understand the concepts of the domain, proposals, time and, of course, the object of interaction. Communication includes the attributes under negotiation as well as the constants that represent the interaction attributes' value and any other needed symbols. An interaction protocol is necessary to manage the exchange of a series of messages among agents, i.e., a conversation (CASTRO, 2013).

A MAS has two types of operational control: centralized and decentralized, as depicted Figure in 2.4. In centralized operation, there is a coordinator responsible for agents interaction orchestration, that coordination works such as a "mission control" calling other agents to solve problems or part of problems, after that summarizing the final solution. In a decentralized operation, agents communicate to others in a peer-to-peer mode, with no need of a coordinator intervention. In this operation mode, agents often solve decoupled problems and send the result to another agent(s) that will use the action generated by the previous one, and there is not a "bird eyes" entity guiding them.

Figure 2.4 - Centralized (left) vs decentralized (right) multi-agent system operational control.



Source: Wu (2015).

2.6 Competitive Equilibrium

Competitive equilibrium or "Walrasian[1] Equilibrium" (NISAN et al., 2007) is a concept from economic theory, it is a condition where the interaction of profit-maximizing producers and utility-maximizing[2] consumers in competitive markets with freely determined prices arrive at an equilibrium price. At this equilibrium price, the quantity supplied is equal to the quantity demanded. Competitive equilibrium is a state of the market, characterized by a set of prices and an allocation of commodities, such that at equilibrium prices, each agent maximizes its objective function subject to its resource constraints.

Formally, we can say that for a given bidder valuation v_i and given item prices $p_1, ..., p_m$, a bundle T is called a demand of bidder i if for every other bundle S we have that $v_i(S) - \sum_{j \in S} p_j \leq v_i(T) - \sum_{j \in T} p_j$; i.e., given a set of prices, the demand of each bidder is the bundle that maximizes its utility.

[1]Walras was an economist who published mathematical analyses of general equilibria in markets.
[2]Utility represents individual preference, and a utility function is a mathematical representation that computes such preference.

A second definition is that a set of nonnegative prices $p_1^*, ..., p_m^*$ and an allocation $S_1^*, ..., S_m^*$ of the items is a Walrasian Equilibrium if for every player i, S_i^* is a demand of bidder i at prices $p_1^*, ..., p_m^*$ and for any item j that is not allocated (i.e., $j \notin U_{j=1}^n S_i^*$) we have $p_j^* = 0$; i.e., bidder receives a bundle in its demand set, and unallocated items have zero prices.

According to Nisan et al. (2007), Walrasian equilibria, if they exist, are economically efficient; i.e., they necessarily obtain the optimal welfare. Walrasian Equilibrium is a variant of the classic economic result known as the First Welfare Theorem. First Welfare Theorem states that given $p_1^*, ..., p_m^*$ and $S_1^*, ..., S_n^*$ are a competitive equilibrium, then the allocation $S_1^*, ..., S_n^*$ maximizes social welfare.

Competitive equilibrium theory could be thought of as a specialized branch of game theory that deals with making decisions in large markets; it resembles an n-person game, in which the players are the consumers, producers; and the "market participant" or the "auctioneer" chooses the price. Competitive equilibrium is not a game in a strict sense, considering that the strategy set of a player is not fixed but depends on the others' choices.

Competitive equilibrium implementation via a multi-agent system is a demonstration on the intersection of computer science and economic theory. This thesis takes advantage of such intersection to propose an agent-based aircraft assignment algorithm.

2.7 Ascending Auctions

A possible approach to find competitive equilibrium is by deploying ascending auctions. Ascending auctions are a subclass of iterative auctions with demand queries in which the prices can only increase.

In this class of auctions, the auctioneer publishes prices, initially set to zero (or some other minimum prices), and the bidders repeatedly respond to the current prices by bidding on their most desired bundle of goods under the current prices. The auctioneer then repeatedly updates the prices by increasing some of them in some manner, until it reaches a level of prices where the auctioneer can declare an allocation.

This thesis presents two families of ascending auctions: one family uses a simple pricing scheme (item prices) and the second family uses a more sophisticated pricing scheme (bundle prices).

2.7.1 Ascending Item-Price Auctions

Algorithm 1 describes an ascending item-price auction, for a set of items M, that increases prices gradually by ϵ, maintaining a tentative allocation $S_i = D_i$, until one bidder i no longer demands the item j another bidder k tentatively holds. Intuitively, at this point demand D equals supply S and we are close to the competitive equilibrium.

A drawback in such procedure is that the auction does not ensure that items are not under-demanded: an item that was previously demanded by a bidder may be no longer so. The following class of valuations is the one in which competitive equilibrium cannot happen.

Algorithm 1 An item-price ascending auction.

Require: For every item $j \in M$, set $p_j \longleftarrow 0$.
Require: For every bidder i let $S_i \longleftarrow \emptyset$.

```
1: repeat
2:     For each i, let D_i be the demand of i at the following prices:
       p_j for j ∈ S_i and p_j + ϵ for j ∉ S_i.
3:     If for all i S_i = D_i, exit the loop;
4:     Find a bidder i with S_i ≠ Di and update:
       a: For every item j ∈ D_i\S_i set p_j ⟵ p_j + ϵ
       b: S_i ⟵ D_j
       c: For every bidder k ≠ i, S_k ⟵ S_k\D_i
5: until Output the allocation S_1 ··· S_n.
```

2.7.2 Ascending Bundle-price Auctions

Ascending bundle-price auctions reach equilibrium using a more complex pricing scheme. It allows personalized bundle prices, i.e, distinct price $p_i(S)$ per each possible bundle S and for each bidder i. We can naturally generalize the notion of the demand of bidder i under such prices to $argmax_S(v_i(S) - p_i(S))$; where $v_i(S)$ is the valuation of bundle S.

Personalized bundle prices and an allocation are called a competitive equilibrium if:

- For every bidder i, S_i is a demand bundle and for any other bundle T_i that is subset of items set M; it follows that, $T_i \subseteq M, v_i(S_i) - p_i(S_i) \geq v_i(T_i) - p_i(T_i)$;

- The allocation S maximizes seller's revenue under the current prices, i.e., for any other allocation $(T_1, ..., T_n)$, $\sum_{i=1}^{n} p_i(S_i) \geq \sum_{i}^{n} p_i(T_i)$.

Nisan et al. (2007) points out that with personalized bundle prices, competitive equilibria always exist: any welfare-maximizing allocation with the prices $p_i(S) = v_i(S)$ gives a competitive equilibrium.

Several iterative auctions are designed to end up with competitive equilibria. Algorithm 2 describes a bundle-price auction: At each stage, the auctioneer computes a tentative allocation that maximizes its revenue at current prices (current bids). All the losing bidders then "raise their bids" on their currently demanded bundle. When no losing bidder is willing to do so, we terminate with an approximately competitive equilibrium (NISAN et al., 2007).

Bundle-price auction terminates with an approximate competitive equilibrium or ϵ-competitive equilibrium, that is, a bundle S is a demand for a player i under the bundle valuation $v_i(S)$ and bundle prices $p_i(S)$ if for any other bundle T, $v_i(S) - p_i(S) \geq v_i(T) - p_i(T) - \epsilon$.

Algorithm 2 A bundle-price ascending auction

Require: For every player i and bundle S, let $p_i(S) \longleftarrow 0$.

1: **repeat**

2: Find an allocation $T_1, \cdots, T_n$ that maximizes revenue at current prices, *i.e.*, $\sum_{i=1}^{n} p_i(T_i) \geq \sum_{i=1}^{n} p_i(Y_i)$ for any other allocation $Y_1, \cdots, Y_n$. (Bundles with zero prices will not be allocated, *i.e.* $p_i(T_i) > 0$ for every i.)

3: Let L be the set of losing bidders, *i.e.*, L $= \{i | T_i = \emptyset\}$.

4: For every $i \in$ L let D_i be a demand bundle of i under the prices p_i.

5: If for all $i \in$ L, $D_i = \emptyset$ then terminate.

6: For all $i \in$ L with $D_i \neq \emptyset$, let $p_i(D_i) \longleftarrow p_i(D_i) + \epsilon$.

7: **until**

2.8 Fault Tree Analysis

Fault Tree Analysis (FTA) is a failure analysis technique that, due to its ease of use and effectiveness in discovering and representing the interaction of component failures in a system.

Since the seventies, industries such as nuclear power generation, aviation, and automotive industries adopt FTA as part of their safety assessment procedure. In (SAE, 1996) there is a detailed description of the application of FTA on aircraft systems safety assessment.

During the FTA process, graphical diagrams called "fault trees" are produced in order to investigate what are the possible causes for an undesired and unsafe system state, called the "top event." Fault trees represent sequences of events that may lead to the unsafe top event. These sequences usually start from faults originated in system components, which combined with other component faults cause failures that will propagate through the system.

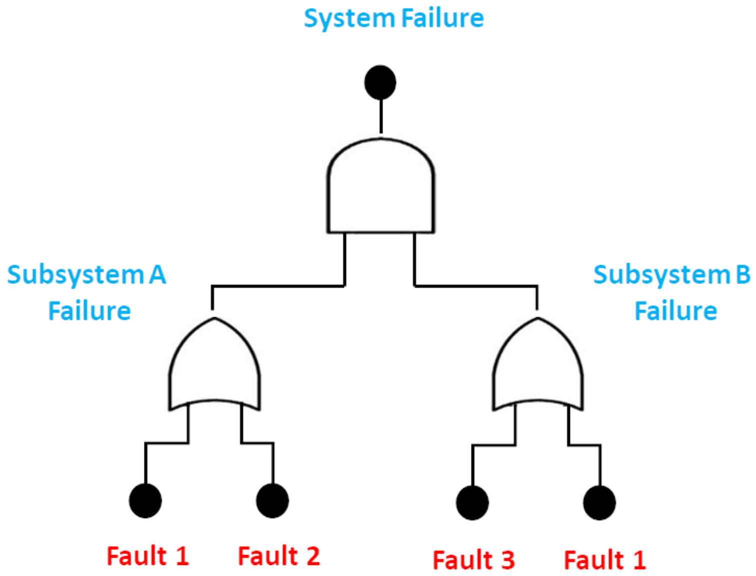
The essential elements of a fault tree diagram are an undesired top event, intermediate events, and primary events. Intermediate events represent failures propagated through the system and can be represented as logical combinations of primary events and other intermediate events, most commonly using the AND ($\wedge$) and the OR ($\vee$) logical operators. Other operators are allowed in fault tree analysis, but they are not relevant for the present work. Primary events are events in the bottom level in the fault tree, and they usually represent component faults. It is possible to attribute a probability of occurrence to each of the primary event in a given operating scenario. If the probabilities of all the primary events are known, it is possible to calculate the probability of the top event. Figure 2.5 shows an example of a simple fault tree.

Considering Subsystem A Failure (FA), Subsystem B Failure (FB) basic events, namely Fault 1 (F1), Fault 2 (F2) and Fault 3 (F3) in the Figure 2.5 are independent occurrences; the output (probability) of port OR for FA, port OR for FB and port AND for system failure are computed by equations 2.1, 2.2 and 2.3, respectively.

$$P_{OR-A} = P_{F1} + P_{F2} - (P_{F1} * P_{F2}) \tag{2.1}$$

$$P_{OR-B} = P_{F1} + P_{F3} - (P_{F1} * P_{F3}) \tag{2.2}$$

Figure 2.5 - Fault tree example.



Source: Ferri et al. (2013).

$$P_{AND} = P_{FA} * P_{FB} \tag{2.3}$$

If we add more terms with additional OR gate components, the probability of port OR P_{OR} for a set of N components e_i through OR gates is shown in Equation 2.4.

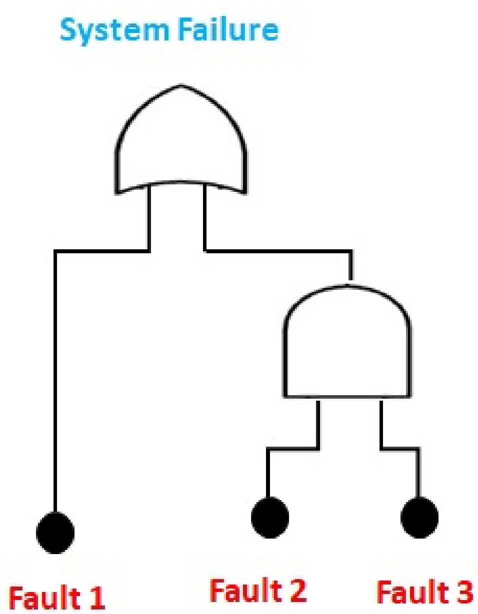
$$\begin{aligned} P_{OR} = \sum_{i=1}^{N} P(e_i) - \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} P(e_i * e_j) + \\ \sum_{i=1}^{N-2} \sum_{j=i+1}^{N-1} \sum_{k=j+1}^{N} P(e_i * e_j * e_k) ... + (-1)^N P(e_1 * e_2 * e_3 ... e_N) \end{aligned} \tag{2.4}$$

The rare-event approximation is often used to simplify Equation 2.4. The approximation simply drops the third term in Equation 2.1 and Equation 2.2, and all but the first term in Equation 2.4. This approximation is accurate to within about 10% of the true probability when $P(e_i) < 0.1$. This is almost always true with modern failure data. Further, any errors induced by this approximation are on the conservative side. The rare event approximation (Equation 2.5) is commonly used for failure analysis fault trees. The full formula in Equation 2.4 can be used for OR gates when extremely precise results are required (MURTHA, 2009).

$$P_{OR} = \sum_{i=1}^{N} P(e_i) \tag{2.5}$$

On the other hand, assuming that all basic events are independent, a convenient form of calculating the top event probability is by transforming the fault tree into its union of cut sets form. A cut set c_i is a combination of basic events that leads to the occurrence of the top event. In the union of cut sets form, we represent all combinations that lead to the top event below an OR logical gate. Figure 2.6 shows the same fault tree as in Figure 2.5 represented in its union of cut sets form. Currently, there are efforts to derive such cut sets systematically. Ary (2018), for example, presented a method to identify critical fault tree components and cut sets by means of fault tree analysis, component importance, event severity, Pareto analysis, component life data analysis, mean time between failures and mean time between unscheduled removals.

Figure 2.6 - Cut sets representation



Source: Ferri et al. (2013).

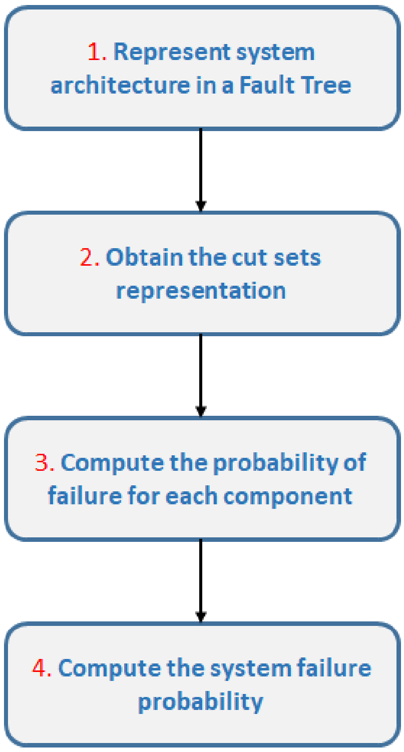
Each input of the top OR gate is by itself a sufficient cause for the top event. We can obtain the probability of the top event by calculating the union probability of all cut sets. Otherwise, if the primary events are mutually independent, the probability of each cut set can be obtained by calculating the joint probability of the events that compose the cut set. If all the primary events are mutually independent, the joint probability of a cut set is just the product of all its primary events. When using the union of cut sets c_i representation, top event occurrence probability can be calculated using Equation 2.6 (RODRIGUES et al., 2015).

$$P_T = 1 - \prod_{i=1}^{m}(1 - P(c_i)) \quad (2.6)$$

2.9 System Level RUL Estimation

System Level Remaining Useful Life (SRUL) estimation is a methodology proposed by Ferri et al. (2013) that represents a VLRS output; we can obtain it by using the system architecture knowledge represented by a system fault tree and the RUL distributions for each component from a PHM system. The procedure to calculate the SRUL is summarized in Figure 2.7.

Figure 2.7 - SRUL calculation procedure



Source: Ferri et al. (2013).

The first required step is to represent in fault tree format target critical system. Based on such fault tree representation, it is possible to obtain the minimal cut sets list representation. In this representation, the probabilities of each cut set and of the top event can be computed by Equations 2.7 and 2.8, respectively.

$$P(c_i) = P(e_1 \cap e_2 ... \cap e_n) = \prod_{j=1}^{n} P(e_j) \tag{2.7}$$

$$P_T = P(c_1 \cup c_2 ... \cup c_n) \tag{2.8}$$

where $P(c_i)$ denotes the probability of the $i-th$ cut set, $P(e_j)$ denotes the probability of an event e_j, n is the number of events in a cut set and P_T is the probability of the top event.

At Step 3 of the procedure presented in Figure 2.7, the probabilities of failure for all components are calculated using the RUL predictions from a PHM system for each component. After this, in Step 4, it is possible to calculate the probability of a system failure to occur using the expressions presented in Equations 2.7 and 2.8. The procedure in Steps 3 and 4 repeats over analysis horizon time steps. This procedure will result in a Cumulative Distribution Function (CDF) representing the probability of system failure before a given instant in time.

Although many of the prognostic failure methods focus on estimating the remaining useful life of individual components, RUL estimates of systems comprising sets of components are more useful for operation and maintenance planning purposes (KHORASGANI et al., 2016). In this thesis, SRUL is applied to calculate aircraft probability of failure, considering the architecture of critical systems. SRUL integrates individual components PHM information to create vehicle level degradation information.

System-level prognostic methods consider the degradation level of components, and also how these components interact in order to define system behavior. In this thesis, we represent the interactions between components using a fault tree. We can see examples of the application of this approach in previous works such as (RODRIGUES et al., 2015), (RODRIGUES, 2018) and (RODRIGUES; GOMES, 2018).

3 PROPOSED SOLUTION

Chapter 3 presents an agent-based solution that takes advantage of multi-agent systems framework (section 2.5), competitive equilibrium theory (section 2.6) to represent aircraft, routes and to perform their interaction; considering PHM (section 2.2) and APM (section 2.1) information.

3.1 Agent-based Aircraft Assignment

This thesis states agent-based aircraft assignment as follows:

- A set of aircraft N;
- A set of routes X;
- A set of possible assignment pairs W; and
- A function $u : W \Rightarrow R$ that outcomes the value associated with each possible route-aircraft combination.

An assignment is a set of pairs $A \subseteq W$ such that each aircraft (agent) $i \in N$ and each route (object) $j \in X$ is in at most one pair in A. A feasible assignment is one in which each route is assigned to one aircraft. A feasible assignment A is optimal if it maximizes $\sum_{(i,j)\in A} u(i,j)$.

3.2 Applied Competitive Equilibrium

Competitive equilibrium introduced in Section 2.6 is instantiated to fit the aircraft assignment problem. So, imagine that each route in X has associated importance instead of a price. This importance vector is $d = (d_1, ..., d_n)$, where d_j is the importance of route j. Given an assignment $A \subseteq W$ cost $c(i,j)$ and a importance vector d define the utility $u(i,j)$ for an assignment of route j to aircraft i. An assignment and a set of values, that represent route importance, are in competitive equilibrium when it binds each aircraft to the route that maximizes its utility, given the current importance values.

The importance vector p for each route j comes from Equation (3.1), that is the summation of flight importance values w_k that are part of the subset of flights in route j.

$$d(j) = \sum_{k=1}^{|j|} w_k \qquad (3.1)$$

The cost matrix $c(i, j)$ for each pair <aircraft i, route j> comes from equation

$$c(i, j) = r(j) * f(i) * C \qquad (3.2)$$

Where:

- $r(j)$ is the required fuel, in metric tons (mt), to fly over route j;
- $f(i)$ is the aircraft i fuel consumption performance degradation factor, it emulates an estimative from the APM system, as stated in Section 1.1; and
- C is the fuel price constant $\$/mt$.

Remembering from Section 1.1 that this thesis aims to obtain a solution that minimizes fuel consumption while considering flight priority; there are slightly differences that come up with this. First, d_j represents route priority (aggregation of flights priority); second $c(i, j)$ represents fuel consumption cost that depends on the combination of aircraft i and route j. As a consequence, this thesis uses Equation 3.3 to compute utility function $u(i, j)$. It means there is a reward d_j for operating the route that is decremented by the fuel expenses and maintenance penalization computed in $c(i, j)$.

$$u(i, j) = d_j - c(i, j) \qquad (3.3)$$

Formally we can state that a feasible assignment A and an importance vector d are in competitive equilibrium when for every pairing $(i, j) \in A$ it is the case that $\forall k \in X - \{j\}, u(i, j) \geq u(i, k)$. If a feasible assignment A and an importance vector d satisfy the competitive equilibrium condition then A is an optimal assignment. Furthermore, for any optimal solution A, there exists an importance vector d such that d and A satisfy the competitive equilibrium condition (SHOHAM; LEYTON-BROWN, 2008).

One way to search for assignment problem solutions is to focus on the search space of competitive equilibria. In doing so, a possible procedure to explore that space is an auction-like algorithm, in which individual agents bid for different resources in a predefined way. In this thesis, agents (aircraft) bid for objects (routes), and this bid is evaluated by a coordinator agent that will be introduced in Section 3.3. In this thesis proposed model, it was adopted the ascending bundle-price auctions as presented in Section 2.7.2.

In order to explain the auction-like procedure, consider the naive algorithm presented in Algorithm 3. It begins with no routes allocated. Then the importance vector d is initialized (lines 1-3). Next, bid steps come up (lines 5-7). In line 6, the algorithm finds a route $j \in X$ that offers i maximal value at current importance value (reward). In line 7, the algorithm computes the $i's$ bid increment for j, which is the difference between the value to i of the best and second-best objects at current importance value. Note that $i's$ bid will be the current importance less its bid decrement. The assignment stage takes place in lines 8-11. In line 12, the algorithm updates importance vector d and terminates when A contains an assignment for all $i \in N$, i.e. when all routes have an aircraft assigned to it. The solution obtained with Algorithm 3 is a feasible solution, and it reaches competitive equilibrium.

Algorithm 3 Agent-based Assignment

Require: $A \longleftarrow \emptyset$
1: **for** j ∈ X **do**
2: $\quad d_j \longleftarrow \sum_{k=1}^{|j|} w_k$
3: **end for**
4: **repeat**
5: $\quad$ let $i \in$ N be an unassigned aircraft
6: $\quad j \in \arg\max_{j|(i,j)\in W}(d_j - v(i,j))$
7: $\quad b_i \longleftarrow (d_j - c(i,j)) - \max_{k|(i,k)\in W; k\neq j}(d_k - c(i,k))$
8: $\quad$ add the pair (i, j) to the assignment A
9: $\quad$ **if** there is another pair (i', j) **then**
10: $\quad\quad$ remove (i', j) from the assignment A
11: $\quad$ **end if**
12: $\quad$ decrease the value d_j by b_i
13: **until** A is feasible

When Algorithm 3 terminates, it provides a feasible solution for the problem under consideration. The problem, however, is that it may not terminate. It can occur when more than one object offers maximal value for a given agent. In this case, agent's bid decrement (line 7 in Algorithm 3) will be zero. If two items also happen to be equally the best items for another agent, they will enter into an infinite bidding race in which importance will never go down, and in such condition, the auction algorithm does not converge.

