Probabilistic Modeling of Workload Deviations in Aircraft Light Maintenance Using Bayesian Networks

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Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

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Abstract

This dissertation, developed in the context of preventive maintenance on commercial aircraft, aims at analyzing probabilistically the discrepancies between workloads predicted by aircraft manufacturers for light periodic inspections tasks and the ones registered upon their execution.

The dissertation is based on a sample of historical data of ”A-checks” inspections conducted on Airbus A330 and A340, between 2013 and 2020, provided by *MESA* – *HiFly*'s Maintenance and Engineering services provider.

A Bayesian networks framework is used to model probabilistically the deviations from the workloads predicted by the aircraft's manufacturer, from the available data.

The adopted methodology requires a review of the evolution, planning and registration of aircraft maintenance, along with a detailed analysis of workcards and the *Maintenance Planning Document*. The basic principles and processes of the development of Bayesian networks models through data and validation through sensitivity analyses are presented.

Two Bayesian networks are developed from the data: one for the modeling of checks, where the sensitivity analysis identifies that $2A$ items and maintenance performed at the base station are likelier to present high deviations, and one for tasks, where it is evaluated that *General Visual Inspections*, zones 400 and 700, and *Powerplant* and *Airframe* skills are the variables with higher impacts in the deviations. Two practical examples of application of the models for maintenance capacity planning are presented.

It is expected that the dissertation will bring benefits in the planning of these inspections, given that the degree of uncertainty of this activity can be reduced through the developed models.

Keywords

BN's; Aircraft Maintenance; A-checks; Workload Deviations; Capacity Planning.

Resumo

Esta dissertação insere-se no contexto da manutenção preventiva de aeronaves comerciais, tendo como objetivo analisar probabilisticamente desvios entre cargas de trabalho previstas pelo fabricante de aeronaves para tarefas de inspeções periódicas ligeiras e as registadas na sua realização.

O desenvolvimento da dissertação baseia-se numa amostra de dados históricos de inspeções intituladas “A-checks” em Airbus A330 e A340, realizadas entre 2013 e 2020, fornecida pela *MESA* – empresa de Manutenção e Engenharia do grupo *HiFly*.

É utilizada uma ferramenta de redes Bayesianas para modelar probabilisticamente os desvios nas cargas de trabalho previstas pelo fabricante das aeronaves a partir dos dados disponíveis.

A metodologia adotada requer uma revisão da evolução, planeamento e registo da manutenção de aeronaves, bem como uma análise detalhada de cartas de trabalho e do *Maintenance Planning Document*. Apresentam-se os princípios básicos e processos de desenvolvimento de modelos de redes Bayesianas a partir de dados e de validação através de análises de sensibilidade.

São desenvolvidas duas redes Bayesianas a partir dos dados: uma para modelação de checks, onde a análise de sensibilidade identifica que itens $2A$ e trabalhos realizados na base de manutenção são os mais propensos a apresentar desvios altos, e uma para tarefas, onde se avalia que *General Visual Inspections*, zonas 400 e 700, e skills *Powerplant* e *Airframe* são as variáveis mais impactuantes. São apresentados dois exemplos práticos da aplicação dos modelos ao planeamento de capacidade.

Espera-se que o projeto seja benéfico no planeamento destas inspeções, dado que o grau de incerteza desta atividade pode ser reduzido através dos modelos concebidos.

Palavras Chave

BN’s; Manutenção; A-checks; Desvios de Cargas de Trabalho; Planeamento de Capacidade.

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List of Variables

β	Shape Parameter
η	Scale Parameter
γ	Location Parameter
A	Random Variable
B	Random Variable
C	Random Variable
CIL	Cosmetic Items Labor
CIM	Cosmetic Items Material
e	State of the Y Variable
EOL	Engineering Order Labor
EOM	Engineering Order Material
f	State of the Y Variable
LBR	Labor Rate
MEF	MRO Efficiency Factor
MLC	MRO Labor Capacity
MTC	Maintenance Costs
MTL	MPD Tasks Labor
MTM	MPD Tasks Material
NFL	Nonroutine Labor Factor

NFM Nonroutine Material Factor

NRM Nonroutine Material

S Sensitivity

TAT Turnaround Time

WL_Dev Workload Deviation

X Random Variable

Y Random Variable

Acronyms

AC Advisory Circulars

AD Airworthiness Directives

AF Airframe

AKL Auckland

AL Airworthiness Limitations

AMM Aircraft Maintenance Manual

AMP Approved Maintenance Program

APU Auxiliary Power Unit

ATA Air Transport Association

AV Instrument

BDPA Big Data and Predictive Analytics

BN Bayesian Network

BNE Brisbane

BRU Brussels

BWN Brunei

BYJ Beja

CAA Civil Aviation Authority

CAMO Continuing Airworthiness Management Organisation

CCPM Critical Chain Project Management

CIL Cosmetic Items Labor

CIM Cosmetic Items Material

CM Condition Monitoring

CMR	Certification Maintenance Requirements
COVID-19	Coronavirus Disease 2019
CPT	Conditional Probability Table
DAG	Directed Acyclic Graph
DET	Detailed Inspection
DIS	Discard
DY	Calendar Days
EASA	European Aviation Safety Agency
EL	Electrical
EM	Expectation-Maximization
EN	Powerplant
EOL	Engineering Order Labor
EOM	Engineering Order Material
FAA	Federal Aviation Administration
FC	Flight Cycles
FH	Flight Hours
FNC	Functional Check
GDP	Gross Domestic Product
GVI	General Visual Inspection
IATA	International Air Transport Association
IVHM	Integrated Vehicle Health Management
JTA	Job Task Analysis
KPMG	Klynveld Peat Marwick Goerdeler
LBR	Labor Rate
LIS	Lisbon
LUB	Lubrication
MEF	MRO Efficiency Factor
M/H	Man-Hour Units
MLC	MRO Labor Capacity

MoU	Memorandum of Understanding
MPD	Maintenance Planning Document
MRB	Maintenance Review Board
MRBR	Maintenance Review Board Report
MRO	Maintenance, Repair and Overhaul
MSG	Maintenance Steering Group
MTL	MPD Tasks Labor
MTM	MPD Tasks Material
NFL	Nonroutine Labor Factor
NFM	Nonroutine Material Factor
NRL	Nonroutine Labor
NRM	Nonroutine Material
OAMP	Operators Approved Maintenance Program
OSL	Oslo
OPC	Operational Check
RA	Radio
RAM	Reliability, Availability, Maintainability
RFID	Radio-Frequency Identification
RPK	Revenue Passenger Kilometers
RST	Restoration
SB	Service Bulletins
SHM	Structural Health Monitoring
SL	Service Letters
SVC	Servicing
TAT	Turnaround Time
TC	Type Certificate

1

Introduction

Contents

1.1 Motivation

It is known that the aviation sector represents a key role in globalisation through the generation of economic growth, creation of jobs and enabling of the international trade, since it offers a fast, efficient and reliable method of transport.

Prior to the arise of the Coronavirus Disease 2019 (COVID-19), the aviation industry, as well as the businesses that support it, were experiencing unparalleled growth thanks to the increase in the global population able to afford air travel [1]. Rising incomes that potentiate consumer spending were pushing passenger travel to record levels, and from a long-term historical perspective the cluster was doubling in size every fifteen years [2]. Around $1\,303$ scheduled airlines were operating over $31\,717$ aircraft, serving a total of $3\,759$ airports thanks to the support of 170 air navigation service providers.