In order to overcome such issues, related to equal maximal bid values, we added a mechanism to ensure that prices continue to increase when objects are contested by a group of agents. So that, a quite straightforward extension is: to add an amount ϵ to the bidding decrement of an agent $i \in N$ as in Equation 3.4.

$$b_i = u(i,j) - \max_{k|(i,k) \in W; k \neq j} u(i,k) + \epsilon \tag{3.4}$$

The terminating auction protocol would proceed, at each iteration, increasing by at least ϵ the price for the preferred item. Because the prices must increase by at least ϵ at every round, agents may "overbid" on some objects. For this reason, we took advantage of a notion of ϵ-competitive equilibrium.

In ϵ-competitive equilibrium, an assignment A and the associated importance vector p satisfy the $\epsilon - \textit{competitive}$ equilibrium criterion when, for each $i \in N$, if there is a pair $(i,j) \in A$ then $\forall k \in X - \{j\}, u(i,j) + \epsilon \geq u(i,k)$. A feasible assignment A with n goods that forms an $\epsilon - \textit{competitive}$ equilibrium with some importance vector is within $n\epsilon$ of optimal (SHOHAM; LEYTON-BROWN, 2008).

3.3 MAS Architecture

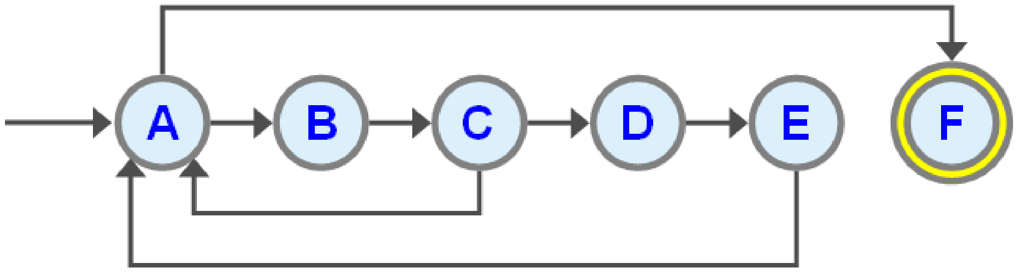
The MAS used in this thesis is composed of two types of agents: tail assignment agents (TAS) and aircraft agents (ACFT).

A Tail Assignment Agent is responsible for assignment and coordination. It comprises the following components:

- **Assignment:** It checks if all routes have an aircraft assigned to;
- **Coordination:** It commands and controls request from and response to aircraft agent.

The Tail Assignment agent is represented by a finite state machine (FSM), as shown in Figure 3.1. The states in the FSM that represents TAS agent is the following:

Figure 3.1 - TAS FSM.



- **State A (Check Assignment):** It verifies whether all routes are covered;
- **State B (Send CFP):** It sends a call for proposal (CFP) to aircraft fleet;
- **State C (Check Proposal):** It receives a proposal to operate the route addressed by the CFP from each eligible aircraft;
- **State D (Send Feedback):** It sends a message to proponent aircraft to inform if it is the auction winner or not;
- **State E (Check Update):** It checks if the winner aircraft sent a message informing on its bid update;
- **State F (Finish Assignment):** whenever the algorithm covers each route by an aircraft, it presents the final solution.

In order to complete the task assignment agent FSM description, we can define the transitions between states as follows:

- **Transition A → F (from Check Assignment to Finish Assignment):** This transition is enabled if all routes have aircraft assigned to;
- **Transition A → B (from Check Assignment to Send CFP):** This transition is enabled if there is at least one route that has no aircraft assigned to;
- **Transition B → C (from Send CFP to Check Proposal):** This transition is enabled by default whenever TAS agent sends CFP message;
- **Transition C → D (from Check Proposal to Send Feedback):** This transition comes up if exist at least one proposal from aircraft agent(s);

- **Transition C → A (from Check Proposal to Check Assignment):** This transition is enabled if there is no proposal from aircraft agent(s) at that iteration;

- **Transition D → E (from Send Feedback to Check Update):** This transition is enabled by default whenever TAS sends feedback to winning and losing proponent aircraft agents;

- **Transition E → A (from Check Update to Check Assignment):** This transition is enabled by default whenever TAS confirms the winner proponent price was updated.

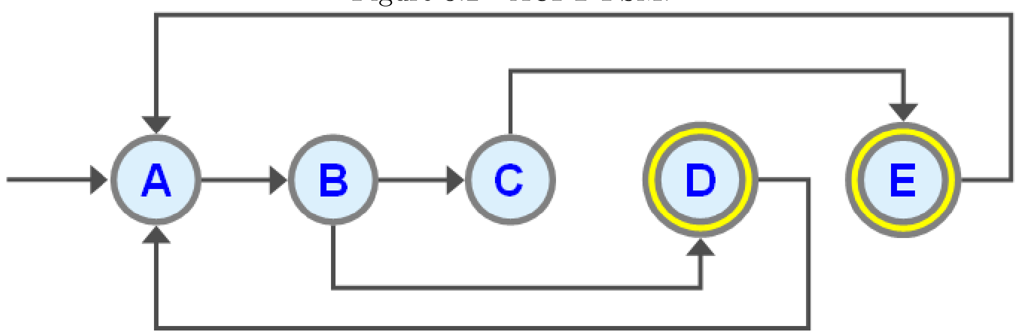
An aircraft Agent (ACFT) is responsible for checking itself if it is a suitable option to operate a route and provides information on the aircraft condition (fuel consumption performance and health degradation). The ACFT comprises the following components:

- **Admission:** It verifies, for a given route, if the aircraft is eligible to operate that route, currently it checks if current aircraft location is the same of route first flight departure location and in the case that ACFT demands maintenance in accordance with Section 3.5, it also verifies if the route contains a maintenance base;

- **Bid Update:** It updates aircraft agent bid. It sums up bid increment and ϵ parameter value to the current bid.

Aircraft agents can also be represented by a finite state machine, as shown in Figure 3.2. The states in the FSM that represents ACFT agents behavior are the following:

Figure 3.2 - ACFT FSM.



- **State A (Check CFP):** It checks and receives CFP messages from TAS;
- **State B (Check Admission):** It calls **admission component** to verify if its eligible to operate route, according to criteria in previous **admission component** description;
- **State C (Send Proposal):** It sends a proposal in order to respond CFP, and this message has the aircraft cost (fuel expenses + penalization factor) and maintenance status (aircraft health assessment) as content;
- **State D (Send Refuse):** It sends a refusal message to TAS if aircraft is not eligible to participate in the auction process;
- **State E (Update Bid):** It calls **bid update component** to update its bid to the next auction iteration.

In order to complete the aircraft agent FSM description, the transitions between states are defined as follows:

- **Transition A → B (from Check CFP to Check Admission:)** This transition is enabled if ACFT agent receive a CFP message and get CFP content unpacked;
- **Transition B → C (from Check Admission to Send Proposal):** This transition is enabled if admission component returns aircraft as eligible to be assigned to the route;
- **Transition B → D (from Check Admission to Send Refuse):** This transition is enabled if admission component returns aircraft as not eligible to be assigned to the route;

- **Transition C → E (from Send Propose to Update Bid):** This transition is enabled by default after ACFT sends proposal message;

- **Transition E → A (from Update Bid to Check CFP):** This transition is enabled by default after ACFT updates its bid;

- **Transition D → A (from Send Refuse to Check CFP):** This transition is enabled by default after ACFT sends a refusal message.

3.4 Interaction Protocol

Another important mechanism in MAS is an interaction protocol that defines the flow of messages among agents. Such exchanged messages over agents interaction flow that we deployed to our MAS modeling approach in order to properly run communication among agents are detailed in Table 3.1.

Table 3.1 - Interaction messages.

Message	Description
call-for-proposal (CFP)	Action to initiate a negotiation process by making a call for proposal. It includes the sender agent (TAS), the receiver agent (ACFT), the CFP ID and the route to be assigned.
propose	An answer to CFP auction-like process. It includes the sender agent (ACFT), receiver agent (TAS), proposal ID, cost of allocating that proponent aircraft and aircraft health status (maintenance demand).
refuse	The action of refusing to candidate to assign for a route. It includes sender agent (ACFT), receiver agent (TAS) and refusal message ID.
accept-proposal	An acceptance of a proposal that was previously submitted. It is an n-tuple that includes sender agent (TAS), receiver agent (ACFT).
reject-proposal	The action of rejecting a proposal that was previously submitted. It includes sender agent (TAS), receiver agent (ACFT), the ID of the rejected proposal.
inform	An information from the sender (ACFT) to receiver agent that a proposition is true, in this application it informs that ACFT updated its cost.

The interaction protocol deployed to play automatic negotiation among agents is designed based on the FIPA[1] standard for contract net interaction protocol implementation (FIPA TC COMMUNICATION, 2002), for convenience reproduced in Figure 3.3.

Taking advantage of contract net protocol, considering ACFT and TAS FSM and messages exchange mechanisms defined, so we can describe the MAS cycle as follow:

a) The TAS agent iterates over a list of unassigned routes;

b) It selects an unassigned route, sends a CFP to the aircraft fleet in order to find the aircraft that best fits that unassigned route;

c) Each ACFT agent receives a CFP from TAS and checks if it is eligible to operate the route under consideration;

d) If ACFT is eligible, it sends a proposal message to TAS; otherwise it sends a refusal message;

e) The TAS agent receives assignment cost and maintenance status for each proponent (candidate aircraft) considering the current unassigned route in CFP;

f) Then, the TAS evaluates the proposals based on route importance, fuel consumption and maintenance restriction;

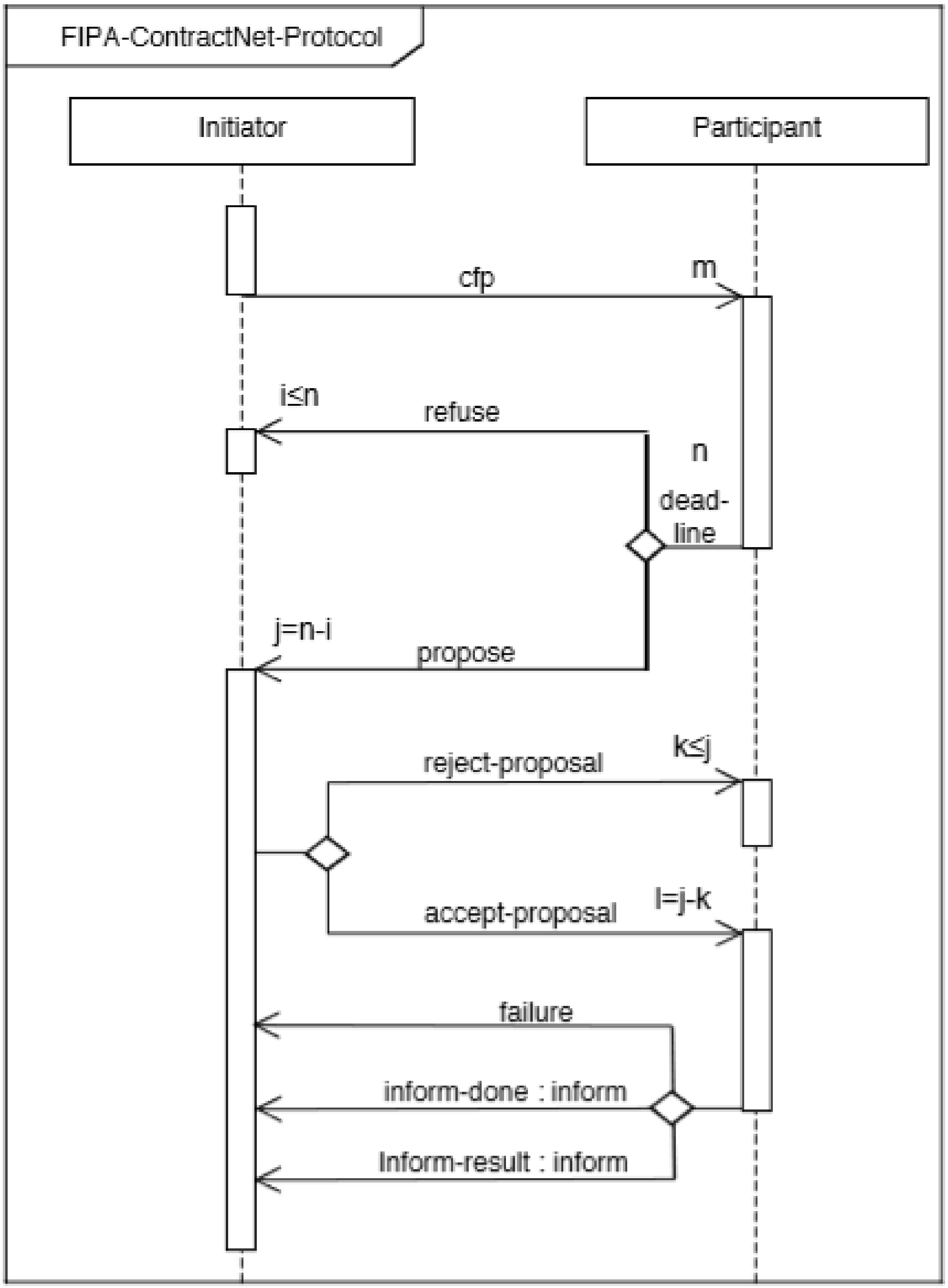
g) Next, the TAS picks the best proposal and sends a feedback message to proponents via accept-proposal to the winner and via reject-proposal to the losers proponents;

h) Finally, winner ACFT agent updates its costs and sends an informative message to the TAS communicating about update operation, finishing the protocol iteration;

i) Once there are no unassigned routes in the list, the protocol terminates.

[1]Foundation for Intelligent Physical Agents (FIPA) is an IEEE Computer Society standards organization that promotes agent-based technology and the interoperability of its standards with other technologies.

Figure 3.3 - Contract Net Interaction Protocol.



Source: FIPA TC COMMUNICATION (2002).

3.5 Integrating health information to aircraft assignment model

SRUL predictions are obtained by using RUL predictions for each component and taking advantage of the fault tree to represent the interactions among individual components within the system (RODRIGUES et al., 2015).

This thesis integrates SRUL predictions to the agent-based aircraft assignment algorithm as part of admission component inside the ACFT agent that is deployed in "Check Admission" and "Send Proposal" states. In that state, each aircraft calls its PHM system that assesses aircraft components health. After that, SRUL takes advantage of fault tree representation to take into consideration critical systems architecture. In doing so, SRUL module can compute the probability of failure at time t at the system level or vehicle level, so that aggregating aircraft components health state, along with demanded downtime to get maintenance task performed. Once SRUL module outputs failure probability value, as we refer in Section 2.9; we compare it to two discretionary thresholds:

- Opportunistic maintenance threshold τ and
- Required maintenance threshold ω.

By using those thresholds, we can derive the following health status for each aircraft:

- **No Maintenance:** In this condition, $SRUL < \tau$ and the probability that the aircraft demands a maintenance action is below an acceptance criterion; therefore no constraints in terms of maintenance base;
- **Opportunistic Maintenance:** In this condition, $\tau \leq SRUL \leq \omega$, and maintenance takes place if there is an opportunity to place maintenance on schedule;
- **Mandatory Maintenance:** In this condition, $SRUL > \omega$, and the aircraft will be unavailable if the airline does not perform maintenance action.

Considering the three possible health status, when the TAS agent sends a call for proposal to the aircraft fleet in order to get an assignment, any aircraft in "no maintenance" status could candidate itself constrained to the condition that it is in the same departure location of route's first flight. Aircraft in "opportunistic maintenance" status can candidate itself to any route if it does not violate location constraint. However, when a route assigned to an aircraft on "opportunistic maintenance" status does not contain a maintenance base and required downtime, then a penalty factor σ is added to aircraft cost. Aircraft in "mandatory maintenance" status can candidate itself to routes that contain a maintenance base, that do not violate the location and required downtime constraint. Once the algorithm decides to schedule a maintenance task; the algorithm allocates it in the first suitable (i.e., it fits required downtime) time slot available in the route.

In the case that "opportunistic maintenance" penalty comes into play for aircraft agent j, Equation 3.4 would be replaced with Equation 3.5:

$$b_i = u(i,j) - \max_{k|(i,k)\in W; k\neq j} u(i,k) + \epsilon + \sigma_j \tag{3.5}$$

Another restriction considered in our model is related to the downtime requirement. ACFT agents check if there is enough time to perform required maintenance tasks without causing flight delays, considering that there is a maintenance base in the middle of the route. In the case that maintenance base is the last flight of the route, this time restriction is relaxed because we assume that there will be enough time to perform such required maintenance tasks overnight up to next flight.

4 SIMULATION

This chapter describes a case study in Section 4.1 that is represented by six scenarios. Those six scenarios are based on three airlines fleet and flight schedules. The multi-agent system architecture was developed and run by a framework called JADE (Java Agent DEvelopment Framework), that this chapter introduces in Section 4.2.

4.1 Scenarios

In this work, we simulated scenarios by considering three airline schedules[1], for a day of operation, in which the scenarios exhibit the following fleet and schedule characteristics:

- Airline#1: 42 aircraft to cover 219 flights distributed over 42 routes;
- Airline#2: 22 aircraft to cover 93 flights distributed over 22 routes;
- Airline#3: 8 aircraft to cover 50 flights distributed over 8 routes.

In order to validate this thesis approach to integrate aircraft health information to aircraft assignment problem, we designed scenarios to evaluate opportunistic maintenance and mandatory maintenance demand in the end and the mid of the day of operation. To accomplish this, we duly set up opportunistic maintenance threshold τ, a required maintenance threshold ω and maintenance bases[2]. Moreover, required downtime as follows:

a) Scenario A

- Airline #1;
- $\tau = 30\%$;
- $\omega = 70\%$;
- $\sigma = 1,000$;
- Aircraft 115, 102; $SRUL = 31\%$;
- Maintenance bases: IND[3], CHS;

[1] Complete airlines schedules could are available in Apppendix B.
[2] Maintenance bases are airports capable of providing maintenance facilities and workforce.
[3] Three-letter International Air Transport Association (IATA) code of a location (airport, city) is used to identify airports that compound each route.

- Required downtime: 30 minutes.

b) Scenario B

- Airline #1;
- $\tau = 30\%$;
- $\omega = 70\%$;
- $\sigma = 0$;
- Aircraft 115, 102; $SRUL = 31\%$;
- Maintenance base:IND, CHS;
- Required downtime: 30 minutes.

c) Scenario C

- Airline #2;
- $\tau = 30\%$;
- $\omega = 70\%$;
- $\sigma = 1,000$;
- Aircraft EZV, EZD; $SRUL = 98\%$;
- Maintenance bases: AMS, BGO;
- Required downtime: 30 minutes.

d) Scenario D

- Airline #2;
- $\tau = 30\%$;
- $\omega = 70\%$;
- $\sigma = 1,000$;
- Aircraft EZV, EZD; $SRUL = 98\%$;
- Maintenance bases: AMS, BGO;
- Required downtime: 30 minutes;
- Overnight maintenance only.

e) Scenario E

- Airline #3

- $\tau = 30\%$
- $\omega = 70\%$
- $\sigma = 1,000$;
- Aircraft: 101, 107, 108; $SRUL = 31\%$
- Maintenance bases: POA, BSB
- Required downtime: 40 minutes.

f) Scenario F

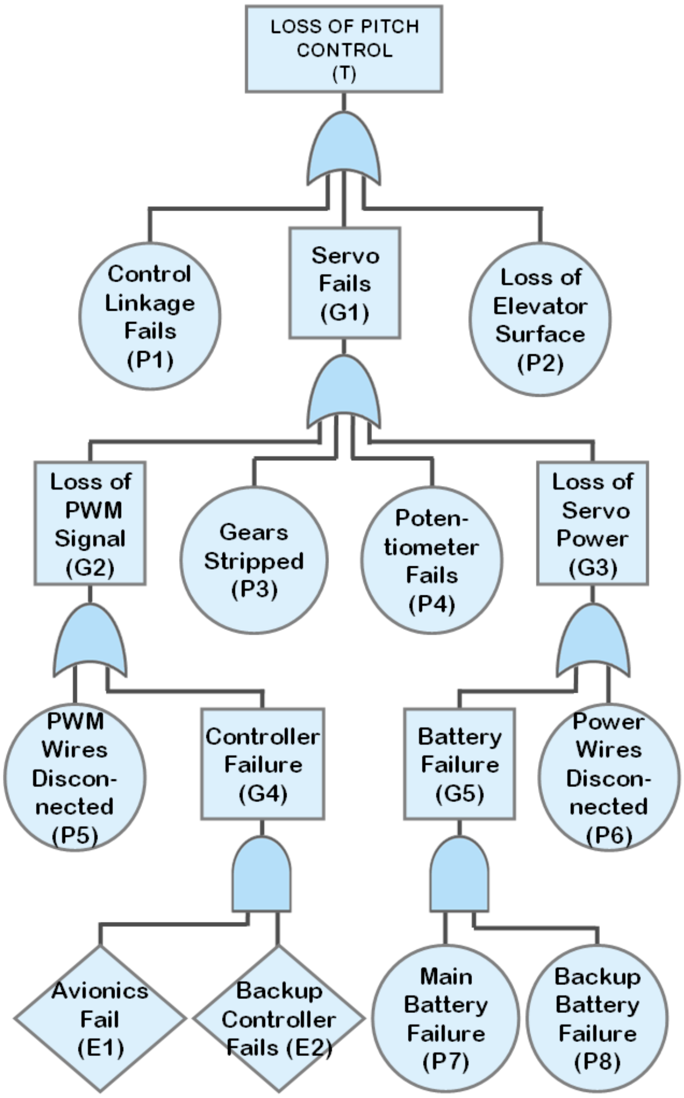
- Airline #3
- $\tau = 30\%$
- $\omega = 70\%$
- $\sigma = 1,000$;
- Aircraft: 101, 107, 108; $SRUL = 31\%$
- Maintenance bases: POA, BSB
- Required downtime: 40 minutes.
- Overnight maintenance only.

Opportunistic and mandatory maintenance thresholds were arbitrarily set for this case study. Maintenance penalty σ was chosen empirically to handle opportunistic maintenance restriction. An additional restriction was simulated relating to the execution of maintenance only at the end of the day of operation in scenarios D and F.

In the aforementioned scenarios, there are selected aircraft with associated SRUL. The SRUL value for each selected aircraft was computed by the procedure described in Section 2.9.

Scenarios A, B, E and F SRUL's computation came from a fault tree of a pitch control system, presented in Figure 4.1. The top event considered is a loss of pitch control that is a catastrophic event.

Figure 4.1 - Loss of pitch control fault tree.



Source: Murtha (2009).