As of 2019, contribution of aviation to the global economy was approximately equivalent to the overall Gross Domestic Product (GDP) of the United Kingdom [2]. However, in the last few decades, this industry has been characterized by an extremely competitive and dynamic market that is highly susceptible to the influence of external social, economic and political factors – this is evidenced in Figure 1.1, graphing Eurocontrol's study on the daily variation (flights) compared to equivalent days in 2019, due to the effects of COVID-19. This vulnerability, along with several others, affects the ability of airlines to generate revenue. Therefore, to stay in business, companies have been forced to enhance their operative and financial conditions through the implementation of different business strategies.

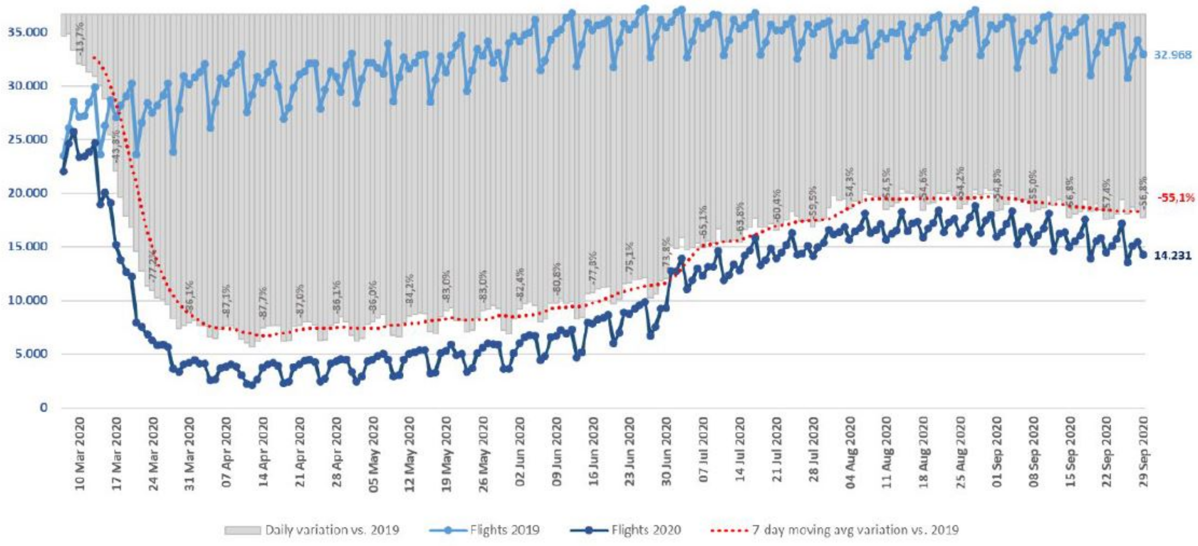


Figure 1.1: Daily flights compared to equivalent days in 2019 [3].

Before the financial impacts of COVID-19, airlines aimed at planning their maintenance in an efficient way, so that the aircraft's availability would be optimized [4]. Rising costs and fierce competition were the two most common challenges highlighted by airline executives, as reported by Klynveld Peat Marwick

Goerdeler (KPMG) [5]. However, the spreading of the pandemic affected nearly every business sector, and aviation was not an exception to this trend; it demanded a shift of the main concern from aircraft availability to a necessity to reduce the costs associated to the maintenance process, due to expected financial difficulties arising from cutbacks in revenue (according to ICAO [6], a 55% decline of Revenue Passenger Kilometers (RPK) in comparison to 2019 values).

Since the regulations demand aircraft operators to have a maintenance program – regardless of whether it is performed internally or outsourced, aircraft maintenance is a compulsory activity for airlines.

The primary aim of the maintenance field is to operate aircraft at the lowest possible prices without compromising safety and quality [7], maintaining high levels of service and offering competitive delivery times. On a more particular tone, many efforts have been put on the improvement of turnaround times as a way of reducing costs.

All maintenance programs contain periodic tasks that must be performed to keep the equipment in perfect working order [8] – for aircraft, besides the replenishment of consumable materials and the replacement of parts and components that have reached their operating limit, a vast number of maintenance tasks include some type of inspection – the group of tasks included in the maintenance program make up the so called *scheduled maintenance*, while the repair/replacement tasks that might result from inspections make up the *unscheduled maintenance*.

Preventive maintenance is a type of work in which the components are exchanged or remade before wearing down (through schedules planned by the manufacturers of said items), designed to reduce the likelihood of failure or degradation in the operational lifespan of a product. Lubrication, cleaning or clearing are also considered preventive maintenance [9]. Corrective maintenance, on the other hand, takes place when the equipment is either defective or ceases to operate; consequently, the scheduled maintenance is *preventive*, while the unscheduled maintenance is *corrective*.

In theory, scheduled maintenance workload can be estimated through the suggestions of the tasks' execution times given by aircraft manufacturers; notwithstanding this, unexpected deviations and disruptions are very prone to occur during an aircraft's maintenance check, which will have a significant impact on airlines' performances by causing surges in overtimes, increasing the incidence of errors and reworks, reducing aircraft utilization and affecting overall service quality. Ultimately, maintenance planning is a probabilistic problem characterized by a high level of uncertainty, that can result in increased operating costs and reduced revenue.

A substantial amount of information is generated when performing aircraft maintenance (about the vehicles, operators, interventions), and it is still yet to provide a decisive competitive advantage to Part 145 or Maintenance, Repair and Overhaul (MRO) organizations [10] due to the fact that little or no sensitivity and robustness analysis of aircraft maintenance data is performed by airlines [11].

An aircraft maintenance check consists of several tasks that must be performed accordingly. The workload for these tasks suggested in the manufacturer's Maintenance Planning Document (MPD) [12, 13], in Man-Hour Units (M/H), does not always agree with the actual values registered in the work-cards by the operator's maintenance technicians upon performing the work – some tasks require less manpower while others require significantly higher than expected, which can be represented by a problem of an essentially probabilistic nature that affects the final length of the check.

1.2 Topic Overview

According to European Aviation Safety Agency (EASA) [14], the content of scheduled maintenance consists of two distinct groups of tasks: a set of scheduled tasks to be accomplished at specific intervals, of which the objective is to prevent the deterioration of the inherent safety and reliability of the aircraft (and this can be defined by each operator, in its Operators Approved Maintenance Program (OAMP)), along with a group of non-scheduled tasks that result from findings performing the aforementioned scheduled tasks, malfunctions reports, or even reports of potential failures.

The main types of aircraft maintenance events can be differentiated by location (as presented in [15]):

- **Line Maintenance** involves routine tasks with low intervals, and it is generally performed at line stations or at the flight line of an airline's base station.
- **Base Maintenance** is performed at the airline's maintenance base station, that has the manpower and facilities to do all kinds of maintenance work.

or regarding the interval of applicability (as defined in HiFly's OAMP):

- **Light (Minor) Maintenance** checks comprise A-checks, executed in intervals of around 800 Flight Hours (FH) taking about $50 - 70$ M/H to be completed.
- **Intermediate Maintenance** consists of C-checks, performed every $20 - 24$ months, and it requires ground times of up to 7 days. Lower or higher interval tasks may be included to optimize task accomplishment or the available ground time.
- **Heavy Maintenance** encompasses D-checks, done every $6 - 10$ years. It requires an aircraft downtime of over 7 days, and it includes structural inspections and repairs and major modifications.

The M/H unit is, as explained by Kazaz et al. [16], the time required for a labor unit to finish a unit work amount. Capacity planning is the process through which maintenance services providers establish the required manpower to face expected maintenance workload of incoming aircraft.

It is also important to explain that because B-checks are not very common anymore, the concept will not be further addressed by this thesis.

It is essential that airlines adopt a maintenance planning strategy that is able to account for the unexpected deviations that can arise from concluding the scheduled tasks in the aforementioned checks, on the grounds that these events can be difficult to predict and may result in negative consequences for the operating companies.