This thesis assumption is that an existing PHM system provides the probability of failure of each component, as stated in Section 1.1. Table 4.1 presents those failure probabilities for vehicles defined in scenarios A, B, E and F.

Table 4.1 - Loss of pitch control failure probabilities.

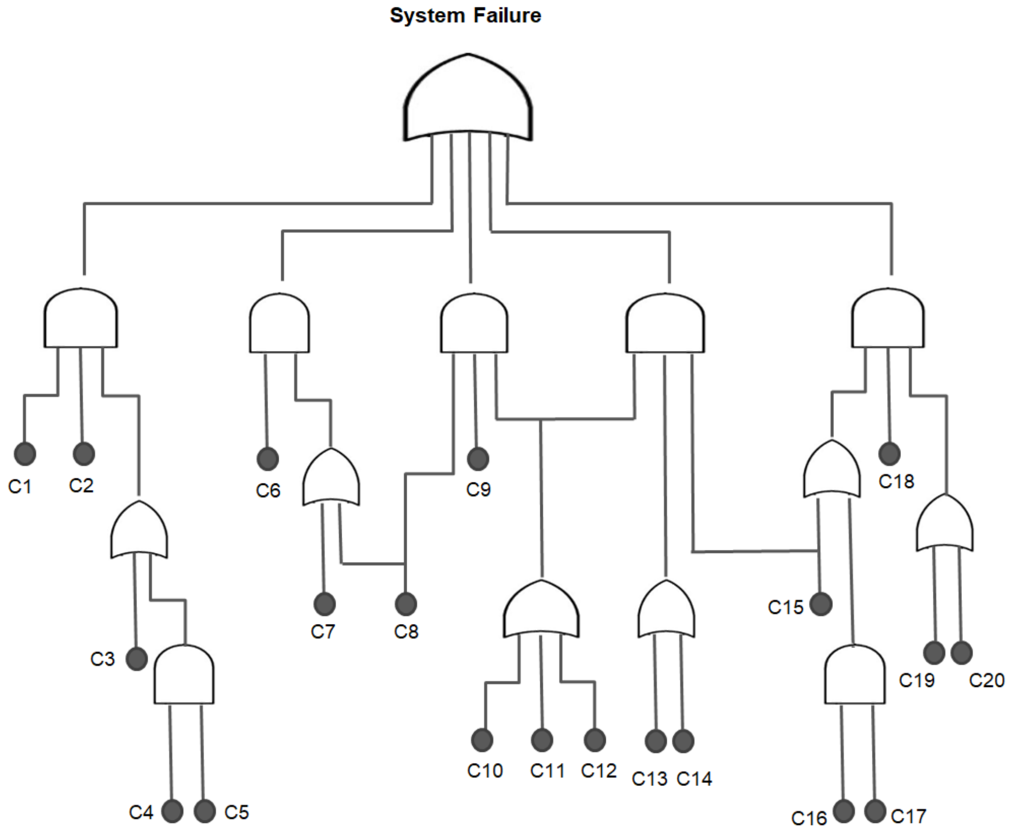
Event	Probability	Event	Probability
P1	0.131	P7	0.170
P2	0.021	P8	0.098
P3	0.033	E1	0.015
P4	0.081	E2	0.280
P5	0.053	**SRUL**	0.310
P6	0.016		

After that, based on the data from Table 4.1; along with the system fault tree in Figure 4.1; so we compute SRUL estimate for the system by the application of Equation 2.6 as follows:

$$\begin{aligned} P_T &= 1-[(1-P_1)\times(1-P_2)\times(1-P_3)\times \\ &\quad \times(1-P_4)\times(1-P_5)\times(1-P_6)\times \\ &\quad \times(1-(P_7\times P_8))\times(1-(E_1\times E_2))] \end{aligned} \tag{4.1}$$

Scenarios C and D SRUL's computation came from a generic fault tree, presented in Figure 4.2. Considering it is also a critical system and that top event is a catastrophic event; the probability of failure of each component is given by a PHM system as presented in Table 4.2, for vehicles defined in scenarios C and D, cut sets are as in Table 4.3.

Figure 4.2 - Generic fault tree.



Source: Rodrigues et al. (2015).

So that, based on the data in Table 4.2; system fault tree in Figure 4.2 and cut sets definition in Table 4.3, we are able to compute SRUL estimate for this system representation by using Equation 2.6 as follows:

$$
\begin{aligned}
P_T \;=\; & 1 - [(1 - P_1) \times (1 - P_2) \times (1 - P_3) \times \\
& \times (1 - P_4) \times (1 - P_5) \times (1 - P_6) \times \\
& \times (1 - P_7) \times (1 - P_8) \times (1 - P_9) \times \\
& \times (1 - P_{10}) \times (1 - P_{11}) \times (1 - P_{12}) \times \\
& \times (1 - P_{13}) \times (1 - P_{14}) \times (1 - P_{15}) \times \\
& \times (1 - P_{16}) \times (1 - P_{17})]
\end{aligned} \tag{4.2}
$$

Based on the statement of Section 3.2, in order to run the algorithm simulation we also need to define the parameter ϵ value, a function $v(i, j)$ that outcomes the

Table 4.2 - Generic fault tree components failure probabilities

Component	Probability	Component	Probability	Component	Probability
C01	0.944	C08	0.878	C15	0.999
C02	0.999	C09	0.443	C16	0.159
C03	0.557	C10	0.078	C17	0.074
C04	0.945	C11	0.788	C18	0.252
C05	0.999	C12	0.227	C19	0.018
C06	0.369	C13	0.067	C20	0.999
C07	0.077	C14	0.012		

Table 4.3 - Generic fault tree cut sets

ID	Cut Set	Prob.	ID	Cut Set	Prob.
P1	$C01 \wedge C02 \wedge C03$	0.525	P10	$C11 \wedge C13 \wedge C15$	0.052
P2	$C01 \wedge C02 \wedge C04 \wedge C05$	0.890	P11	$C11 \wedge C14 \wedge C15$	0.009
P3	$C06 \wedge C07$	0.028	P12	$C12 \wedge C13 \wedge C15$	0.015
P4	$C06 \wedge C08$	0.323	P13	$C12 \wedge C14 \wedge C15$	0.002
P5	$C08 \wedge C09 \wedge C10$	0.030	P14	$C15 \wedge C18 \wedge C19$	0.004
P6	$C08 \wedge C09 \wedge C11$	0.306	P15	$C15 \wedge C18 \wedge C20$	0.251
P7	$C08 \wedge C09 \wedge C12$	0.088	P16	$C16 \wedge C17 \wedge C18 \wedge C19$	5.337E-5
P8	$C10 \wedge C13 \wedge C15$	0.005	P17	$C16 \wedge C17 \wedge C18 \wedge C20$	0.002
P9	$C10 \wedge C14 \wedge C15$	9.350E-4	**SRUL**		0.9857

value associated with each possible route i and aircraft j combination; and the price vector is $p = (p_1, ..., p_n)$, where p_j is the price of route j.

We chose the parameter ϵ value via sensitivity analysis, for each fleet. It is related to the number of iterations that algorithm takes to converge (terminate) and total utility value of assignment (J), given by Equation 4.3.

$$J = \sum_{(i,j) \in A} u(i,j) \tag{4.3}$$

The function $u(i,j)$ is given by Equation 3.3.

In this case study, as mentioned in Section 3.2, assignment cost matrix c and importance vector d are given by Equation 3.2 and 3.1, respectively. Cost matrix c components are set up as follows:

- $r(j)$ comes from a discrete uniform distribution $U\{5,10\}$ for airline#1 and airline#3. for airline#2 we had access to real data;

- $f(i)$ takes value from a discrete random variable $X \in \{1.000, 1.005, 1.010, 1.015, ..., 1.045, 1.050\}$; and

- C constant value is 541 \$/mt.

In order to compute routes importance value as per Equation 3.1; for each flight a value w_k is assigned from a discrete uniform distribution $U\{$ 5,000; 10,000$\}$, which we could use to model flight revenue or priority, for instance.

4.2 MAS Development Framework

The simulations of scenarios A, B, C, D, E, and F were done by deploying JADE (Java Agent DEvelopment Framework) (BELLIFEMINE et al., 2005), a software that plays the role of middleware to implement the agent-based model as described in Chapter 3. JADE is FIPA compliant which grants that development follows a standard, so that it is compatible with any other multi-agent systems following FIPA standards too.

JADE API offers a default communication language and mechanisms to send, receive and filter messages among agents, which allowed the implementation of section 3.3. Besides that, it provides ready-to-use protocol implementations such as contract net protocol (SMITH, 1980), that allowed the implementation of Section 3.4. That framework also provides a concept called "behavior", which enable to represent agents' actions, like the actions presented in Figures 3.1 and 3.2, so that way an agent can perceive and act in the environment, which is compliant with this thesis' demanded capabilities for multi-agent system development as introduced in Section 2.5.

Besides, JADE is already prepared to run over a network of computational resources, taking advantage of distributed processing capabilities. We could take advantage of such capability, for instance, to be able to integrate legacy system or data sources by modeling them as agents or objects to be handled by agents in MAS architecture, which is useful for effective deployment of this solution in airlines infrastructure, for example.

Figure 4.3, presents JADE's architecture. Each running an instance of JADE's runtime environment defines a container as it can contain several agents. In our case, tail assignment agent and aircraft agents. The set of active containers are called a platform. A single particular main container must always be active in a platform, and all other containers must register with it as soon as they start.

Besides the ability to accept registrations from other containers, the main container differs from normal containers as it holds two special agents (automatically started when JADE launches the main container):

- AMS (Agent Management System): it provides naming service (responsible for agents unique identification) and represents the authority in a platform (for instance it is possible to create/kill agents on remote containers by requesting that to the AMS).

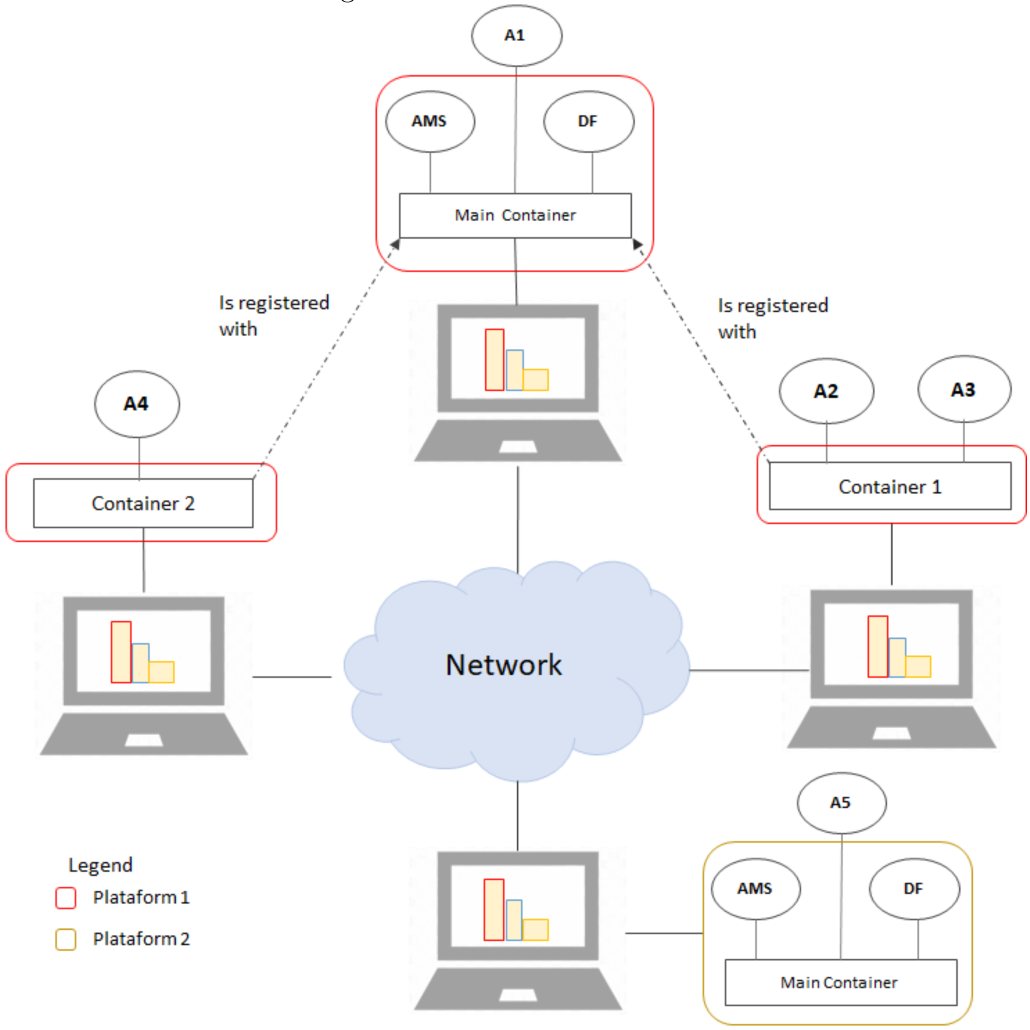
- DF (Directory Facilitator): it provides a "yellow pages" service through which an agent can find other agents providing the services it requires in order to achieve its goals.

AMS is involved at the beginning of the simulation to create and set up a fleet, flights, routes, and the tail assignment agent, while the DF, conversely, was not used in the final implementation. However, in a previous implementation version of this work it was used to inform about agent capability, for example, a tail assignment agent consulted the DF to search for aircraft agent that are candidates to be allocated to a given route.

Figure 4.4 describes an agent life cycle in JADE. The actual job an agent has to do is typically carried out within "behaviors", that are tasks that an agent is capable of doing; so that, the agent does its initialization at first by setting initial actions (behaviors); after that, it checks if it got scheduled actions finished. Given that it did not finish actions, the agent executes next active action and do it iteratively till there is no longer pendent actions; finally, agents come to clean up operation mode, and it takes down.

As an example of the previously explained cycle, we refer to Section 3.3, about the tail assignment agent (TAS). It sets its initial action "Check Assignment", after that, TAS checks if it got finished that action, and move to "Send CFP" behavior and, once the current action is finished, TAS moves ahead through next scheduled behaviors "Check Proposal", "Send Feedback", "Check Update" and "Finish Assignment". Considering, for instance, that "Finish Assignment" is the last behavior, after that TAS winds up in taking down operations, in our case, it means updating the list of

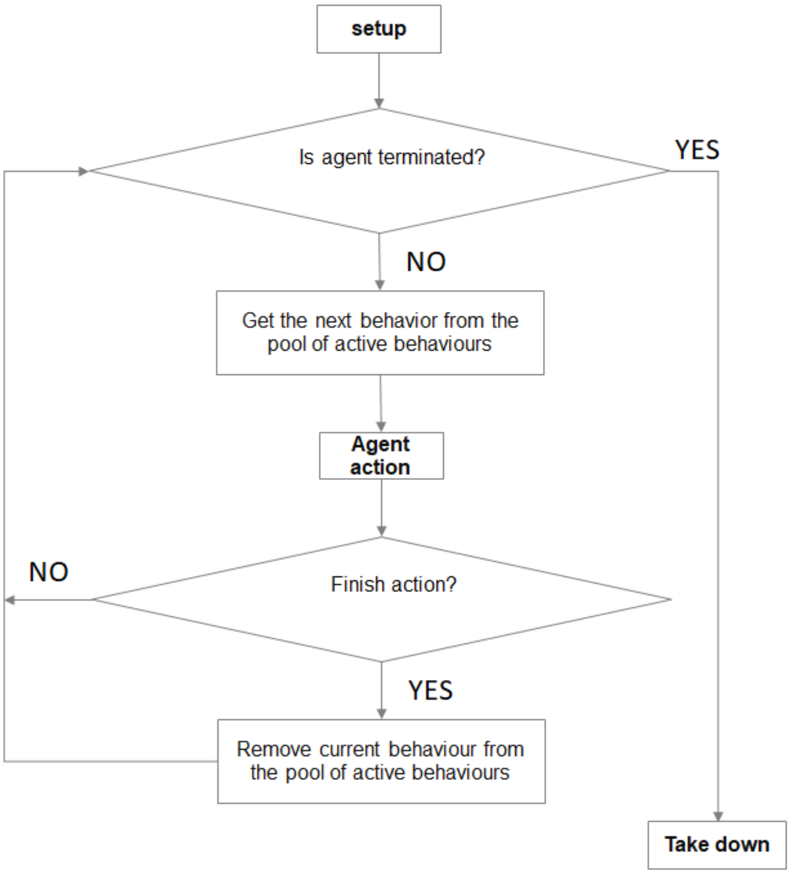
Figure 4.3 - JADE architecture.



Source: Bellifemine et al. (2007).

routes without aircraft allocated and data structure that stores <aircraft, route> mapping.

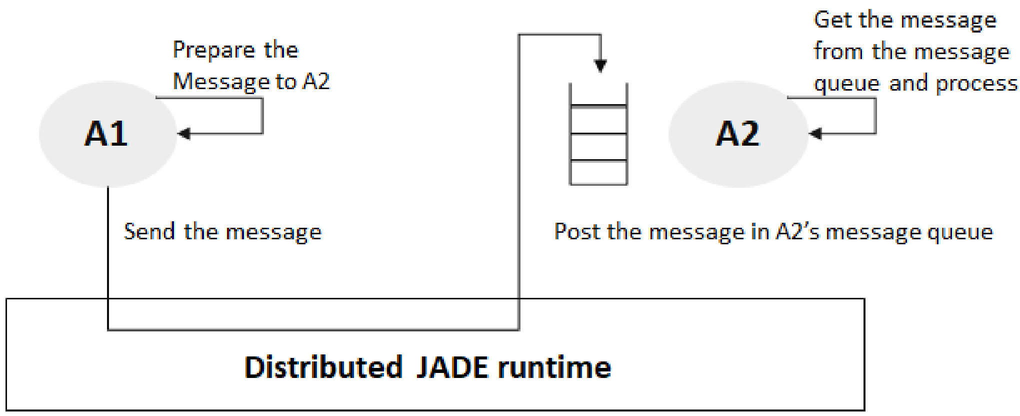
Figure 4.4 - Agent life cycle in JADE.



Source: Bellifemine et al. (2007).

Figure 4.5 presents communication between agents in JADE. JADE agents communicate via asynchronous message exchange; each agent has its message queue, where middleware runtime posts messages sent by other agents; whenever JADE posts a message in the message queue, JADE also notifies the receiving agent. Conversely, JADE does not control if and when an agent picks up messages from the queue.

Figure 4.5 - Communication between agents in JADE.



Source: Bellifemine et al. (2007).

This thesis took advantage of the asynchronous message exchange mechanism provided by JADE framework to perform the exchange of the messages presented in Table 3.1 between aircraft agents and tail assignment agent, as part of the interaction protocol introduced in Section 3.4.

5 RESULTS

Simulation results include sensitivity analysis charts for each airline scenario without maintenance constraints. It was possible to choose a proper value for the ϵ parameter, considering the number of iterations the ϵ-competitive equilibrium algorithm took to converge and total utility value. For each airline and for each ϵ value, we ran 10 trials (see appendix A), and we present herein iterations mode and mean utility value.

Figure 5.1 and Figure 5.2 present number of iterations versus ϵ parameter and total utility value versus ϵ parameter, respectively, for Airline#1. For this scenario, an ϵ parameter value close to 10 would be a reasonable choice as it outputs maximum utility value and almost the minimum number of iterations. Additionally, Figure 5.2 states that total utility is maximized for ϵ parameter value in interval $[0.03, 10]$. Figure 5.1 shows that for $\epsilon < 10$ the number of iterations demanded for ϵ-competitive equilibrium algorithm to converge is significantly higher than when $\epsilon \geq 10$; indeed, in this former interval, minimum number of iterations requested for assignment algorithm to converge is reached, but it does not pay off.

Figure 5.1 - ϵ parameter vs iterations (Airline#1).

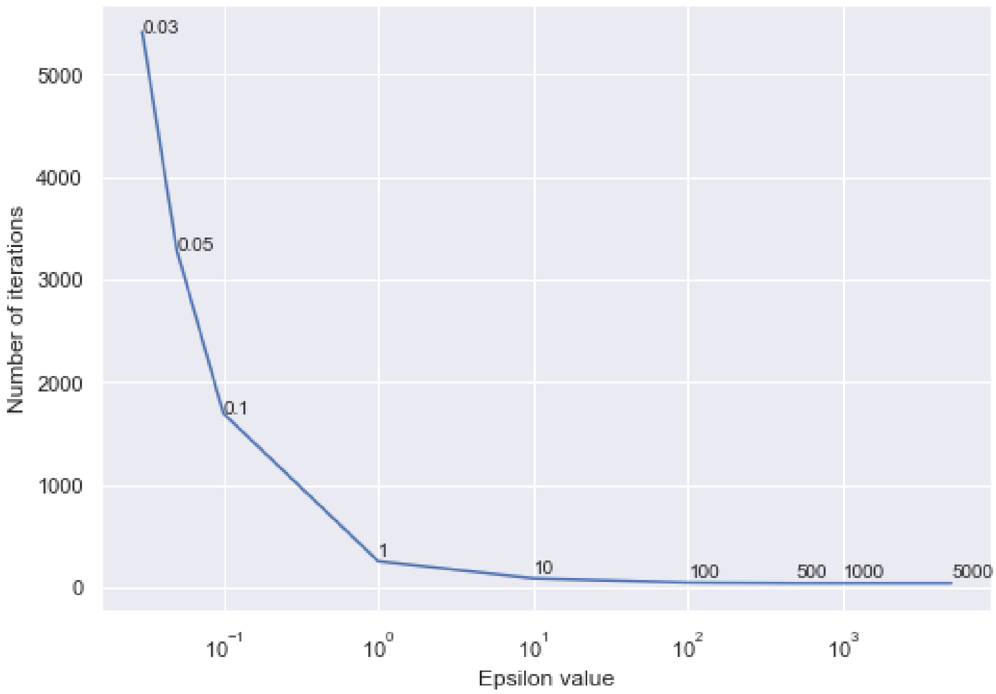


Figure 5.2 - ϵ parameter vs utility (Airline#1).