There are several techniques for uncertainty modeling, but Bayesian networks provide the most appropriate framework for the problem described above. This methodology was first proposed in 1980, with the aim of going beyond the limits of expert systems, provided it could take into account uncertainty in reasoning [17].

Bayesian networks are frequently mentioned in the literature as an adequate and powerful tool to address problems regarding uncertainties due to their ability to incorporate both *a priori* knowledge and experimental knowledge, providing an adaptation process that redefines conditional probabilities from new evidence, making it possible to build an initial network with limited knowledge and improve it as new data becomes available. The modeling technique originated in the artificial intelligence field [18], where it is used as a robust and efficient framework for reasoning under uncertain knowledge. A Bayesian Network (BN) consists of two main parts: (i) qualitative part – a directed acyclic graph and (ii) quantitative part – a set of conditional probability functions , and both can be derived from expert knowledge and/or data learning techniques.

1.3 Objectives

This dissertation aims to develop a probabilistic model for the workload of a maintenance check (in terms of its duration), as an attempt to reduce the unpredictability associated to the maintenance planning process through the identification of the variables that could have an impact on a task's workload. Bayesian networks present several advantages representing problems of probabilistic nature; therefore, BNs are developed to model the causal relationships between variables such as the aircraft's model, FH and tail # or even the task's zone and skill codes, and the check or task's total workload, from real maintenance data. A sensitivity analysis is then performed to quantify the influence of each parameter contributing to the output – the workload deviation of a single task or a check.

Finally, two examples illustrate the benefits of the BN models for aircraft maintenance capacity planning.

The data used in this dissertation is provided by a EASA Part 145 regarding the light maintenance work done on a portuguese wet lease and charter airline's fleet, more specifically focused on A-check inspections for the Airbus A330 and A340.

1.4 Research Questions

In order to obtain a clear definition of the object of study, three research questions were outlined:

1. To what extent does the MPD provide reliable predictions for the tasks' workload?
2. Does the age of the aircraft have a direct impact on the deviations of light periodic inspections?
3. Which other factors can be considered to have an impact on the observed deviations?

Question 1 is very important for the airline contributing to the research, that reports that the lengths for the tasks, in M/H, suggested on the MPD are too optimistic and often fail to consider the time spent in creating the access to specific zones in the aircraft where maintenance work is needed; hence, a full analysis on the existing maintenance records could bring improvements to the planning process, since it would provide with accurate predictions of the tasks' required workloads.

Question 2 comes from the fact that an older aircraft represents a demand for longer and more thorough heavy maintenance work (this statement will be addressed further in chapter 2) – but would the same principle apply to light maintenance (A-checks)? This will be evaluated by examining if the check deviations tend to increase with the growth of the age factor (measured in FH or Flight Cycles (FC)), for the same aircraft model.

Because there are many variables to be accounted for in aircraft maintenance (such as age, location, aircraft zone, type of work being performed and required skill), question 3 is the fundamental goal of this research. A clear understanding of what factors can potentially affect the length of an A-check will be achieved through the development of BN models from data, which are very successful for representing problems with several uncertain variables [19].

1.5 Empirical Data

Considering this is mainly a data analysis problem, the majority of information used is of quantitative nature. However, in an effort to obtain a wider view of the situation, some qualitative data are gathered as well.

Regarding the quantitative information, real operation and maintenance records of a commercial airline are used – A1, A2 and A4 checks, for two different aircraft models: the Airbus A330 (Figure 1.2) and the A340 (Figure 1.3), for the time period comprised between 2013 and 2020. It is important to refer that both the A330 and the A340 are sold in variants that may differ slightly in size and range, but the same basic maintenance program applies for all (owned by the same operator), which is why the only distinction made is regarding the model of the aircraft.