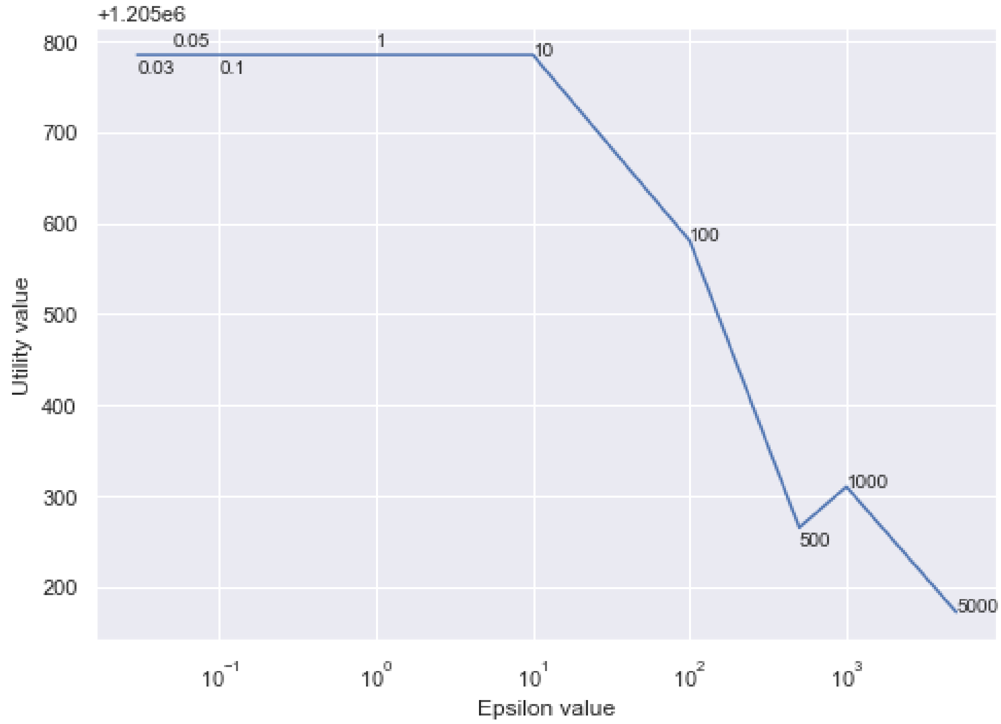


Table 5.1 presents part of the assignment result obtained for Scenario A. For this scenario, based on sensitivity analysis an $\epsilon = 10$ was set up. Considering opportunistic maintenance threshold $\tau = 30\%$ and mandatory maintenance threshold $\omega = 70\%$, aircraft 102 and 115 are in opportunistic maintenance state, as SRUL is 31%, based on fault tree from Figure 4.1. Results show assignment to routes containing maintenance base (CHS and IND). The opportunistic maintenance penalty $\sigma = 1,000$ was enough to drive assignment algorithm toward maintenance task scheduling option over fuel efficiency performance demand as can be seen in the case of aircraft 115. That one is the worst performance in terms of fuel consumption among all the aircraft departing from MIA; even though aircraft 115 assignment to MIA-ATL-MIA-CZM-MIA-IND route, which contains a maintenance base (IND), but such route requires more fuel than other routes that do not contain a maintenance base.

The interval between flights also matches required downtime, as aircraft 102 maintenance task assignment between flights MIA-CHS (departure: 15h20, arrival: 17h00) and CHS-MIA (departure: 17h30, arrival: 19h12) and aircraft 115 maintenance task placed after last flight in route MIA-IND. On the other hand, aircraft 102 assignment is a perfect match of allocating a fuel-efficient aircraft to route MIA-NAS-MIA-CHS-MIA-GSO that comparatively requires a higher quantity of fuel, and it is also a critical route (higher value).

Table 5.1 - Assignment for Scenario A.

Acft.	Route	Perf.	Fuel (kg)	Value
110	MIA-MSY-MIA-RIC	1.020	10,000	24,000
102	MIA-NAS-MIA-CHS-MIA-GSO	1.010	24,000	38,000
115	MIA-ATL-MIA-CZM-MIA-IND	1.030	21,000	37,000
139	MIA-ATL-MIA	1.025	5,000	12,000

Table 5.2 presents part of assignment result obtained for Scenario B. Scenario B is slightly different from Scenario A due to absence of opportunistic maintenance penalty ($\sigma = 0$). There were assignment changes in comparison to result presented in Table 5.1 as aircraft assignment algorithm prioritized the allocation of fuel-efficient aircraft like 102 and 110 aircraft to fuel demanding routes MIA-NAS-MIA-CHS-MIA-GSO (24,000 kg) and MIA-ATL-MIA-CZM-MIA-IND (21,000 kg), respectively. Aircraft 102 was kept in route containing a maintenance base (CHS), but aircraft 115 assignment did not change for a route containing aerodromes capable of providing maintenance, but there would be no operational impacts as it was an opportunistic maintenance demand.

Table 5.2 - Assignment for Scenario B.

Acft.	Route	Perf.	Fuel (kg)	Value
110	MIA-ATL-MIA-CZM-MIA-IND	1.020	21,000	37,000
102	MIA-NAS-MIA-CHS-MIA-GSO	1.010	24,000	38,000
115	MIA-ATL-MIA	1.030	5,000	12,000
139	MIA-MSY-MIA-RIC	1.025	10,000	24,000

Figure 5.3 and Figure 5.4 present the number of iteration versus ϵ parameter and total utility value versus ϵ parameter, respectively, for Airline#2 trial. Hence, considering charts exhibited in Figure 5.3 and Figure 5.4, an ϵ parameter value close to 10 would be a suitable choice, considering trade-off between minimum number of iterations and maximization of total utility. It is also possible to observe from Figure 5.3 and Figure 5.4 that for $\epsilon > 10$ there is a convergence for minimum number of iteration demanded from assignment algorithm; however, it represents a significant reduction of total utility value. Figure 5.4 also shows an increase in total utility for $\epsilon \geq 500$, such increase is explained by the standard deviation of trials for $\epsilon 500$, $\epsilon 1000$

and ϵ5000 are bigger than the increase presented, as we can see in Appendix A.

Figure 5.3 - ϵ parameter vs iteration (Airline#2).

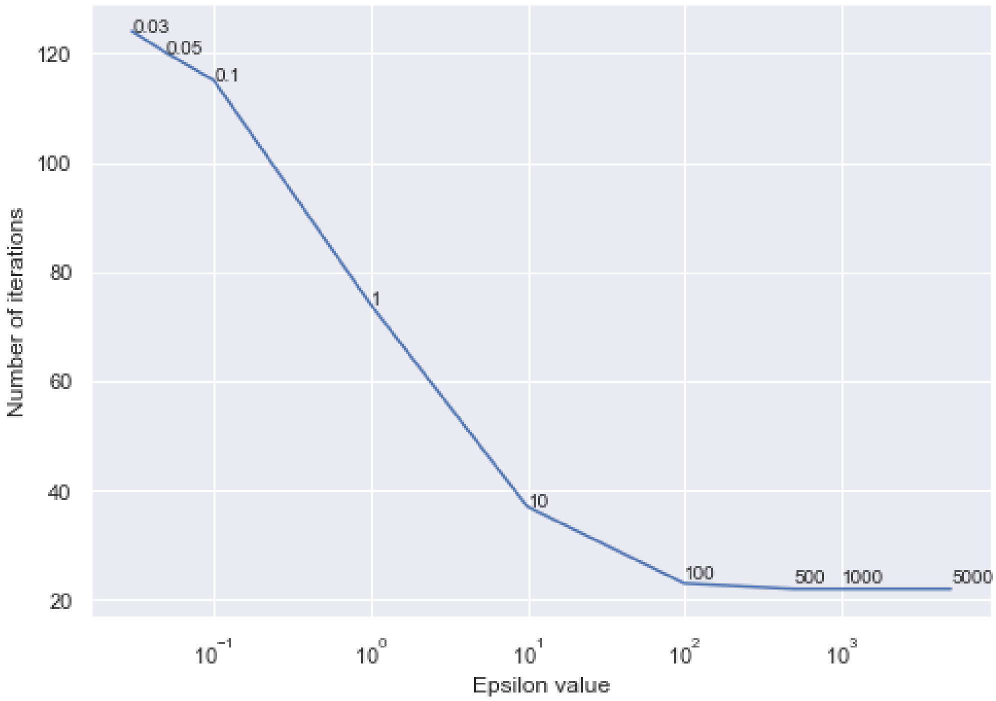


Figure 5.4 - ϵ parameter vs utility (Airline#2).

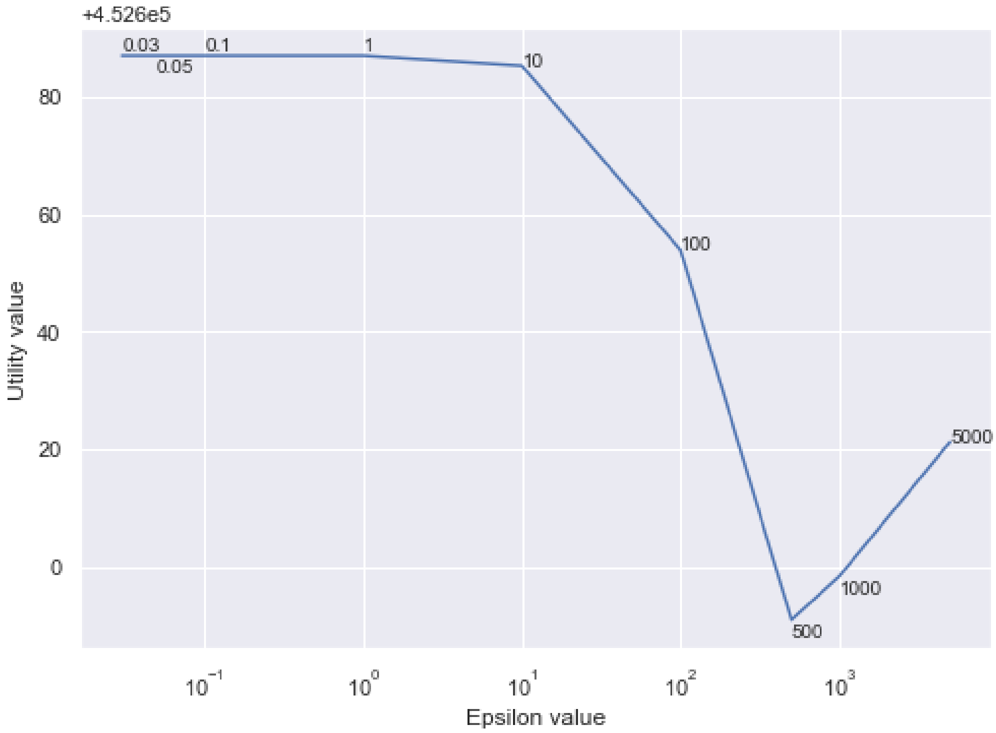


Table 5.3 presents the result for Scenario C. For this scenario, based on sensitivity analysis an $\epsilon = 10$ was set up. Considering opportunistic maintenance threshold of $\tau = 30\%$, and mandatory maintenance threshold $\omega = 70\%$; aircraft EZD and EZV are in a mandatory maintenance state, as SRUL is 98%, based on fault tree from Figure 4.2. Both aircraft allocated to routes containing a maintenance base (AMS). We can also observe that aircraft EZV assigned to route AMS-DUS-AMS-PRG, it means a high fuel consumption aircraft assigned to low fuel requirement route in comparison to the other assignments. It demonstrates how the solution minimizes the overall fuel consumption, taking into consideration the route value (importance) and in compliance with mandatory maintenance restrictions. Analyzing 30 minutes downtime assignment restriction, we observed that EZD maintenance task was scheduled to after BLQ-AMS flight (departure: 11h15, arrival: 13h20) as there was not enough time to perform maintenance task between flights PRG-AMS (departure: 06h30, arrival: 08h25) and AMS-BLQ (departure: 08h45, arrival: 10h35); EZV maintenance task was scheduled between flights DUS-AMS (departure: 10h25, arrival: 11h25) and AMS-PRG (departure: 12h05, arrival: 13h35).

Additionally, none of the aircraft demanding maintenance were assigned to BGO, which is also a maintenance base. Aircraft EZD was not assigned to a route containing the maintenance base BGO because it is efficient in terms of fuel consumption, so the algorithm assigned to the route AMS-PRG-AMS-BLQ-AMS, which is a route containing a maintenance base and requires a higher quantity of fuel in comparison to route AMS-GOT-AMS-BGO-AMS. Aircraft EZV is not fuel efficient, so algorithm assigned to route AMS-DUS-AMS-PRG, which contains a maintenance base and requires a lower quantity of fuel in comparison with route AMS-GOT-AMS-BGO-AMS.

Table 5.3 - Assignment for Scenario C

Acft.	Route	Perf.	Fuel (kg)	Value
EZD	AMS-PRG-AMS-BLQ-AMS	1.015	24,020	30,000
EZV	AMS-DUS-AMS-PRG	1.030	11,251	23,000
EZE	AMS-ABZ-AMS-BHX-AMS	1.020	18,923	34,000
EZO	AMS-GVA-AMS-TLS-AMS	1.005	24,208	31,000
EZT	AMS-GOT-AMS-BGO-AMS	1.025	17,883	29,000

Table 5.4 presents the result for Scenario D. Scenario D differs from Scenario C due to a restriction on performing maintenance only overnight; as a consequence

assignment algorithm is just allowed to place maintenance task in maintenance bases at the end of routes. The algorithm assigned aircraft EZD to route AMS-GVA-AMS-TLS-AMS, and aircraft EZV to route AMS-GOT-AMS-BGO-AMS, different from the previous route assigned in Scenario C. EZV was allocated to a route that fulfills overnight restriction, and that route is the second less fuel demanding route. EZV is the worst in term of fuel consumption performance, and it could not be assigned to first less fuel demanding route as it does not fit overnight constraint. Assignment changes from Scenario C to Scenario D kept total utility very close, 452,686 and 452,669 respectively, also the number of iterations 33 and 38 respectively.

Table 5.4 - Assignment for Scenario D

Acft.	Route	Perf.	Fuel (kg)	Value
EZD	AMS-GVA-AMS-TLS-AMS	1.015	24,208	31,000
EZV	AMS-GOT-AMS-BGO-AMS	1.030	17,883	29,000
EZE	AMS-ABZ-AMS-BHX-AMS	1.020	18,923	34,000
EZO	AMS-PRG-AMS-BLQ-AMS	1.005	24,020	30,000
EZT	AMS-DUS-AMS-PRG	1.025	11,251	23,000

Figure 5.5 and Figure 5.6 present number of iteration versus ϵ parameter and total utility value versus ϵ parameter, respectively, for Airline#3. An ϵ parameter value around 0.1 grants trade-off between number of iterations demanded for assignment algorithm convergence and total utility value. An interesting observation in Figure 5.6 is the erratic curve in the range $(10; 5,000]$, it due to standard deviation for that range of value as we can see in Appendix A. Number of iteration are almost constant; but total utility value into $[0,03; 10]$ interval correspond to maximum value in this trial.

Figure 5.5 - ϵ parameter vs iteration (Airline#3).

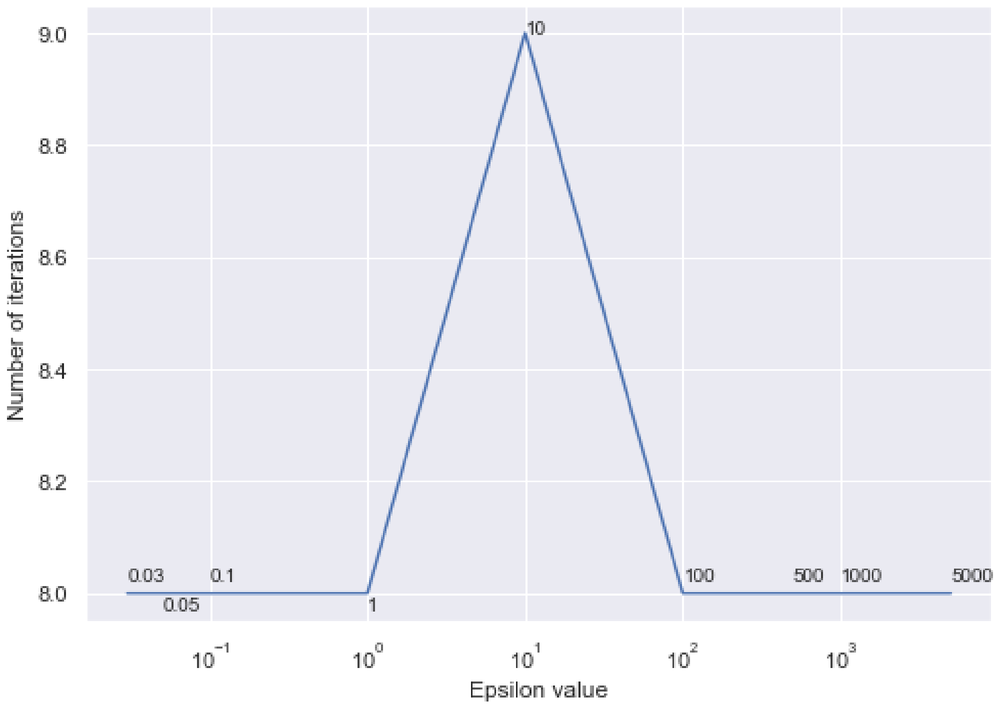


Figure 5.6 - ϵ parameter vs utility (Airline#3).

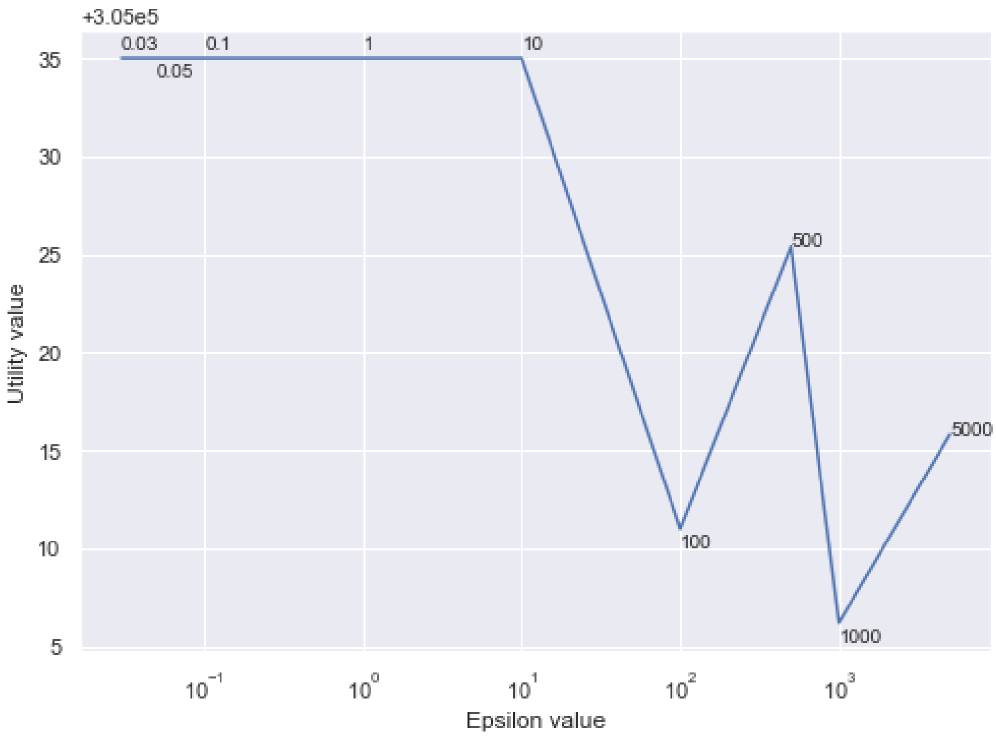


Table 6.1 presents the result for Scenario E. For this scenario, based on sensitivity analysis an $\epsilon = 1$ was set up. Considering an opportunistic maintenance threshold $\tau = 30\%$ and mandatory maintenance threshold $\omega = 70\%$, aircraft 101, 107 and 108 are in opportunistic maintenance state, as SRUL is 31%, based on fault tree from Figure 4.1. Also in this scenario, opportunistic maintenance penalty $\sigma = 1,000$ was enough, so the algorithm assigned aircraft 101, 107 and 108 to routes containing maintenance bases (BSB and POA). Finally, relating to 40 minutes downtime requirement for this simulated scenario, aircraft 101 maintenance was scheduled between flights from FLN-POA (departure: 11h30, arrival: 12h30) and from POA-FLN (departure: 18h00, arrival: 19h00), that means more than 5 hours to perform maintenance task; the algorithm also placed aircraft 107 maintenance between flights GRU-BSB (departure: 09h00, arrival: 10h00) and BSB-GRU (departure: 12h00, arrival: 14h00), it means aircraft 107 would be 2 hours available for maintenance intervention and aircraft 108 maintenance was scheduled to the end of day, so maintenance could fit overnight constraint.

Table 5.5 - Assignment for Scenario E

Acft.	Route	Perf.	Fuel (kg)	Value
103	GIG-GRU-GIG-GRU-GIG-GRU-GIG-GRU-GIG	1.030	28,000	72,000
107	GIG-GRU-BSB-MAO-BSB-GRU-GIG	1.040	19,000	51,000
108	POA-GRU-REC-MAO-REC-GRU-POA	1.010	21,000	36,000
106	POA-FLN-CWB-GRU-CWB-FLN-POA	1.050	21,000	51,000
101	GRU-CWB-FLN-POA-FLN-CWB-GRU	1.015	15,000	48,000
105	GRU-GIG-SSA-REC-SSA-GIG-GRU	1.030	15,000	42,000

Table 5.6 presents the result for Scenario F. Scenario F is almost the same as Scenario E except for the restriction on performing maintenance only overnight. Results are the same relating to aircraft assignment, but total utility in penalized twice because aircraft 101 and 107 opportunistic maintenance tasks would not happen; due to aerodromes at the end of daily operations not being maintenance bases. There is a maintenance base in the middle of the routes assigned for both aircraft, but it does not match overnight restriction.

Table 5.6 - Assignment for Scenario F

Acft.	Route	Perf.	Fuel (kg)	Value
103	GIG-GRU-GIG-GRU-GIG-GRU-GIG-GRU-GIG	1.030	28,000	72,000
107	GIG-GRU-BSB-MAO-BSB-GRU-GIG	1.040	19,000	51,000
108	POA-GRU-REC-MAO-REC-GRU-POA	1.010	21,000	36,000
106	POA-FLN-CWB-GRU-CWB-FLN-POA	1.050	21,000	51,000
101	GRU-CWB-FLN-POA-FLN-CWB-GRU	1.015	15,000	48,000
105	GRU-GIG-SSA-REC-SSA-GIG-GRU	1.030	15,000	42,000

6 CONCLUSIONS

This thesis solved the aircraft assignment problem from the integrated vehicle health management perspective. Our assumption is that a PHM system provides aircraft components future state of health and SRUL approach aggregates at vehicle level as a vehicle level reasoning system. A second assumption is that aircraft fuel consumption performance is given by an APM system; it is also taken into consideration to optimize fuel expenses. Besides, we integrated flight importance in the utility function so that we can prioritize flights in the schedule.

The distributed aircraft assignment model developed in this thesis, based on a multi-agent system framework, presented acceptable results relating to aircraft allocation for scenarios evaluated in Chapter 5, considering fuel consumption optimization and subject to maintenance constraints and aerodrome maintenance support capability.

Fault tree representation made possible to take into consideration vehicle systems architectures and vehicles safety assessment, along with SRUL methodology it put together system architecture and PHM information, in doing so, it was a mechanism to integrate predictive maintenance to aircraft assignment model.

This thesis proposed model also provides to decision makers the possibility of adjusting opportunistic maintenance τ and mandatory maintenance ω thresholds that best describe their operational policies relating to maintenance management. The framework presented over this thesis also provides an opportunistic maintenance penalty parameter σ in order to weight opportunistic maintenance importance.

Competitive equilibrium approach played an essential role in order to explore search space for an assignment solution and its implementation via ascending-bid auction provided a way for the algorithm to converge and terminate, given that constraints are satisfied.

Our framework demands proper adjustment of the ϵ parameter value, so that, in order to select a suitable value for ϵ, our approach run sensitivity analysis by varying the ϵ value and evaluating the number of iterations algorithm took to terminate and the total utility value outcome.

Scenario A and Scenario B verified opportunistic maintenance penalty effect in aircraft allocation, once enabled and conveniently set up. Scenario C verified mandatory maintenance compliance; Scenario D verified mandatory maintenance compliance subject to overnight maintenance restriction. Scenarios E and F verified opportunistic maintenance subject to required downtime and overnight constraints.

Proposing an agent-based approach to model the aircraft assignment problem considering fuel consumption performance and health condition of aircraft, and demonstrating it in different scenarios are the main contributions of this thesis. Besides that, integration of system remaining useful life approach (SRUL) as maintenance constraint is also a novelty as a vehicle level reasoning system. This approach also allows for integrating other decision entities (intelligent agents) to deal with other aspects of airline operation such as PHM-based inventory management.

Table 6.1 is a summary of selected related work that is comparable to this thesis proposal. In "Literature contribution" column, there is a description on related work contribution and in "Comparison" column, there is a description on this thesis addition in comparison to the reference mentioned.

Table 6.1 - Comparison to related works.

Literature contribution	Comparison
Gronkvist (2005) proposed a combination of column generation, constraint programming, and local search. An approach to aircraft assignment which captures operational constraints, including minimum connection times, airport curfews, maintenance, and preassigned activities and can model various types of objective functions.	This thesis uses an agent-based approach that does not demand involved mathematical modeling. It does not capture minimum connection times, airport curfews. It considers maintenance; it can deal with preassigned activities and various types of objectives functions.
Hottenrott (2015) adopted an adaptive large neighborhood search algorithm for the aircraft assignment problem of airlines to also capture maintenance requirements and operational restrictions, such as minimum turn times, curfews and maintenance capacities.	This thesis proposed solution is also an iterative algorithm like large neighborhood heuristic; but in the last, a complete solution is evaluated and subject to destroy and repair procedure, in the former at each iteration a route assignment is evaluated and possible assignments are computed in a distributed manner. This thesis also captures maintenance requirements and operational restrictions.

Lapp and Wikenhauser (2012) took advantage of linear programming modeling to solve the aircraft assignment problem; it incorporates aircraft fuel consumption efficiency estimative in the model.	This thesis also incorporated aircraft fuel consumption efficiency estimative in the model; besides that, this thesis does take into account maintenance and operational restrictions too.
Kalina (2014) presented a reformulation of the vehicle routing problem with time window as a multi-agent optimization problem within a society of agents representing individual vehicles being part of the problem. It also evaluates tasks relocation based on cost and randomly	This thesis approach was explicitly deployed to aircraft assignment problem, but it could be used for any fleet of vehicles too. This thesis approach uses competitive equilibrium framework and it does not insert any randomness in the assignment process.
Tang et al. (2006) developed SEMOR (Self Evolving Maintenance and Operations Reasoning System) based on model-based reasoning, case-based reasoning, and reinforcement learning; that also uses a multi-agent system approach.	In comparison to Tang et al. (2006) work, this thesis covers the gap of aggregating components health at vehicle level and providing a framework to consider such information in vehicle allocation.
Camci et al. (2007) designs an architecture to integrate available PHM information into the maintenance and logistics infrastructure. It presents a multi-agent approach to model maintenance scheduling and inventory management.	This thesis considers PHM information integrated into system architecture information to aggregate it at the system level. In comparison to Camci et al. (2007), this thesis solution offers an optimization algorithm for vehicle allocation that is subject to the vehicle health condition.
Feng et al. (2012) proposes a condition-based maintenance decision-making method based on multi-agent that uses PHM information and heuristic rules to define vehicle condition of health and maintenance schedule.	This thesis provides a methodology to aggregate vehicle components health at vehicle level and also optimizes operations expense, e.g., fuel expenses that depend on aircraft performance.

7 FUTURE WORK

During the development of this thesis, we observed aspects that could be improved such as:

a) Consideration of different maintenance cost for different maintenance bases;

b) Addition of a "no go" criterion (e.g., $SRUL > \Theta$), so aircraft would to be part of available fleet;

c) Development of a multi-fleet version as this thesis proposal assumption is a single fleet configuration;

d) Development of flight-based assignment over a route-based assignment, so that the algorithm would be able to derive new routes (flight sets) in order to optimize fuel consumption and accommodate maintenance demands. The heuristics presented by Kalina (2014) could be deployed to build routes;

e) Integration of an irregular operation management agent, responsible for handling cases involving aircraft unavailability. It could be caused by mandatory maintenance that was not performed, for example. That would treat the case in which the algorithm does not provide a solution for the assignment problem due to maintenance restriction. In doing so, it would be an extension toward a fleet management scope. It could be thought as a robust aircraft assignment version too.

f) Our solution indicates opportunistic maintenance and mandatory maintenance, but it does not recommend which component(s) to remove. A simple approach would be to remove the ones presenting worst health index; but we can take advantage of SRUL approach as suggested by Rodrigues et al. (2015) in order to consider PHM information, system architecture, and maintenance cost to generate component removal list, it also can be integrated as part of the distributed framework.

g) This thesis does not include aerodrome capacity in the model, i.e., the number of aircraft aerodrome can perform maintenance simultaneously. We could model it by adding an agent representing a maintenance base, and there would be communication between this agent and aircraft assignment agent to consult on aerodrome maintenance capacity. Another possible solution would be to add such verification during the admission phase in the proposed framework.

h) Rodrigues (2013) proposed in his thesis an application of PHM in inventory management. A method is presented to estimate future demands for spare parts of non-repairable items based on information obtained from a PHM system. That proposal brought insight on a future work integrating inventory management agent that would take advantage of SRUL information in order to recommend parts stock level, so that, it would match opportunistic and mandatory maintenance demands.

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A - PARAMETER ϵ SENSITIVITY ANALYSIS

This appendix presents sensitivity analysis for ϵ parameter value. It is possible to observe from tables and violin plots figures, that a slightly deviation among iterations and utility values over trials. It is due to the different sequence aircraft agents respond to tail assignment agent requests for each trial.

A.1 Airline#1

Table A.1 is a summary of *Airline*#1 on the mode of number of iteration and average of utility value for each ϵ parameter value $(5000, 1000, 500, 100, 10, 1, 0.1, 0.05, 0.03)$. Tables A.2, A.3, A.4, A.5, A.6, A.7, A.8, A.9, A.10 present ten trials number of iterations and total utility value; and, mode of number of iterations, average of total utility value, standard deviation and percent deviation; for ϵ parameter value $5000, 1000, 500, 100, 10, 1, 0.1, 0.05, 0.03$; respectively.

Table A.1 - Airline#1 mode of number of iterations and mean of utility value for each ϵ parameter value.

ϵ	Iterations	Utility
0.03	5.416	1,205,785.00
0.05	3.295	1,205,785.00
0.1	1.697	1,205,785.00
1	255	1,205,785.00
10	89	1,205,785.00
100	47	1,205,580.80
500	42	1,205,265.30
1000	42	1,205,310.20
5000	42	1,205,172.60

Table A.2 - Number of iterations and utility value for each trial when setting $\epsilon = 5,000$.

Trial	Iterations	Utility
1	42	1,205,023.00
2	42	1,205,079.00
3	42	1,205,182.00
4	42	1,205,275.00
5	42	1,205,127.00
6	42	1,205,021.00
7	42	1,205,334.00
8	42	1,205,355.00
9	42	1,205,023.00
10	42	1,205,307.00
Mode/Average	42	1,205,172.60
Deviation	-	129.05
Percent Deviation	-	0.01%

Table A.3 - Number of iterations and utility value for each trial when setting $\epsilon = 1,000$.

Trial	Iterations	Utility
1	42	1,205,204.00
2	42	1,205,241.00
3	42	1,205,307.00
4	42	1,205,153.00
5	42	1,205,398.00
6	42	1,205,172.00
7	42	1,205,313.00
8	42	1,205,514.00
9	42	1,205,477.00
10	42	1,205,323.00
Mode/Average	42	1,205,310.20
Deviation	-	117.10
Percent Deviation	-	0.010%

Table A.4 - Number of iterations and utility value for each trial when setting $\epsilon = 500$.

Trial	Iterations	Utility
1	42	1,205,413.00
2	42	1,205,413.00
3	42	1,204,986.00
4	42	1,205,493.00
5	42	1,205,329.00
6	42	1,204,880.00
7	42	1,205,419.00
8	42	1,205,175.00
9	42	1,205,400.00
10	42	1,205,145.00
Mode/Average	42	1,205,265.30
Deviation	-	197.58
Percent Deviation	-	0.016%

Table A.5 - Number of iterations and utility value for each trial when setting $\epsilon = 100$.

Trial	Iterations	Utility
1	48	1,205,668.00
2	49	1,205,682.00
3	49	1,205,490.00
4	46	1,205,644.00
5	50	1,205,605.00
6	47	1,205,506.00
7	47	1,205,533.00
8	47	1,205,559.00
9	48	1,205,514.00
10	50	1,205,607.00
Mode/Average	47	1,205,580.80
Deviation	-	66.46
Percent Deviation	-	0.0055%

Table A.6 - Number of iterations and utility value for each trial when setting $\epsilon = 10$.

Trial	Iterations	Utility
1	89	1,205,775.00
2	89	1,205,775.00
3	96	1,205,783.00
4	87	1,205,775.00
5	83	1,205,777.00
6	85	1,205,785.00
7	82	1,205,785.00
8	83	1,205,777.00
9	82	1,205,783.00
10	87	1,205,783.00
Mode/Average	89	1,205,785.00
Deviation	-	4.11
Percent Deviation	-	0.0003%

Table A.7 - Number of iterations and utility value for each trial when setting $\epsilon = 1$.

Trial	Iterations	Utility
1	258	1,205,785.00
2	255	1,205,785.00
3	259	1,205,785.00
4	252	1,205,785.00
5	255	1,205,785.00
6	250	1,205,785.00
7	259	1,205,785.00
8	250	1,205,785.00
9	257	1,205,785.00
10	260	1,205,785.00
Mode/Average	255	1,205,785.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Table A.8 - Number of iterations and utility value for each trial when setting $\epsilon = 0.1$.

Trial	Iterations	Utility
1	1,696	1,205,785.00
2	1,694	1,205,785.00
3	1,692	1,205,785.00
4	1,697	1,205,785.00
5	1,697	1,205,785.00
6	1,699	1,205,785.00
7	1,700	1,205,785.00
8	1,698	1,205,785.00
9	1,703	1,205,785.00
10	1,697	1,205,785.00
Mode/Average	1,697	1,205,785.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Table A.9 - Number of iterations and utility value for each trial when setting $\epsilon = 0.05$.

Trial	Iterations	Utility
1	3,289	1,205,785.00
2	3,301	1,205,785.00
3	3,295	1,205,785.00
4	3,292	1,205,785.00
5	3,293	1,205,785.00
6	3,295	1,205,785.00
7	3,295	1,205,785.00
8	3,288	1,205,785.00
9	3,288	1,205,785.00
10	3,290	1,205,785.00
Mode/Average	3,295	1,205,785.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Table A.10 - Number of iterations and utility value for each trial when setting $\epsilon = 0.03$.

Trial	Iterations	Utility
1	5,412	1,205,785.00
2	5,418	1,205,785.00
3	5,426	1,205,785.00
4	5,415	1,205,785.00
5	5,414	1,205,785.00
6	5,416	1,205,785.00
7	5,421	1,205,785.00
8	5,416	1,205,785.00
9	5,422	1,205,785.00
10	5,416	1,205,785.00
Mode/Average	5,416	1,205,785.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Violin plot in Figure A.1 and A.2 confirms the acceptable number of iterations standard deviation and total utility value over trials for ϵ values tested, for *Airline*#1. Figure A.1 shows that number of iteration presents a relatively small variation only for 1,10 and 100 values. Figure A.2 also shows that total utility presents a relatively small variation only for $\epsilon > 1$ values.

Figure A.1 - ϵ parameter value vs number of iterations violin plot (Airline#1).

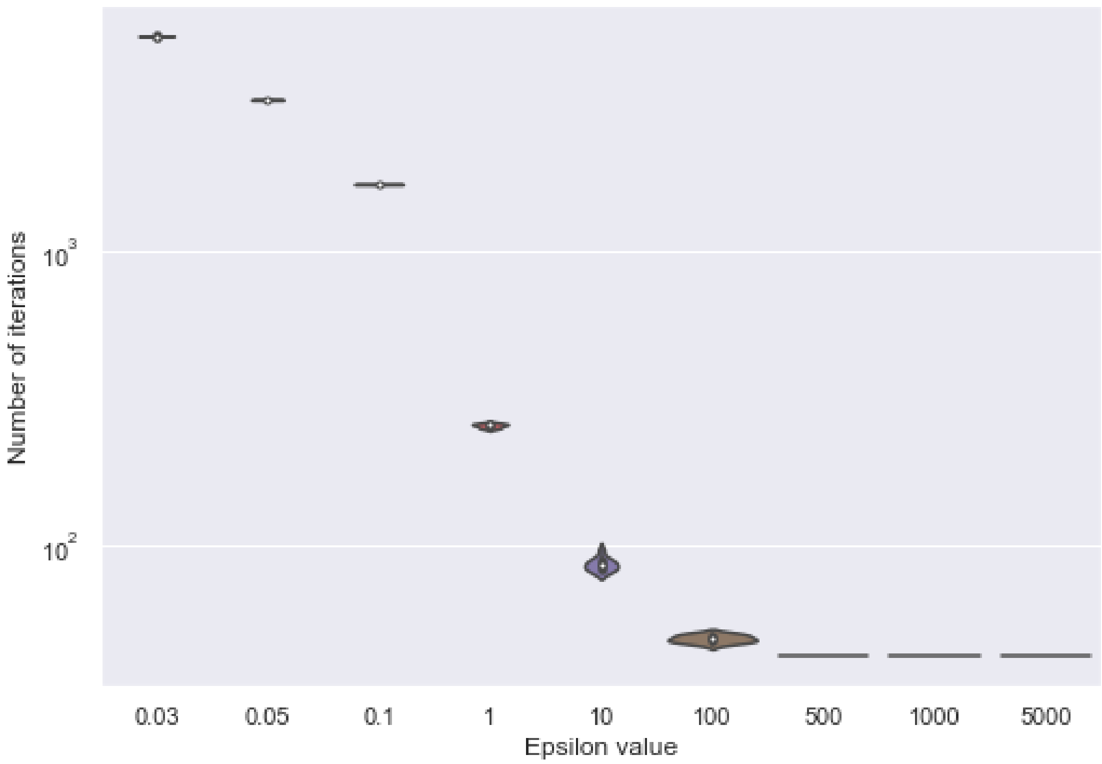
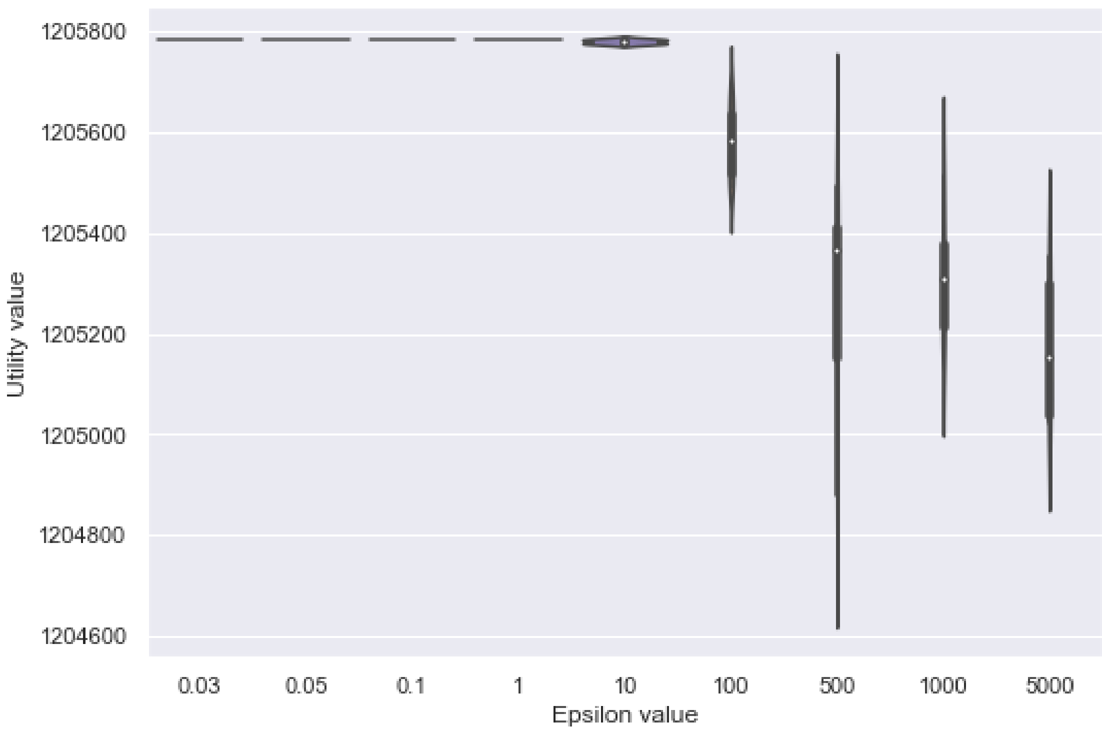


Figure A.2 - ϵ parameter value vs utility value violin plot (Airline#1).



A.2 Airline#2

Table A.11 is a summary of *Airline*#2 on the mode of number of iteration and average of utility value for each ϵ parameter value $(5000, 1000, 500, 100, 10, 1, 0.1, 0.05, 0.03)$. Tables A.12, A.13, A.14, A.15, A.16, A.17, A.18, A.19, A.20 present ten trials number of iterations and total utility value; and, mode of number of iterations, average of total utility value, standard deviation and percent deviation; for ϵ parameter value $5000, 1000, 500, 100, 10, 1, 0.1, 0.05, 0.03$; respectively.

Table A.11 - Airline#2 mode of number of iterations mode and mean of utility value for each ϵ parameter value.

ϵ	Iterations	Utility
0.03	124	452,687.00
0.05	120	452,687.00
0.1	115	452,687.00
1	74	452,687.00
10	37	452,685.30
100	23	452,653.90
500	22	452,590.90
1000	22	452,598.30
5000	22	452,621.20

Table A.12 - Number of iterations and utility value for each trial when setting $\epsilon = 5,000$.

Trial	Iterations	Utility
1	22	452,646.00
2	22	452,614.00
3	22	452,656.00
4	22	452,518.00
5	22	452,583.00
6	22	452,579.00
7	22	452,674.00
8	22	452,627.00
9	22	452,646.00
10	22	452,669.00
Mode/Average	22	452,621.20
Deviation	-	46.35
Percent Deviation	-	0.010%

Table A.13 - Number of iterations and utility value for each trial when setting $\epsilon = 1,000$.

Trial	Iterations	Utility
1	22	452,483.00
2	22	452,669.00
3	22	452,668.00
4	22	452,512.00
5	22	452,668.00
6	22	452,669.00
7	22	452,602.00
8	22	452,483.00
9	22	452,646.00
10	22	452,583.00
Mode/Average	22	452,598.30
Deviation	-	75.01
Percent Deviation	-	0.017%

Table A.14 - Number of iterations and utility value for each trial when setting $\epsilon = 500$.

Trial	Iterations	Utility
1	22	452,627.00
2	22	452,512.00
3	22	452,674.00
4	22	452,669.00
5	22	452,512.00
6	22	452,579.00
7	22	452,587.00
8	22	452,518.00
9	22	452,602.00
10	22	452,629.00
Mode/Average	22	452,590.90
Deviation	-	58.14
Percent Deviation	-	0.013%

Table A.15 - Number of iterations and utility value for each trial when setting $\epsilon = 100$.

Trial	Iterations	Utility
1	24	452,664.00
2	23	452,614.00
3	23	452,645.00
4	22	452,668.00
5	24	452,686.00
6	23	452,629.00
7	23	452,649.00
8	24	452,686.00
9	23	452,670.00
10	23	452,628.00
Mode/Average	23	452,653.90
Deviation	-	23.67
Percent Deviation	-	0.0052%

Table A.16 - Number of iterations and utility value for each trial when setting $\epsilon = 10$.

Trial	Iterations	Utility
1	35	452,686.00
2	40	452,683.00
3	37	452,686.00
4	35	452,686.00
5	36	452,684.00
6	37	452,686.00
7	38	452,686.00
8	37	452,686.00
9	37	452,683.00
10	35	452,687.00
Mode/Average	37	452,685.30
Deviation	-	1.34
Percent Deviation	-	0.0003%

Table A.17 - Number of iterations and utility value for each trial when setting $\epsilon = 1$.

Trial	Iterations	Utility
1	71	452,686.00
2	73	452,686.00
3	71	452,687.00
4	74	452,687.00
5	75	452,687.00
6	74	452,687.00
7	73	452,686.00
8	74	452,687.00
9	76	452,687.00
10	76	452,687.00
Mode/Average	74	452,686.70
Deviation	-	0.45
Percent Deviation	-	0.0001%

Table A.18 - Number of iterations and utility value for each trial when setting $\epsilon = 0.1$.

Trial	Iterations	Utility
1	115	452,687.00
2	118	452,687.00
3	113	452,687.00
4	121	452,687.00
5	116	452,687.00
6	114	452,687.00
7	115	452,687.00
8	114	452,687.00
9	122	452,687.00
10	118	452,687.00
Mode/Average	115	452,687.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Table A.19 - Number of iterations and utility value for each trial when setting $\epsilon = 0.05$.

Trial	Iterations	Utility
1	125	452,687.00
2	124	452,687.00
3	130	452,687.00
4	127	452,687.00
5	125	452,687.00
6	129	452,687.00
7	130	452,687.00
8	120	452,687.00
9	120	452,687.00
10	120	452,687.00
Mode/Average	120	452,687.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Table A.20 - Number of iterations and utility value for each trial when setting $\epsilon = 0.03$.

Trial	Iterations	Utility
1	124	452,687.00
2	122	452,687.00
3	126	452,687.00
4	124	452,687.00
5	130	452,687.00
6	125	452,687.00
7	124	452,687.00
8	129	452,687.00
9	126	452,687.00
10	127	452,687.00
Mode/Average	124	452,687.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Violin plot in Figure A.3 and A.4 confirms the acceptable number of iterations standard deviation and total utility value over trials for ϵ values tested, for *Airline*#2. Figure A.3 shows that number of iteration presents no variation for $\epsilon > 100$ values, it also reaches the minimum number of iteration for Airline2, i.e., 22 iterations. Figure A.2 also shows that total utility presents no variation for $\epsilon < 1$ values, that is also maximum value computed over trials.