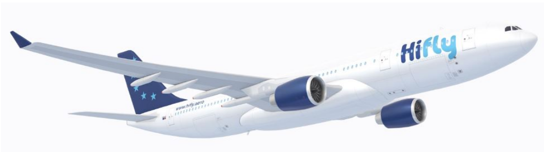


Figure 1.2: Airbus A330-200 [20].

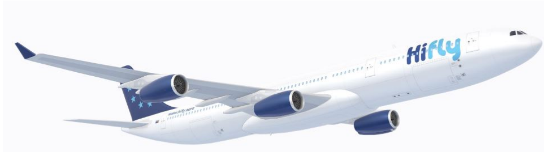


Figure 1.3: Airbus A340-300 [21].

For the qualitative component, three experts in the aviation industry were consulted, each with expertise in different parts of the planning process (planning management, Continuing Airworthiness Management Organisation (CAMO) operations and maintenance management). They provided valuable ideas during the discussion meetings as well as their own personal opinions concerning the object of study.

For confidentiality reasons, specific details of the meetings will not be disclosed. Also, all sensitive data (such as the full values of the operational and maintenance records) are not presented.

Below is transcribed the opinion provided by one of the consulted experts, from the CAMO field, regarding the theme of the thesis and how beneficial it could be for the involved parties.

> ”I consider this subject to be of extreme importance [...]. We might reach curious results such that, for the same task, a given technician registered different M/H performing it on different aircraft. I believe that with the development of the theme we will get to a clear notion of deviations and their relevance.
>
> I consider the age of the aircraft to be a somewhat relevant input. A lot of cabling works, per example, can take longer depending on the years of operation. On another note, lubrication or discarding tasks tend to follow the MPD suggested times for it.
>
> This work will always be relevant [regardless of the COVID-19 situation] because aircraft will still have to undergo maintenance checks. One of the main rewards of this analysis will be getting the average/balanced values of M/H for tasks, and establishing them as standard for the company”.

1.6 Thesis Outline

The aforementioned questions and the work’s objectives will be developed through the course of the following chapters:

- Chapter 1: Introduction;
- Chapter 2: State of the Art;
- Chapter 3: Methodology;

- Chapter 4: Results and Discussion;
- Chapter 5: Conclusions and Future Work.

The present chapter introduces the research performed in collaboration with a certified EASA Part 145 by making a short description of the problem, addressing the primary definitions of the industry, stating the work objectives and the research questions.

Chapter 2 presents the state of the art of aircraft maintenance, including several attempts of improvements and innovations made over the years and its main problems (with respect to costs, human factors, delays). A general overview on BN applications is also presented, with a peculiar focus on its reported benefits for the maintenance field.

Chapter 3 provides a brief review on maintenance history and EASA applications, along with the development and identification of maintenance tasks and programs. It also delineates the methods used to approach the gathered data, and how it was filtered, graphed and prioritized in a relevant way. The chapter ends with the description of the Bayesian theory, how it is applied to Bayesian networks to model uncertainty-related problems, how the network validation is performed and the adopted sensitivity formulation.

Chapter 4 assesses the data concerning the problem following the methods defined in the previous chapter, and provides empirical answers to the questions posed in 1.4, either through statistical analysis or sensitivity analysis over the developed BN models. Two examples of the practical benefits of the BNs applied to maintenance capacity planning are also presented.

The thesis is completed with chapter 5, in which the main conclusions of the research are presented, along with a reflection regarding the answers obtained to the questions. A succinct evaluation of the investigation's limitations is made, accompanied by suggestions for improvements as well as for future work.

2

State of the Art

Contents

2.1 Aircraft Maintenance

It can be stated that flight safety relies on three main factors [22]: man, environment, and machine, and if one of them fails then airworthiness as a whole gets compromised; consequently, aircraft maintenance is closely linked to said factors. In [23], International Air Transport Association (IATA) alongside the members of the Industry Affairs Committee try to anticipate the key risks and opportunities that global commercial aviation will face between now and 2035, with the aim of setting out some recommendations. Any company that operates aircraft for the purpose of transporting passengers or cargo has the fundamental responsibility to maintain it in safe and airworthy conditions.