Figure A.3 - ϵ parameter value vs number of iterations violin plot (Airline#2).

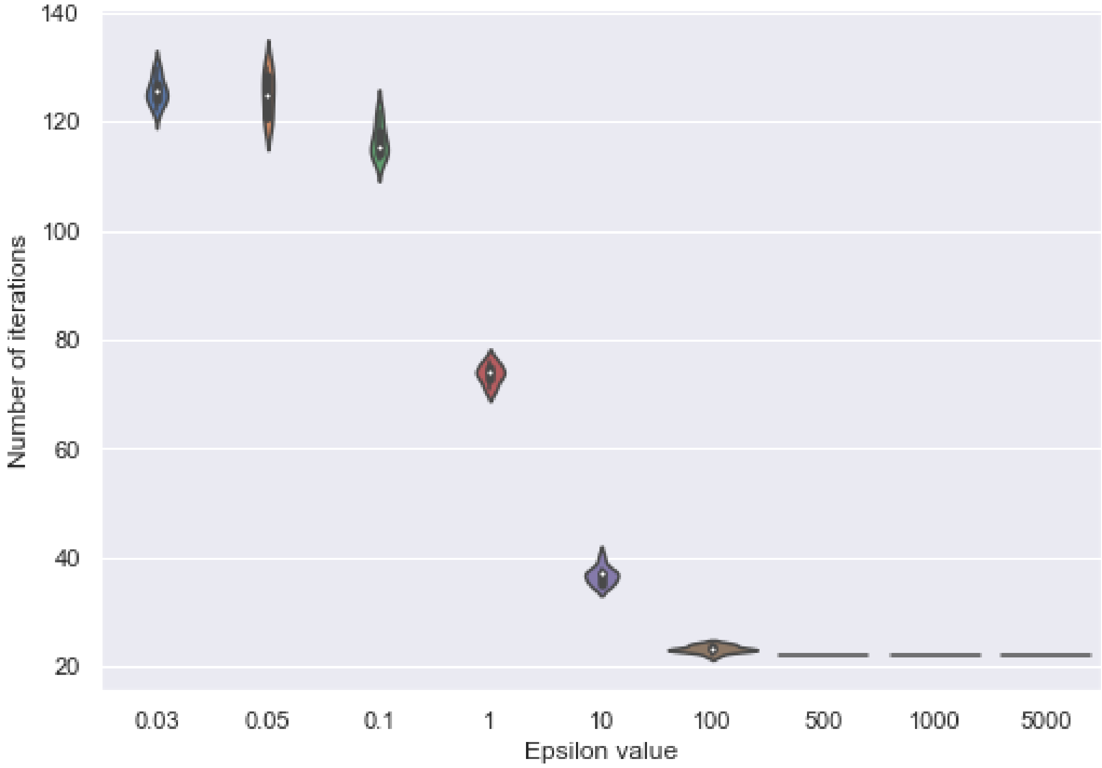
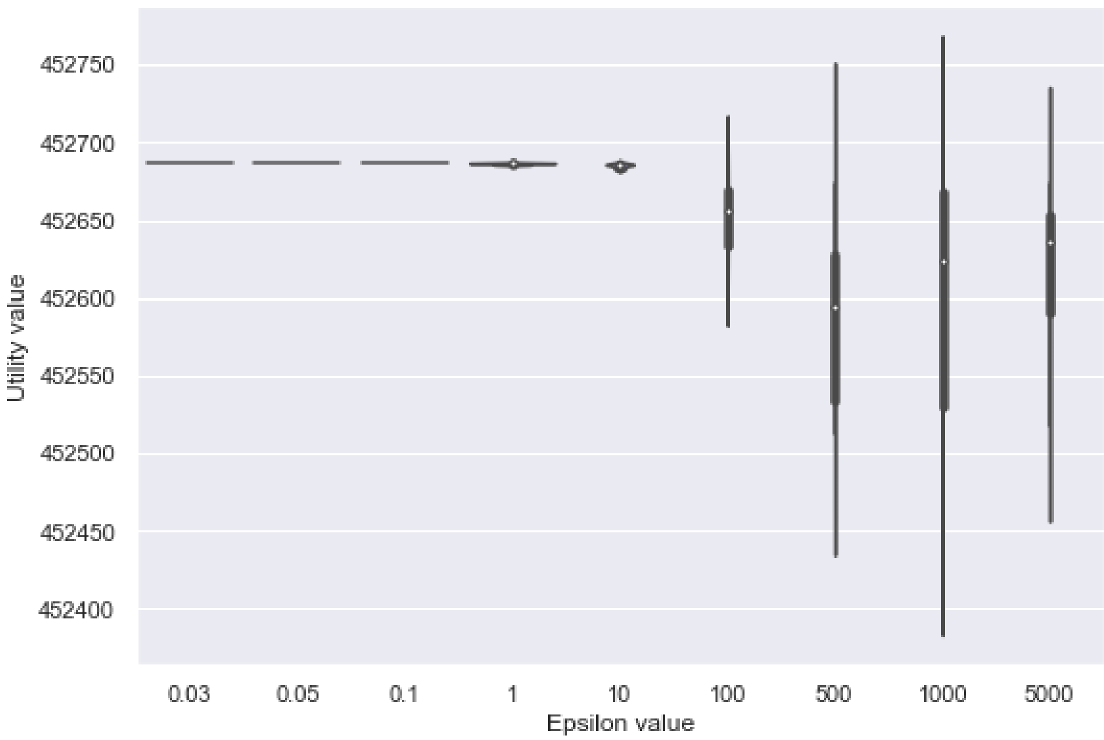


Figure A.4 - ϵ parameter value vs utility value violin plot (Airline#2).



A.3 Airline#3

Table A.21 is a summary of *Airline*#3 on the mode of number of iteration and average of utility value for each ϵ parameter value $(5000, 1000, 500, 100, 10, 1, 0.1, 0.05, 0.03)$. Tables A.22, A.23, A.24, A.25, A.26, A.27, A.28, A.29, A.30 present ten trials number of iterations and total utility value; and, mode of number of iterations, average of total utility value, standard deviation and percent deviation; for ϵ parameter value $5000, 1000, 500, 100, 10, 1, 0.1, 0.05, 0.03$; respectively.

Table A.21 - Airline#3 mode of number of iterations and mean of utility value for each ϵ parameter value.

ϵ	Iterations	Utility
0.03	8	305,035.00
0.05	8	305,035.00
0.1	8	305,035.00
1	8	305,035.00
10	9	305,035.00
100	8	305,011.00
500	8	305,025.40
1000	8	305,006.20
5000	8	305,015.80

Table A.22 - Number of iterations and utility value for each trial when setting $\epsilon = 5,000$.

Trial	Iterations	Utility
1	8	305,035.00
2	8	304,987.00
3	8	305,035.00
4	8	304,987.00
5	8	305,035.00
6	8	305,035.00
7	8	304,987.00
8	8	305,035.00
9	8	305,035.00
10	8	304,987.00
Mode/Average	8	305,015.80
Deviation	-	23.51
Percent Deviation	-	0.008%

Table A.23 - Number of iterations and utility value for each trial when setting $\epsilon = 1,000$.

Trial	Iterations	Utility
1	8	305,035.00
2	8	304,987.00
3	8	304,987.00
4	8	304,987.00
5	8	304,987.00
6	8	305,035.00
7	8	304,987.00
8	8	304,987.00
9	8	305,035.00
10	8	305,035.00
Mode/Average	8	305,006.20
Deviation	-	23.51
Percent Deviation	-	0.008%

Table A.24 - Number of iterations and utility value for each trial when setting $\epsilon = 500$.

Trial	Iterations	Utility
1	8	305,035.00
2	8	304,987.00
3	8	305,035.00
4	8	305,035.00
5	8	304,987.00
6	8	305,035.00
7	8	305,035.00
8	8	305,035.00
9	8	305,035.00
10	8	305,035.00
Mode/Average	8	305,025.40
Deviation	-	19.20
Percent Deviation	-	0.006%

Table A.25 - Number of iterations and utility value for each trial when setting $\epsilon = 100$.

Trial	Iterations	Utility
1	8	305,035.00
2	8	305,035.00
3	8	305,035.00
4	8	304,987.00
5	8	304,987.00
6	8	304,987.00
7	8	305,035.00
8	8	305,035.00
9	8	304,987.00
10	8	304,987.00
Mode/Average	8	305,011.00
Deviation	-	24.00
Percent Deviation	-	0.0079%

Table A.26 - Number of iterations and utility value for each trial when setting $\epsilon = 10$.

Trial	Iterations	Utility
1	9	305,035.00
2	9	305,035.00
3	8	305,035.00
4	9	305,035.00
5	8	305,035.00
6	8	305,035.00
7	9	305,035.00
8	9	305,035.00
9	8	305,035.00
10	8	305,035.00
Mode/Average	9	305,035.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Table A.27 - Number of iterations and utility value for each trial when setting $\epsilon = 1$.

Trial	Iterations	Utility
1	8	305,035.00
2	8	305,035.00
3	9	305,035.00
4	8	305,035.00
5	8	305,035.00
6	8	305,035.00
7	8	305,035.00
8	9	305,035.00
9	9	305,035.00
10	9	305,035.00
Mode/Average	8	305,035.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Table A.28 - Number of iterations and utility value for each trial when setting $\epsilon = 0.1$.

Trial	Iterations	Utility
1	8	305,035.00
2	9	305,035.00
3	8	305,035.00
4	8	305,035.00
5	8	305,035.00
6	8	305,035.00
7	8	305,035.00
8	8	305,035.00
9	8	305,035.00
10	9	305,035.00
Mode/Average	8	305,035.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Table A.29 - Number of iterations and utility value for each trial when setting $\epsilon = 0.05$.

Trial	Iterations	Utility
1	9	305,035.00
2	9	305,035.00
3	8	305,035.00
4	8	305,035.00
5	8	305,035.00
6	8	305,035.00
7	8	305,035.00
8	8	305,035.00
9	9	305,035.00
10	8	305,035.00
Mode/Average	8	305,035.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Table A.30 - Number of iterations and utility value for each trial when setting $\epsilon = 0.03$.

Trial	Iterations	Utility
1	8	305,035.00
2	8	305,035.00
3	8	305,035.00
4	9	305,035.00
5	8	305,035.00
6	8	305,035.00
7	8	305,035.00
8	8	305,035.00
9	9	305,035.00
10	8	305,035.00
Mode/Average	8	305,035.00
Deviation	-	0.00
Percent Deviation	-	0.00%

Violin plot in Figure A.5 and A.6 shows that in practical terms there is no variation for the number of iterations and total utility value over trials for ϵ values tested, for *Airline*#3, as expected, given that it is a not a complicated scenario in comparison with *Airline*#1 and *Airline*#2 scenarios.

Figure A.5 - ϵ parameter value vs number of iterations violin plot (Airline#3).

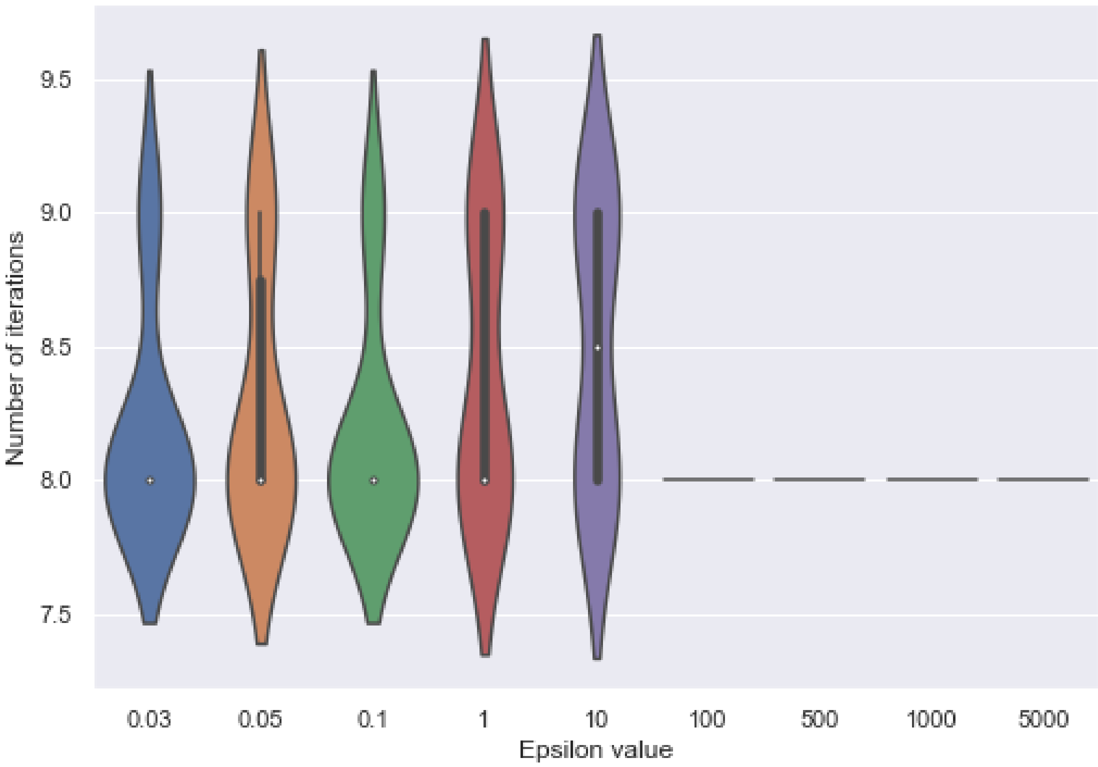
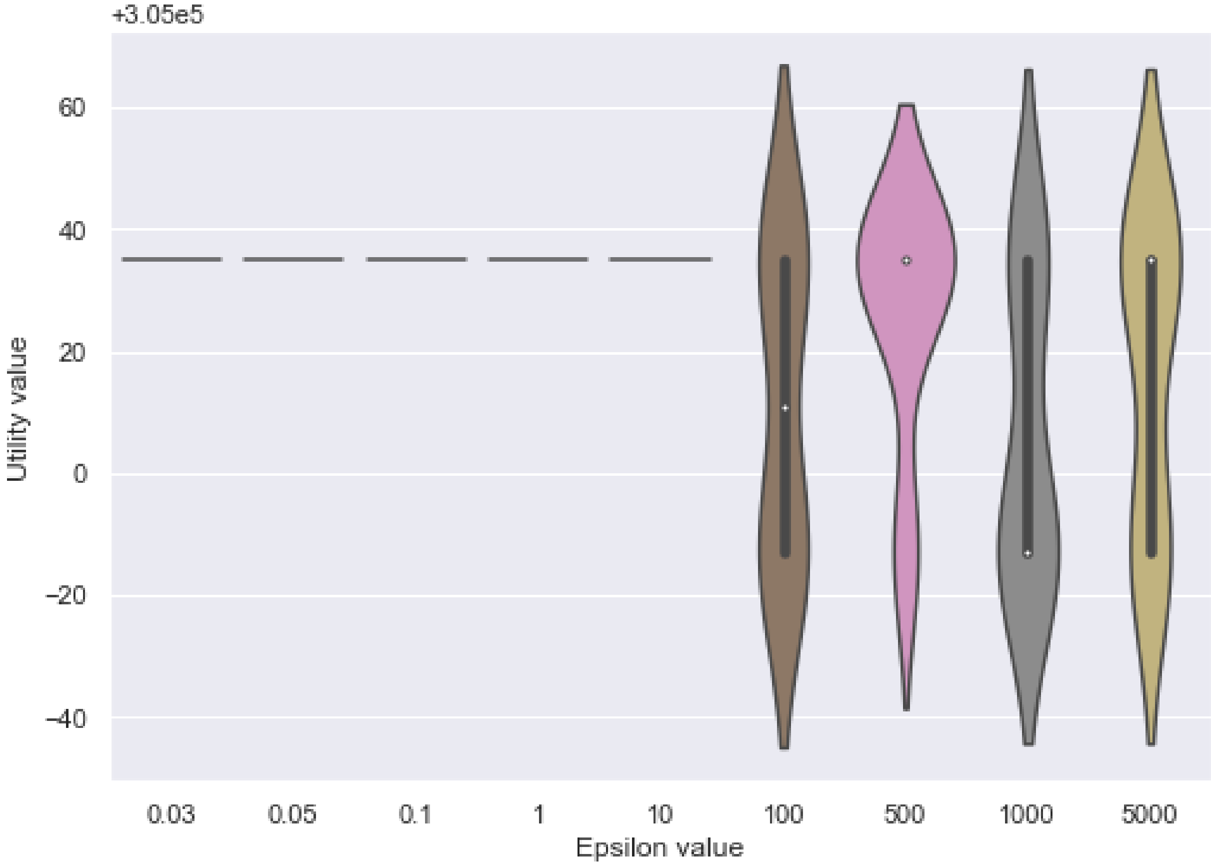


Figure A.6 - ϵ parameter value vs utility value violin plot (Airline#3).



B - AIRLINES #1, #2 and #3 FLIGHT SCHEDULE

This appendix presents full flight schedules for Airlines#1,#2 and #3.

Table B.1 - Flight Schedule Airline#1

Flight number	Origin	Destination	Estimated time of departure	Estimated time of arrival
4271	PNS	MIA	4/1/2016 07:05	4/1/2016 08:44
4295	MIA	PLS	4/1/2016 09:44	4/1/2016 11:34
4295	PLS	MIA	4/1/2016 12:15	4/1/2016 14:11
4331A	MIA	BNA	4/1/2016 15:20	4/1/2016 17:44
4331B	BNA	MIA	4/1/2016 18:20	4/1/2016 20:35
4277	MIA	PNS	4/1/2016 21:54	4/1/2016 23:45
4223A	MIA	ATL	4/1/2016 06:59	4/1/2016 08:59
4223B	ATL	MIA	4/1/2016 09:36	4/1/2016 11:31
4338	MIA	CZM	4/1/2016 12:45	4/1/2016 15:40
4339	CZM	MIA	4/1/2016 16:25	4/1/2016 17:03
4393	MIA	IND	4/1/2016 18:25	4/1/2016 21:16
4314	IND	LGA	4/1/2016 06:30	4/1/2016 08:46
4321A	LGA	ATL	4/1/2016 09:33	4/1/2016 12:15
4321B	ATL	LGA	4/1/2016 12:45	4/1/2016 14:47
4315	LGA	PIT	4/1/2016 15:40	4/1/2016 17:25
4390	PIT	MIA	4/1/2016 17:57	4/1/2016 20:46
4245	MIA	JAX	4/1/2016 21:44	4/1/2016 23:07
4296	CHS	MIA	4/1/2016 07:00	4/1/2016 08:47
4335A	MIA	NAS	4/1/2016 09:44	4/1/2016 10:51
4335B	NAS	MIA	4/1/2016 11:35	4/1/2016 12:45
4307A	MIA	JAX	4/1/2016 14:07	4/1/2016 15:24
4307B	JAX	MIA	4/1/2016 15:57	4/1/2016 17:15
4240A	MIA	EYW	4/1/2016 18:20	4/1/2016 19:12
4240B	EYW	MIA	4/1/2016 20:00	4/1/2016 20:47
4244	MIA	NAS	4/1/2016 21:54	4/1/2016 22:57
4248	DTW	ORD	4/1/2016 05:38	4/1/2016 07:19
4253A	ORD	ATL	4/1/2016 07:51	4/1/2016 09:54
4253B	ATL	ORD	4/1/2016 10:24	4/1/2016 12:39
4251A	ORD	PIT	4/1/2016 17:52	4/1/2016 19:20
4251B	PIT	ORD	4/1/2016 20:05	4/1/2016 21:53
4304	ORD	DTW	4/1/2016 23:05	4/2/2016 00:27
4337	LIR	MIA	4/1/2016 09:12	4/1/2016 11:57

4323A	MIA	FPO	4/1/2016 13:30	4/1/2016 14:16
4323B	FPO	MIA	4/1/2016 15:00	4/1/2016 15:46
4336	MIA	LIR	4/1/2016 18:05	4/1/2016 21:03
4247	CLE	MIA	4/1/2016 07:00	4/1/2016 10:08
4241	MIA	ATL	4/1/2016 12:15	4/1/2016 14:13
4382	ATL	ORD	4/1/2016 14:44	4/1/2016 16:59
4401A	ORD	IND	4/1/2016 17:42	4/1/2016 18:48
4401B	IND	ORD	4/1/2016 19:18	4/1/2016 20:34
4232	ORD	MEM	4/1/2016 21:19	4/1/2016 23:11
4360	PIT	MIA	4/1/2016 06:00	4/1/2016 8:56
4365A	MIA	JAX	4/1/2016 09:39	4/1/2016 11:03
4365B	JAX	MIA	4/1/2016 11:50	4/1/2016 13:05
4275A	MIA	GGT	4/1/2016 14:15	4/1/2016 15:26
4275B	GGT	MIA	4/1/2016 16:35	4/1/2016 17:51
4361	MIA	BNA	4/1/2016 21:29	4/1/2016 23:58
4221	IND	ORD	4/1/2016 07:05	4/1/2016 08:33
4260A	ORD	DCA	4/1/2016 10:34	4/1/2016 12:27
4260B	DCA	ORD	4/1/2016 13:10	4/1/2016 15:35
4235A	ORD	SDF	4/1/2016 16:15	4/1/2016 17:33
4235B	SDF	ORD	4/1/2016 18:25	4/1/2016 20:02
4274	ORD	DEN	4/1/2016 21:30	4/2/2016 00:20
4383A	MIA	ATL	4/1/2016 09:30	4/1/2016 11:35
4383B	ATL	MIA	4/1/2016 12:20	4/1/2016 14:13
4286	SDF	MIA	4/1/2016 06:05	4/1/2016 08:44
4239A	MIA	EYW	4/1/2016 09:39	4/1/2016 10:38
4239B	EYW	MIA	4/1/2016 11:08	4/1/2016 11:55
4391A	MIA	NAS	4/1/2016 12:47	4/1/2016 13:47
4391B	NAS	MIA	4/1/2016 14:30	4/1/2016 15:36
4373A	MIA	FPO	4/1/2016 17:00	4/1/2016 17:46
4373B	FPO	MIA	4/1/2016 18:30	4/1/2016 19:16
4318	ORD	PHL	4/1/2016 08:05	4/1/2016 10:12
4350	PHL	ORD	4/1/2016 11:11	4/1/2016 13:43
4317A	ORD	MEM	4/1/2016 14:23	4/1/2016 16:10
4317B	MEM	ORD	4/1/2016 16:40	4/1/2016 18:39
4257	ORD	PIT	4/1/2016 19:20	4/1/2016 20:49
4387	IAH	ORD	4/1/2016 09:06	4/1/2016 11:50
4355	ORD	ATL	4/1/2016 12:45	4/1/2016 14:44

4328	ATL	MIA	4/1/2016 15:14	4/1/2016 17:12
4340	MIA	MTY	4/1/2016 18:15	4/1/2016 21:57
4374	BNA	MIA	4/1/2016 07:00	4/1/2016 09:16
4237A	MIA	BNA	4/1/2016 10:04	4/1/2016 12:38
4237B	BNA	MIA	4/1/2016 13:30	4/1/2016 15:44
4380	MIA	PIT	4/1/2016 18:51	4/1/2016 21:30
4334A	MIA	NAS	4/1/2016 07:05	4/1/2016 08:06
4334B	NAS	MIA	4/1/2016 08:50	4/1/2016 09:56
4366A	MIA	CHS	4/1/2016 15:20	4/1/2016 17:00
4366B	CHS	MIA	4/1/2016 17:30	4/1/2016 19:12
4299	MIA	GSO	4/1/2016 19:59	4/1/2016 22:09
4370	PIT	ORD	4/1/2016 08:20	4/1/2016 10:26
4386A	ORD	DTW	4/1/2016 13:20	4/1/2016 14:45
4386B	DTW	ORD	4/1/2016 15:15	4/1/2016 16:41
4385A	ORD	ATL	4/1/2016 17:30	4/1/2016 19:30
4385B	ATL	ORD	4/1/2016 20:00	4/1/2016 22:15
4325A	ORD	DTW	4/1/2016 08:17	4/1/2016 09:43
4325B	DTW	ORD	4/1/2016 10:40	4/1/2016 12:08
4290A	ORD	BDL	4/1/2016 13:15	4/1/2016 15:25
4290B	BDL	ORD	4/1/2016 15:58	4/1/2016 18:46
4362	ORD	SDF	4/1/2016 19:50	4/1/2016 21:08
4300	MEM	ORD	4/1/2016 06:05	4/1/2016 08:04
4262A	ORD	ATL	4/1/2016 09:30	4/1/2016 11:34
4262B	ATL	ORD	4/1/2016 12:05	4/1/2016 14:20
4222A	ORD	SAT	4/1/2016 15:00	4/1/2016 18:10
4222B	SAT	ORD	4/1/2016 18:51	4/1/2016 21:40
4298	GSO	MIA	4/1/2016 06:30	4/1/2016 08:40
4356A	MIA	FPO	4/1/2016 09:44	4/1/2016 10:39
4356B	FPO	MIA	4/1/2016 11:19	4/1/2016 12:05
4278A	MIA	GGT	4/1/2016 12:50	4/1/2016 14:01
4278B	GGT	MIA	4/1/2016 14:41	4/1/2016 15:57
4398A	MIA	NAS	4/1/2016 16:55	4/1/2016 17:53
4398B	NAS	MIA	4/1/2016 18:33	4/1/2016 19:38
4326	MIA	SDF	4/1/2016 20:24	4/1/2016 23:00
4238	IND	MIA	4/1/2016 07:30	4/1/2016 10:23
4242A	MIA	MHH	4/1/2016 11:10	4/1/2016 12:09
4242B	MHH	MIA	4/1/2016 12:49	4/1/2016 13:48

4259A	MIA	MSY	4/1/2016 15:20	4/1/2016 17:38
4259B	MSY	MIA	4/1/2016 18:45	4/1/2016 20:42
4230	MIA	CLE	4/1/2016 21:59	4/2/2016 00:57
4369	SDF	ORD	4/1/2016 08:30	4/1/2016 10:15
4313A	ORD	ABQ	4/1/2016 11:20	4/1/2016 14:39
4313B	ABQ	ORD	4/1/2016 15:49	4/1/2016 18:44
4261	ORD	IND	4/1/2016 19:24	4/1/2016 20:31
9370	PIT	PHL	4/1/2016 09:05	4/1/2016 10:27
9371	PHL	PVD	4/1/2016 11:20	4/1/2016 12:28
9372	PVD	PHL	4/1/2016 13:00	4/1/2016 14:35
9373	PHL	DCA	4/1/2016 15:35	4/1/2016 16:38
9374	DCA	ATL	4/1/2016 16:59	4/1/2016 19:03
9375	ATL	DCA	4/1/2016 19:35	4/1/2016 21:19
9376	DCA	IND	4/1/2016 22:10	4/1/2016 23:12
4233A	LGA	RDU	4/1/2016 13:25	4/1/2016 15:14
4233B	RDU	LGA	4/1/2016 15:44	4/1/2016 17:29
4273A	LGA	RIC	4/1/2016 18:05	4/1/2016 19:41
4273B	RIC	LGA	4/1/2016 20:15	4/1/2016 21:37
4293	PLS	MIA	4/1/2016 08:15	4/1/2016 10:11
4266A	MIA	PNS	4/1/2016 11:15	4/1/2016 13:04
4266B	PNS	MIA	4/1/2016 14:00	4/1/2016 15:39
4285A	MIA	JAX	4/1/2016 16:50	4/1/2016 18:07
4285B	JAX	MIA	4/1/2016 19:10	4/1/2016 20:30
4284	ORF	MIA	4/1/2016 06:00	4/1/2016 08:31
4256A	MIA	PIT	4/1/2016 09:20	4/1/2016 12:04
4256B	PIT	JFK	4/1/2016 12:34	4/1/2016 14:09
4363	JFK	IND	4/1/2016 14:55	4/1/2016 17:23
4220	IND	MIA	4/1/2016 17:55	4/1/2016 20:36
4375	MIA	CHS	4/1/2016 21:34	4/1/2016 23:20
4357A	ORD	IAH	4/1/2016 08:49	4/1/2016 11:40
4357B	IAH	ORD	4/1/2016 12:19	4/1/2016 15:03
4250	ORD	ATL	4/1/2016 16:00	4/1/2016 18:01
4302	ATL	MIA	4/1/2016 18:34	4/1/2016 20:30
4359	JAX	MIA	4/1/2016 07:00	4/1/2016 08:18
4303	MIA	IND	4/1/2016 09:20	4/1/2016 12:16
4364	IND	JFK	4/1/2016 12:46	4/1/2016 14:51
4390	JFK	PIT	4/1/2016 15:40	4/1/2016 17:27

4263	RIC	MIA	4/1/2016 07:45	4/1/2016 10:16
4282A	MIA	EYW	4/1/2016 10:55	4/1/2016 11:49
4282B	EYW	MIA	4/1/2016 12:31	4/1/2016 13:19
4228	MIA	ATL	4/1/2016 15:20	4/1/2016 17:18
4333	ATL	ORD	4/1/2016 17:54	4/1/2016 20:09
4267	ORD	IAH	4/1/2016 22:25	4/2/2016 01:17
4384	DEN	ORD	4/1/2016 07:35	4/1/2016 10:10
4343A	ORD	MSP	4/1/2016 11:01	4/1/2016 12:29
4343B	MSP	ORD	4/1/2016 13:07	4/1/2016 14:44
4344	ORD	DEN	4/1/2016 15:25	4/1/2016 18:15
4342	DEN	ORD	4/1/2016 19:18	4/1/2016 21:48
4410	BNA	LGA	4/1/2016 09:15	4/1/2016 11:18
4402A	LGA	ATL	4/1/2016 12:10	4/1/2016 14:52
4402B	ATL	LGA	4/1/2016 15:25	4/1/2016 17:30
4316	LGA	BNA	4/1/2016 18:10	4/1/2016 20:53
4227	DCA	JFK	4/1/2016 06:00	4/1/2016 07:14
4367	JFK	DCA	4/1/2016 07:55	4/1/2016 09:16
4258	DCA	STL	4/1/2016 10:17	4/1/2016 12:50
4268	STL	DCA	4/1/2016 13:20	4/1/2016 15:19
4394	DCA	STL	4/1/2016 15:59	4/1/2016 18:30
4330	STL	DCA	4/1/2016 19:10	4/1/2016 21:11
4389	DCA	CMH	4/1/2016 22:05	4/1/2016 23:30
4341	MTY	MIA	4/1/2016 10:15	4/1/2016 13:12
4400A	MIA	NAS	4/1/2016 14:05	4/1/2016 15:03
4400B	NAS	MIA	4/1/2016 15:49	4/1/2016 16:55
4294	MIA	PLS	4/1/2016 18:05	4/1/2016 19:46
4312A	ORD	IAH	4/1/2016 11:05	4/1/2016 13:52
4312B	IAH	ORD	4/1/2016 14:22	4/1/2016 17:12
4272	ORD	JAX	4/1/2016 19:30	4/1/2016 21:54
4283	JAX	ORD	4/1/2016 07:10	4/1/2016 09:59
4368	ORD	HDN	4/1/2016 10:49	4/1/2016 13:50
4368	HDN	ORD	4/1/2016 14:22	4/1/2016 17:10
4351A	ORD	EWR	4/1/2016 17:50	4/1/2016 19:56
4351B	EWR	ORD	4/1/2016 20:29	4/1/2016 23:10
4279	MEM	LGA	4/1/2016 07:00	4/1/2016 09:26
4254A	LGA	MEM	4/1/2016 11:00	4/1/2016 14:14
4254A	MEM	LGA	4/1/2016 14:45	4/1/2016 17:09

4224	LGA	MEM	4/1/2016 18:30	4/1/2016 21:45
4396	MEM	MIA	4/1/2016 08:00	4/1/2016 10:20
4376	MIA	NAS	4/1/2016 11:15	4/1/2016 12:16
4243	NAS	MIA	4/1/2016 13:00	4/1/2016 14:06
4392A	MIA	ATL	4/1/2016 16:50	4/1/2016 18:48
4392B	ATL	MIA	4/1/2016 19:18	4/1/2016 21:11
4229	MIA	ORF	4/1/2016 21:54	4/2/2016 00:15
4264	IND	ORD	4/1/2016 09:00	4/1/2016 10:18
4346A	ORD	ELP	4/1/2016 11:20	4/1/2016 14:48
4346B	ELP	ORD	4/1/2016 15:25	4/1/2016 18:37
4378	ORD	IND	4/1/2016 21:20	4/1/2016 22:27
4324	NAS	MIA	4/1/2016 07:00	4/1/2016 08:04
4288	MIA	CLE	4/1/2016 09:25	4/1/2016 12:23
4276A	CLE	JFK	4/1/2016 13:00	4/1/2016 14:38
4276B	JFK	CLE	4/1/2016 15:25	4/1/2016 17:16
4297	CLE	MIA	4/1/2016 17:49	4/1/2016 20:50
4372	MIA	EYW	4/1/2016 21:34	4/1/2016 22:32
4225A	MIA	MSY	4/1/2016 09:30	4/1/2016 11:55
4225B	MSY	MIA	4/1/2016 12:30	4/1/2016 14:25
4287	MIA	RIC	4/1/2016 17:00	4/1/2016 19:17
4320A	DCA	ATL	4/1/2016 06:25	4/1/2016 08:27
4320B	ATL	DCA	4/1/2016 08:57	4/1/2016 10:41
4395	DCA	STL	4/1/2016 11:36	4/1/2016 14:04
4270	STL	DCA	4/1/2016 14:34	4/1/2016 16:33
4305A	DCA	RSW	4/1/2016 17:13	4/1/2016 20:00
4305B	RSW	DCA	4/1/2016 20:30	4/1/2016 22:56
4280	EYW	MIA	4/1/2016 07:40	4/1/2016 08:27
4265A	MIA	ORF	4/1/2016 11:05	4/1/2016 13:24
4265B	ORF	JFK	4/1/2016 14:10	4/1/2016 15:37
4377A	JFK	DCA	4/1/2016 16:29	4/1/2016 17:50
4377B	DCA	JFK	4/1/2016 19:25	4/1/2016 21:03
4358	JFK	DCA	4/1/2016 21:43	4/1/2016 22:59
4332	CMH	DCA	4/1/2016 07:59	4/1/2016 09:24
4255	DCA	JFK	4/1/2016 10:04	4/1/2016 11:17
4234A	JFK	DCA	4/1/2016 11:57	4/1/2016 13:12
4234B	DCA	JFK	4/1/2016 13:52	4/1/2016 14:59
4246A	JFK	ORF	4/1/2016 15:55	4/1/2016 17:21

4246B	ORF	MIA	4/1/2016 18:00	4/1/2016 20:31
4231	MIA	MEM	4/1/2016 21:34	4/2/2016 00:17

Table B.2 - Flight Schedule Airline#2

Flight number	Origin	Destination	Estimated time of departure	Estimated time of arrival
KL1152	GOT	AMS	5/30/2017 04:20	5/30/2017 05:50
KL1341	AMS	BLL	5/30/2017 06:25	5/30/2017 07:30
KL1342	BLL	AMS	5/30/2017 08:05	5/30/2017 09:15
KL1145	AMS	OSL	5/30/2017 09:50	5/30/2017 11:35
KL1146	OSL	AMS	5/30/2017 12:10	5/30/2017 14:00
KL1880	NUE	AMS	5/30/2017 04:00	5/30/2017 05:20
KL1413	AMS	LYS	5/30/2017 05:55	5/30/2017 07:30
KL1414	LYS	AMS	5/30/2017 08:05	5/30/2017 09:45
KL959	AMS	NCL	5/30/2017 10:25	5/30/2017 11:40
KL960	NCL	AMS	5/30/2017 12:15	5/30/2017 13:35
KL1762	FRA	AMS	5/30/2017 05:00	5/30/2017 06:10
KL1753	AMS	BRE	5/30/2017 06:45	5/30/2017 07:40
KL1754	BRE	AMS	5/30/2017 08:15	5/30/2017 09:10
KL1417	AMS	LYS	5/30/2017 09:45	5/30/2017 11:20
KL1818	LYS	AMS	5/30/2017 11:55	5/30/2017 13:40
KL1351	AMS	PRG	5/30/2017 04:45	5/30/2017 06:15
KL1352	PRG	AMS	5/30/2017 06:50	5/30/2017 08:25
KL1583	AMS	BLQ	5/30/2017 08:45	5/30/2017 10:35
KL1584	BLQ	AMS	5/30/2017 11:15	5/30/2017 13:20
KL1441	AMS	ABZ	5/30/2017 06:15	5/30/2017 07:45
KL1442	ABZ	AMS	5/30/2017 08:15	5/30/2017 09:45
KL1425	AMS	BHX	5/30/2017 10:30	5/30/2017 11:45
KL1426	BHX	AMS	5/30/2017 12:20	5/30/2017 13:30
KL1992	KRK	AMS	5/30/2017 04:40	5/30/2017 06:40
KL1173	AMS	TRD	5/30/2017 07:20	5/30/2017 09:25
KL1174	TRD	AMS	5/30/2017 09:55	5/30/2017 12:10
KL1300	TLS	AMS	5/30/2017 04:10	5/30/2017 06:05
KL1421	AMS	BHX	5/30/2017 06:45	5/30/2017 07:55
KL1422	BHX	AMS	5/30/2017 08:40	5/30/2017 09:50
KL1873	AMS	STR	5/30/2017 10:35	5/30/2017 11:45
KL1874	STR	AMS	5/30/2017 12:20	5/30/2017 13:45
KL1866	STR	AMS	5/30/2017 04:00	5/30/2017 05:20

KL1867	AMS	STR	5/30/2017 05:55	5/30/2017 07:10
KL1868	STR	AMS	5/30/2017 07:45	5/30/2017 09:10
KL1315	AMS	BOD	5/30/2017 09:45	5/30/2017 11:25
KL1316	BOD	AMS	5/30/2017 12:00	5/30/2017 13:50
KL1140	OSL	AMS	5/30/2017 04:30	5/30/2017 06:20
KL1723	AMS	BRU	5/30/2017 07:10	5/30/2017 07:55
KL1724	BRU	AMS	5/30/2017 08:35	5/30/2017 09:35
KL1929	AMS	GVA	5/30/2017 10:10	5/30/2017 11:35
KL1930	GVA	AMS	5/30/2017 12:10	5/30/2017 13:55
KL1554	TRN	AMS	5/30/2017 04:35	5/30/2017 06:35
KL1181	AMS	LPI	5/30/2017 07:30	5/30/2017 09:15
KL1132	LPI	AMS	5/30/2017 09:45	5/30/2017 11:30
KL1687	AMS	BIO	5/30/2017 12:10	5/30/2017 14:15
KL1212	TRF	AMS	5/30/2017 04:15	5/30/2017 05:50
KL1883	AMS	NUE	5/30/2017 06:30	5/30/2017 07:45
KL1884	NUE	AMS	5/30/2017 08:15	5/30/2017 09:30
KL1445	AMS	ABZ	5/30/2017 10:15	5/30/2017 11:45
KL1446	ABZ	AMS	5/30/2017 12:15	5/30/2017 13:45
KL1260	NCE	AMS	5/30/2017 04:25	5/30/2017 06:25
KL1739	AMS	LUX	5/30/2017 07:05	5/30/2017 08:00
KL1740	LUX	AMS	5/30/2017 08:30	5/30/2017 09:35
KL1157	AMS	GOT	5/30/2017 10:15	5/30/2017 11:40
KL1158	GOT	AMS	5/30/2017 12:10	5/30/2017 13:45
KL1855	AMS	DUS	5/30/2017 09:00	5/30/2017 09:50
KL1856	DUS	AMS	5/30/2017 10:25	5/30/2017 11:25
KL1397	AMS	PRG	5/30/2017 12:05	5/30/2017 13:35
KL1178	LPI	AMS	5/30/2017 04:10	5/30/2017 5:55
KL1639	AMS	FLR	5/30/2017 06:40	5/30/2017 8:40
KL1640	FLR	AMS	5/30/2017 09:20	5/30/2017 11:30
KL1684	BIO	AMS	5/30/2017 04:45	5/30/2017 07:00
KL1641	AMS	FKR	5/30/2017 07:35	5/30/2017 09:35
KL1642	FKR	AMS	5/30/2017 10:15	5/30/2017 12:25
KL1172	TRO	AMS	5/30/2017 04:15	5/30/2017 06:30
KL1059	AMS	CWL	5/30/2017 07:10	5/30/2017 08:30
KL1060	CWL	AMS	5/30/2017 09:00	5/30/2017 10:50
KL1781	AMS	HAM	5/30/2017 11:25	5/30/2017 12:30
KL1153	AMS	GOT	5/30/2017 05:45	5/30/2017 07:15

KL1154	GOT	AMS	5/30/2017 07:45	5/30/2017 09:20
KL1187	AMS	BGO	5/30/2017 09:55	5/30/2017 11:35
KL1188	BGO	AMS	5/30/2017 12:05	5/30/2017 13:50
KL1925	AMS	GVA	5/30/2017 05:00	5/30/2017 06:20
KL1926	GVA	AMS	5/30/2017 07:05	5/30/2017 08:45
KL1303	AMS	TLS	5/30/2017 09:45	5/30/2017 11:35
KL1304	TLS	AMS	5/30/2017 12:05	5/30/2017 14:05
KL1232	AES	AMS	5/30/2017 04:30	5/30/2017 06:45
KL1555	AMS	TRN	5/30/2017 07:30	5/30/2017 09:15
KL1556	TRN	AMS	5/30/2017 09:45	5/30/2017 11:40
KL1995	AMS	KRK	5/30/2017 12:25	5/30/2017 14:20
KL1314	BOD	AMS	5/30/2017 04:10	5/30/2017 05:50
KL1185	AMS	BGO	5/30/2017 06:30	5/30/2017 08:10
KL1186	BGO	AMS	5/30/2017 08:40	5/30/2017 10:25
KL1051	AMS	BRS	5/30/2017 11:00	5/30/2017 12:15
KL1582	BLQ	AMS	5/30/2017 04:00	5/30/2017 06:00
KL1301	AMS	TLS	5/30/2017 06:35	5/30/2017 08:25
KL1302	TLS	AMS	5/30/2017 08:55	5/30/2017 10:50
KL1332	ALL	AMS	5/30/2017 04:20	5/30/2017 05:40
KL1049	AMS	BRS	5/30/2017 06:30	5/30/2017 07:45
KL1050	BRS	AMS	5/30/2017 08:15	5/30/2017 09:30
KL1547	AMS	LBA	5/30/2017 10:40	5/30/2017 11:50

Table B.3 - Flight Schedule Airline#3

Flight number	Origin	Destination	Estimated time of departure	Estimated time of arrival
1001	GRU	GIG	5/30/2017 07:00	5/30/2017 08:00
1002	GIG	SSA	5/30/2017 09:00	5/30/2017 10:30
1003	SSA	REC	5/30/2017 11:30	5/30/2017 12:30
1004	REC	SSA	5/30/2017 16:30	5/30/2017 17:30
1005	SSA	GIG	5/30/2017 18:30	5/30/2017 20:00
1006	GIG	GRU	5/30/2017 21:00	5/30/2017 22:00
2007	REC	SSA	5/30/2017 07:30	5/30/2017 08:30
2008	SSA	GIG	5/30/2017 11:30	5/30/2017 13:00
2009	GIG	GRU	5/30/2017 14:30	5/30/2017 15:30
2010	GRU	GIG	5/30/2017 17:00	5/30/2017 18:00
2011	GIG	SSA	5/30/2017 19:00	5/30/2017 20:30
2012	SSA	REC	5/30/2017 21:30	5/30/2017 22:30

3013	GIG	GRU	5/30/2017 07:00	5/30/2017 08:00
3014	GRU	BSB	5/30/2017 09:00	5/30/2017 11:00
3015	BSB	MAO	5/30/2017 12:00	5/30/2017 14:00
3016	MAO	BSB	5/30/2017 15:00	5/30/2017 17:00
3017	BSB	GRU	5/30/2017 18:00	5/30/2017 20:00
3018	GRU	GIG	5/30/2017 21:00	5/30/2017 22:00
4019	MAO	BSB	5/30/2017 06:30	5/30/2017 08:30
4020	BSB	GRU	5/30/2017 09:30	5/30/2017 11:30
4021	GRU	GIG	5/30/2017 12:30	5/30/2017 13:30
4022	GIG	GRU	5/30/2017 15:30	5/30/2017 16:30
4023	GRU	BSB	5/30/2017 17:30	5/30/2017 19:30
4024	BSB	MAO	5/30/2017 20:30	5/30/2017 22:30
5025	GRU	CWB	5/30/2017 07:30	5/30/2017 08:30
5026	CWB	FLN	5/30/2017 09:30	5/30/2017 10:30
5027	FLN	POA	5/30/2017 11:30	5/30/2017 12:30
5028	POA	FLN	5/30/2017 18:00	5/30/2017 19:00
5029	FLN	CWB	5/30/2017 20:00	5/30/2017 21:00
5030	CWB	GRU	5/30/2017 22:00	5/30/2017 23:00
6031	POA	FLN	5/30/2017 07:30	5/30/2017 08:30
6032	FLN	CWB	5/30/2017 09:30	5/30/2017 10:30
6033	CWB	GRU	5/30/2017 11:30	5/30/2017 12:30
6034	GRU	CWB	5/30/2017 18:00	5/30/2017 19:00
6035	CWB	FLN	5/30/2017 20:00	5/30/2017 21:00
6036	FLN	POA	5/30/2017 22:00	5/30/2017 23:00
7037	GIG	GRU	5/30/2017 07:30	5/30/2017 08:30
7038	GRU	GIG	5/30/2017 09:30	5/30/2017 10:30
7039	GIG	GRU	5/30/2017 11:30	5/30/2017 12:30
7040	GRU	GIG	5/30/2017 14:00	5/30/2017 15:00
7041	GIG	GRU	5/30/2017 16:30	5/30/2017 17:30
7042	GRU	GIG	5/30/2017 18:30	5/30/2017 19:30
7043	GIG	GRU	5/30/2017 20:30	5/30/2017 21:30
7044	GRU	GIG	5/30/2017 22:30	5/30/2017 23:30
8045	POA	GRU	5/30/2017 07:00	5/30/2017 08:30
8046	GRU	REC	5/30/2017 09:30	5/30/2017 11:30
8047	REC	MAO	5/30/2017 12:30	5/30/2017 14:30
8048	MAO	REC	5/30/2017 15:30	5/30/2017 17:30
8049	REC	GRU	5/30/2017 18:30	5/30/2017 20:30

8050	GRU	POA	5/30/2017 21:30	5/30/2017 23:00

C - SCENARIOS A, B, C, D, E AND F COMPLETE ASSIGNMENT

This appendix presents complete aircraft assignment in this thesis for Scenarios A, B, C, D, E and F.

Table C.1 - Scenario A

Acft.	Route	Perf.	Fuel (kg)	Value	Flights
114	BNA-LGA-ATL-LGA-BNA	1.005	16,000.00	33,000.00	4410-4402A-4402B-4316
130	BNA-MIA-BNA-MIA-PIT	1.025	10,000.00	26,000.00	4374-4237A-4237B-4380
104	CHS-MIA-NAS-MIA-JAX-MIA-EYW-MIA-NAS	1.020	22,000.00	61,000.00	4296-4335A-4335B-4307A-4307B-4240A-4240B-4244
107	CLE-MIA-ATL-ORD-IND-ORD-MEM	1.005	25,000.00	51,000.00	4247-4241-4382-4401A-4401B-4232
142	CMH-DCA-JFK-DCA-JFK-ORF-MIA-MEM	1.045	28,000.00	52,000.00	4332-4255-4234A-4234B-4246A-4246B-4231
131	DCA-ATL-DCA-STL-DCA-RSW-DCA	1.030	27,000.00	36,000.00	4320A-4320B-4395-4270-4305A-4305B
140	DCA-JFK-DCA-STL-DCA-STL-DCA-CMH	1.005	28,000.00	49,000.00	4227-4367-4258-4268-4394-4330-4389
129	DEN-ORD-MSP-ORD-DEN-ORD	1.030	20,000.00	37,000.00	4384-4343A-4343B-4344-4342
105	DTW-ORD-ATL-ORD-PIT-ORD-DTW	1.025	20,000.00	50,000.00	4248-4253A-4253B-4251A-4251B-4304
141	EYW-MIA-ORF-JFK-DCA-JFK-DCA	1.020	21,000.00	45,000.00	4280-4265A-4265B-4377A-4377B-4358
119	GSO-MIA-FPO-MIA-GGT-MIA-NAS-MIA-SDF	1.000	34,000.00	52,000.00	4298-4356A-4356B-4278A-4278B-4398A-4398B-4326
113	IAH-ORD-ATL-MIA-MTY	1.020	17,000.00	29,000.00	4387-4355-4328-4340
109	IND-LGA-ATL-LGA-PIT-MIA-JAX	1.035	17,000.00	43,000.00	4314-4321A-4321B-4315-4390-4245
137	IND-MIA-MHH-MIA-MSY-MIA-CLE	1.025	24,000.00	50,000.00	4283-4242A-4242B-4259A-4259B-4230
103	IND-ORD-DCA-ORD-SDF-ORD-DEN	1.020	29,000.00	45,000.00	4221-4260A-4260B-4235A-4235B-4274
120	IND-ORD-ELP-ORD-IND	1.050	16,000.00	32,000.00	4264-4346A-4346B-4378
127	JAX-MIA-IND-JFK-PIT	1.030	16,000.00	27,000.00	4359-4303-4364-4390
134	JAX-ORD-HDN-ORD-EWR-ORD	1.015	21,000.00	39,000.00	4283-4368A-4368B-4351A-4351B

123	LGA-RDU-LGA-RIC-LGA	1.050	18,000.00	24,000.00	4233A-4233B-4273A-4273B
106	LIR-MIA-FPO-MIA-LIR	1.015	14,000.00	28,000.00	4337-4323A-4323B-4336
136	MEM-LGA-MEM-LGA-MEM	1.035	10,000.00	32,000.00	4279-4254A-4254B-4224
118	MEM-MIA-NAS-MIA-ATL-MIA-ORF	1.010	15,000.00	50,000.00	4396-4376-4243-4392A-4392B-4229
135	MEM-ORD-ATL-ORD-SAT-ORD	1.040	9,000.00	43,000.00	4300-4262A-4262B-4222A-4122B
139	MIA-ATL-MIA	1.025	5,000.00	12,000.00	4383A-4383B
115	MIA-ATL-MIA-CZM-MIA-IND	1.030	21,000.00	37,000.00	4223A-4223B-4338-4339-4393
110	MIA-MSY-MIA-RIC	1.020	10,000.00	24,000.00	4225A-4225B-4287
102	MIA-NAS-MIA-CHS-MIA-GSO	1.010	24,000.00	38,000.00	4334A-4334B-4366A-4366B-4299
132	MTY-MIA-NAS-MIA-PLS	1.045	12,000.00	29,000.00	4341-4400A-4400B-4294
138	NAS-MIA-CLE-JFK-CLE-MIA-EYW	1.010	27,000.00	39,000.00	4324-4288-4276A-4276B-4297-4372
133	ORD-DTW-ORD-BDL-ORD-SDF	1.015	18,000.00	37,000.00	4325A-4325B-4290A-4290B-4362
112	ORD-IAH-ORD-ATL-MIA	1.015	16,000.00	24,000.00	4357A-4357B-4250-4302
126	ORD-IAH-ORD-JAX	1.035	12,000.00	26,000.00	4312A-4312B-4272
117	ORD-PHL-ORD-MEM-ORD-PIT	1.020	12,000.00	38,000.00	4318-4350-4317A-4317B-4257
125	ORF-MIA-PIT-JFK-IND-MIA-CHS	1.035	28,000.00	50,000.00	4284-4256A-4256B-4363-4220-4375
122	PIT-MIA-JAX-MIA-GGT-MIA-BNA	1.025	24,000.00	46,000.00	4360-4365A-4365B-4275A-4275B-4361
116	PIT-ORD-DTW-ORD-ATL-ORD	1.050	15,000.00	35,000.00	4370-4386A-4386B-4385A-4385B
108	PIT-PHL-PVD-PHL-DCA-ATL-DCA-IND	1.050	15,000.00	49,000.00	9370-9371-9372-9373-9374-9375-9376
124	PLS-MIA-PNS-MIA-JAX-MIA	1.025	13,000.00	42,000.00	4293-4266A-4266B-4285A-4285B
101	PNS-MIA-PLS-MIA-BNA-MIA-PNS	1.010	23,000.00	48,000.00	4271-4295A-4295B-4331A-4331B-4277
128	RIC-MIA-EYW-MIA-ATL-ORD-IAH	1.045	18,000.00	43,000.00	4263-4282A-4282B-4228-4333-4267
121	SDF-MIA-EYW-MIA-NAS-MIA-FPO-MIA	1.000	22,000.00	49,000.00	4286-4239A-4239B-4391A-4391B-4373A-4373B

111	SDF-ORD-ABQ-ORD-IND	1.040	16,000.00	34,000.00	4369-4313A-4313B-4261

Table C.2 - Scenario B

Acft.	Route	Perf.	Fuel (kg)	Value	Flights
114	BNA-LGA-ATL-LGA-BNA	1.005	16,000.00	33,000.00	4410-4402A-4402B-4316
130	BNA-MIA-BNA-MIA-PIT	1.025	10,000.00	26,000.00	4374-4237A-4237B-4380
104	CHS-MIA-NAS-MIA-JAX-MIA-EYW-MIA-NAS	1.020	22,000.00	61,000.00	4296-4335A-4335B-4307A-4307B-4240A-4240B-4244
107	CLE-MIA-ATL-ORD-IND-ORD-MEM	1.005	25,000.00	51,000.00	4247-4241-4382-4401A-4401B-4232
142	CMH-DCA-JFK-DCA-JFK-ORF-MIA-MEM	1.045	28,000.00	52,000.00	4332-4255-4234A-4234B-4246A-4246B-4231
131	DCA-ATL-DCA-STL-DCA-RSW-DCA	1.030	27,000.00	36,000.00	4320A-4320B-4395-4270-4305A-4305B
140	DCA-JFK-DCA-STL-DCA-STL-DCA-CMH	1.005	28,000.00	49,000.00	4227-4367-4258-4268-4394-4330-4389
129	DEN-ORD-MSP-ORD-DEN-ORD	1.030	20,000.00	37,000.00	4384-4343A-4343B-4344-4342
105	DTW-ORD-ATL-ORD-PIT-ORD-DTW	1.025	20,000.00	50,000.00	4248-4253A-4253B-4251A-4251B-4304
141	EYW-MIA-ORF-JFK-DCA-JFK-DCA	1.020	21,000.00	45,000.00	4280-4265A-4265B-4377A-4377B-4358
119	GSO-MIA-FPO-MIA-GGT-MIA-NAS-MIA-SDF	1.000	34,000.00	52,000.00	4298-4356A-4356B-4278A-4278B-4398A-4398B-4326
113	IAH-ORD-ATL-MIA-MTY	1.020	17,000.00	29,000.00	4387-4355-4328-4340
109	IND-LGA-ATL-LGA-PIT-MIA-JAX	1.035	17,000.00	43,000.00	4314-4321A-4321B-4315-4390-4245
137	IND-MIA-MHH-MIA-MSY-MIA-CLE	1.025	24,000.00	50,000.00	4283-4242A-4242B-4259A-4259B-4230
103	IND-ORD-DCA-ORD-SDF-ORD-DEN	1.020	29,000.00	45,000.00	4221-4260A-4260B-4235A-4235B-4274
120	IND-ORD-ELP-ORD-IND	1.050	16,000.00	32,000.00	4264-4346A-4346B-4378
127	JAX-MIA-IND-JFK-PIT	1.030	16,000.00	27,000.00	4359-4303-4364-4390
134	JAX-ORD-HDN-ORD-EWR-ORD	1.015	21,000.00	39,000.00	4283-4368A-4368B-4351A-4351B
123	LGA-RDU-LGA-RIC-LGA	1.050	18,000.00	24,000.00	4233A-4233B-4273A-4273B

106	LIR-MIA-FPO-MIA-LIR	1.015	14,000.00	28,000.00	4337-4323A-4323B-4336
135	MEM-LGA-MEM-LGA-MEM	1.040	10,000.00	32,000.00	4279-4254A-4254B-4224
118	MEM-MIA-NAS-MIA-ATL-MIA-ORF	1.010	15,000.00	50,000.00	4396-4376-4243-4392A-4392B-4229
136	MEM-ORD-ATL-ORD-SAT-ORD	1.035	9,000.00	43,000.00	4300-4262A-4262B-4222A-4122B
115	MIA-ATL-MIA	1.030	5,000.00	12,000.00	4383A-4383B
110	MIA-ATL-MIA-CZM-MIA-IND	1.020	21,000.00	37,000.00	4223A-4223B-4338-4339-4393
139	MIA-MSY-MIA-RIC	1.025	10,000.00	24,000.00	4225A-4225B-4287
102	MIA-NAS-MIA-CHS-MIA-GSO	1.010	24,000.00	38,000.00	4334A-4334B-4366A-4366B-4299
132	MTY-MIA-NAS-MIA-PLS	1.045	12,000.00	29,000.00	4341-4400A-4400B-4294
138	NAS-MIA-CLE-JFK-CLE-MIA-EYW	1.010	27,000.00	39,000.00	4324-4288-4276A-4276B-4297-4372
133	ORD-DTW-ORD-BDL-ORD-SDF	1.015	18,000.00	37,000.00	4325A-4325B-4290A-4290B-4362
112	ORD-IAH-ORD-ATL-MIA	1.015	16,000.00	24,000.00	4357A-4357B-4250-4302
126	ORD-IAH-ORD-JAX	1.035	12,000.00	26,000.00	4312A-4312B-4272
117	ORD-PHL-ORD-MEM-ORD-PIT	1.020	12,000.00	38,000.00	4318-4350-4317A-4317B-4257
125	ORF-MIA-PIT-JFK-IND-MIA-CHS	1.035	28,000.00	50,000.00	4284-4256A-4256B-4363-4220-4375
122	PIT-MIA-JAX-MIA-GGT-MIA-BNA	1.025	24,000.00	46,000.00	4360-4365A-4365B-4275A-4275B-4361
108	PIT-ORD-DTW-ORD-ATL-ORD	1.050	15,000.00	35,000.00	4370-4386A-4386B-4385A-4385B
116	PIT-PHL-PVD-PHL-DCA-ATL-DCA-IND	1.050	15,000.00	49,000.00	9370-9371-9372-9373-9374-9375-9376
124	PLS-MIA-PNS-MIA-JAX-MIA	1.025	13,000.00	42,000.00	4293-4266A-4266B-4285A-4285B
101	PNS-MIA-PLS-MIA-BNA-MIA-PNS	1.010	23,000.00	48,000.00	4271-4295A-4295B-4331A-4331B-4277
128	RIC-MIA-EYW-MIA-ATL-ORD-IAH	1.045	18,000.00	43,000.00	4263-4282A-4282B-4228-4333-4267
121	SDF-MIA-EYW-MIA-NAS-MIA-FPO-MIA	1.000	22,000.00	49,000.00	4286-4239A-4239B-4391A-4391B-4373A-4373B
111	SDF-ORD-ABQ-ORD-IND	1.040	16,000.00	34,000.00	4369-4313A-4313B-4261

Table C.3 - Scenario C

Acft	Route	Perf	Fuel (kg)	Value	Flights
EZW	AES-AMS-TRN-AMS-KRK	1.035	23,408.00	29,000.00	KL1232-KL1555-KL1556-KL1995
EZZ	ALL-AMS-BRS-AMS-LBA	1.050	16,505.00	25,000.00	KL1332-KL1049-KL1050-KL1547
EZE	AMS-ABZ-AMS-BHX-AMS	1.020	18,923.00	34,000.00	KL1441-KL1442-KL1425-KL1426
EZV	AMS-DUS-AMS-PRG	1.030	11,251.00	23,000.00	KL1855-KL1856-KL1397
EZT	AMS-GOT-AMS-BGO-AMS	1.025	17,883.00	29,000.00	KL1153-KL1154-KL1187-KL1188
EZO	AMS-GVA-AMS-TLS-AMS	1.005	24,208.00	31,000.00	KL1925-KL1926-KL1303-KL1304
EZD	AMS-PRG-AMS-BLQ-AMS	1.015	24,020.00	30,000.00	KL1351-KL1352-KL1583-KL1584
EZR	BIO-AMS-FKR-AMS	1.015	15,864.00	27,000.00	KL1684-KL1641-KL1642
EZY	BLQ-AMS-TLS-AMS	1.045	18,310.00	24,000.00	KL1582-KL1301-KL1302
EZX	BOD-AMS-BGO-AMS-BRS	1.040	22,395.00	29,000.00	KL1314-KL1185-KL1186-KL1051
EZC	FRA-AMS-BRE-AMS-LYS-AMS	1.010	19,965.00	32,000.00	KL1762-KL1753-KL1754-KL1417-KL1818
EZA	GOT-AMS-BLL-AMS-OSL-AMS	1.000	24,083.00	37,000.00	KL1152-KL1341-KL1342-KL1145-KL1146
EZF	KRK-AMS-TRD-AMS	1.025	19,356.00	21,000.00	KL1992-KL1173-KL1174
EZP	LPI-AMS-FLR-AMS	1.010	15,324.00	24,000.00	KL1178-KL1639-KL1640
EZN	NCE-AMS-LUX-AMS-GOT-AMS	1.000	21,377.00	40,000.00	KL1260-KL1739-KL1740-KL1157-KL1158
EZB	NUE-AMS-LYS-AMS-NCL-AMS	1.005	22,684.00	39,000.00	KL1880-KL1413-KL1414-KL959-KL960
EZK	OSL-AMS-BRU-AMS-GVA-AMS	1.040	21,530.00	40,000.00	KL1140-KL1723-KL1724-KL1929-KL1930
EZI	STR-AMS-STR-AMS-BOD-AMS	1.035	22,169.00	39,000.00	KL1866-KL1867-KL1868-KL1315-KL1316
EZG	TLS-AMS-BHX-AMS-STR-AMS	1.030	21,451.00	43,000.00	KL1300-KL1421-KL1422-KL1873-KL1874
EZM	TRF-AMS-NUE-AMS-ABZ-AMS	1.050	21,426.00	37,000.00	KL1212-KL1883-KL1884-KL1445-KL1446
EZL	TRN-AMS-LPI-AMS-BIO	1.045	21,508.00	33,000.00	KL1554-KL1181-KL1132-KL1687

EZS	TRO-AMS-CWL-AMS-HAM	1.020	18,048.00	27,000.00	KL1172-KL1059-KL1060-KL1781

Table C.4 - Scenario D

Acft.	Route	Perf.	Fuel (kg)	Value	Flights
EZW	AES-AMS-TRN-AMS-KRK	1.035	23,408.00	29,000.00	KL1232-KL1555-KL1556-KL1995
EZZ	ALL-AMS-BRS-AMS-LBA	1.050	16,505.00	25,000.00	KL1332-KL1049-KL1050-KL1547
EZE	AMS-ABZ-AMS-BHX-AMS	1.020	18,923.00	34,000.00	KL1441-KL1442-KL1425-KL1426
EZT	AMS-DUS-AMS-PRG	1.025	11,251.00	23,000.00	KL1855-KL1856-KL1397
EZV	AMS-GOT-AMS-BGO-AMS	1.030	17,883.00	29,000.00	KL1153-KL1154-KL1187-KL1188
EZD	AMS-GVA-AMS-TLS-AMS	1.015	24,208.00	31,000.00	KL1925-KL1926-KL1303-KL1304
EZO	AMS-PRG-AMS-BLQ-AMS	1.005	24,020.00	30,000.00	KL1351-KL1352-KL1583-KL1584
EZR	BIO-AMS-FKR-AMS	1.015	15,864.00	27,000.00	KL1684-KL1641-KL1642
EZY	BLQ-AMS-TLS-AMS	1.045	18,310.00	24,000.00	KL1582-KL1301-KL1302
EZX	BOD-AMS-BGO-AMS-BRS	1.040	22,395.00	29,000.00	KL1314-KL1185-KL1186-KL1051
EZC	FRA-AMS-BRE-AMS-LYS-AMS	1.010	19,965.00	32,000.00	KL1762-KL1753-KL1754-KL1417-KL1818
EZA	GOT-AMS-BLL-AMS-OSL-AMS	1.000	24,083.00	37,000.00	KL1152-KL1341-KL1342-KL1145-KL1146
EZF	KRK-AMS-TRD-AMS	1.025	19,356.00	21,000.00	KL1992-KL1173-KL1174
EZP	LPI-AMS-FLR-AMS	1.010	15,324.00	24,000.00	KL1178-KL1639-KL1640
EZN	NCE-AMS-LUX-AMS-GOT-AMS	1.000	21,377.00	40,000.00	KL1260-KL1739-KL1740-KL1157-KL1158
EZB	NUE-AMS-LYS-AMS-NCL-AMS	1.005	22,684.00	39,000.00	KL1880-KL1413-KL1414-KL959-KL960
EZK	OSL-AMS-BRU-AMS-GVA-AMS	1.040	21,530.00	40,000.00	KL1140-KL1723-KL1724-KL1929-KL1930
EZI	STR-AMS-STR-AMS-BOD-AMS	1.035	22,169.00	39,000.00	KL1866-KL1867-KL1868-KL1315-KL1316
EZG	TLS-AMS-BHX-AMS-STR-AMS	1.030	21,451.00	43,000.00	KL1300-KL1421-KL1422-KL1873-KL1874

EZM	TRF-AMS-NUE-AMS-ABZ-AMS	1.050	21,426.00	37,000.00	KL1212-KL1883-KL1884-KL1445-KL1446
EZL	TRN-AMS-LPI-AMS-BIO	1.045	21,508.00	33,000.00	KL1554-KL1181-KL1132-KL1687
EZS	TRO-AMS-CWL-AMS-HAM	1.020	18,048.00	27,000.00	KL1172-KL1059-KL1060-KL1781

Table C.5 - Scenario E

Acft	Route	Perf	Fuel (kg)	Value	Flights
107	GIG-GRU-BSB-MAO-BSB-GRU-GIG	1.040	19,000.00	51,000.00	3013-3014-3015-3016-3017-3018
103	GIG-GRU-GIG-GRU-GIG-GRU-GIG-GRU-GIG	1.030	28,000.00	72,000.00	7037-7038-7039-7040-7041-7042-7043-7044
101	GRU-CWB-FLN-POA-FLN-CWB-GRU	1.015	15,000.00	48,000.00	5025-5026-5027-5028-5029-5030
105	GRU-GIG-SSA-REC-SSA-GIG-GRU	1.030	15,000.00	42,000.00	1001-1002-1003-1004-1005-1006
104	MAO-BSB-GRU-GIG-GRU-BSB-MAO	1.045	18,000.00	47,000.00	4019-4020-4021-4022-4023-4024
106	POA-FLN-CWB-GRU-CWB-FLN-POA	1.050	21,000.00	51,000.00	6031-6032-6033-6034-6035-6036
108	POA-GRU-REC-MAO-REC-GRU-POA	1.010	21,000.00	36,000.00	8045-8046-8047-8048-8049-8050
102	REC-SSA-GIG-GRU-GIG-SSA-REC	1.040	27,000.00	48,000.00	2007-2008-2009-2010-2011-2012

Table C.6 - Scenario F

Acft	Route	Perf	Fuel (kg)	Value	Flights
107	GIG-GRU-BSB-MAO-BSB-GRU-GIG	1.040	19,000.00	51,000.00	3013-3014-3015-3016-3017-3018
103	GIG-GRU-GIG-GRU-GIG-GRU-GIG-GRU-GIG	1.030	28,000.00	72,000.00	7037-7038-7039-7040-7041-7042-7043-7044
101	GRU-CWB-FLN-POA-FLN-CWB-GRU	1.015	15,000.00	48,000.00	5025-5026-5027-5028-5029-5030
105	GRU-GIG-SSA-REC-SSA-GIG-GRU	1.030	15,000.00	42,000.00	1001-1002-1003-1004-1005-1006
104	MAO-BSB-GRU-GIG-GRU-BSB-MAO	1.045	18,000.00	47,000.00	4019-4020-4021-4022-4023-4024

106	POA-FLN-CWB-GRU-CWB-FLN-POA	1.050	21,000.00	51,000.00	6031-6032-6033-6034-6035-6036
108	POA-GRU-REC-MAO-REC-GRU-POA	1.010	21,000.00	36,000.00	8045-8046-8047-8048-8049-8050
102	REC-SSA-GIG-GRU-GIG-SSA-REC	1.040	27,000.00	48,000.00	2007-2008-2009-2010-2011-2012

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