According to Gopalan [24], aviation authorities (such as the Federal Aviation Administration (FAA)) provide strict guidelines for aircraft maintenance, with airlines facing severe penalties for violations. Furthermore, poorly maintained aircraft eventually lead to mass cancellation of flights, causing large inconveniences to passengers that might result in a deterioration of the airline's image. In air transport, apart from safety, the operation's economical aspect is a base element for the success of the field.

As Gupta et al. [25] define, the primary goal of the aircraft maintenance program is to deliver aircraft that is safe, airworthy and punctual, and as it is said in [15], airlines can develop their maintenance programs depending on their own operational, commercial and technical requirements. In the industry, the concept of maintenance involves the tasks required to restore/maintain the aircraft's systems, components and structures in an airworthy condition. In [26] it is enumerated that maintenance is required for three main reasons:

- Operational – to keep the aircraft in a serviceable and reliable condition, in order to generate revenue;
- Value Retention – to maintain the current and future value of the aircraft, by reducing physical deterioration of the material throughout its useful life;
- Regulatory Requirements – to meet the regulations established by the aviation authorities of the jurisdiction under which the aircraft is registered.

2.1.1 Maintenance Costs

Because charter airlines commit months ahead to provide transportation services, to increase profits two goals are established: maximizing revenue by selling the largest number of cost-effective flights and minimizing operating costs through an efficient fleet assignment. The stochastic nature of demand is a major challenge for airlines – even with optimized schedules, many flights upon departure present empty seats, while others suffer a lack of seats. Jiang and Barnhart [27] approach this challenge and conduct experiments using data from an american airline, developing a dynamic scheduling approach that re-optimizes elements from the flight schedule during the passenger booking process. Moudani and Mora-Camino [11] present the main concerns with assigning planes to flights in a charter airline, as well as scheduling operations of fleet maintenance. The article looks at the problem of fleet allocation and maintenance scheduling, and although the proposed approach doesn't produce an exact mathematical solution, it appears adaptable to the present operational context of airlines and provides improved solutions. Ozdemir et al. [28] summarize that one of the hardest problems faced in airline planning is fleet assignment, because when and if done correctly (assigning to flights the most appropriate aircraft), it can minimize the costs to the airline. A model that determines the optimal number of aircraft grounded overnight at each airport in order to achieve minimal costs is presented. In [29] a model for the periodic fleet assignment is proposed with time windows, in which departure times are also determined, keeping in mind that anticipated profits depend on the schedule and selection of aircraft types. The computational results for periodic daily schedules are presented on three actual data sets. The work by Clarke et al. [30] provides modeling devices for including maintenance and crew considerations into the basic model of fleet assignment while retaining its solvability. The problem faced by airlines needing to assemble daily schedules for heterogeneous fleets is also assessed in [31], where it is defined that an aircraft schedule consists of a sequence of flight legs to be carried out by an aircraft and the exact times at which these legs should start and end. Undoubtedly, different schedules result in different costs for the airline: a flight leg that can be performed by two aircraft of different capacities might result in a loss of revenue if the smaller plane is chosen when the demand for the leg exceeds its capacity.

Ferguson et al. [32] develop an airline cost model that can be updated whenever any of the contributing factors (e.g. crew, fuel, maintenance and ground costs) change and it considers the type of aircraft when making calculations (both from the perspective of fuel burn and passenger costs). It relies on the fact that researchers are applying more holistic approaches to the feedback control of the air transportation system and many of these approaches are based on economic feedback, and it is found that smaller aircraft have better fuel burn rates and can be flown with higher load factors, which implies that airlines are likely to continue using these aircraft and not upgauge.

Maintenance costs can be a significant factor in an organization's profitability [33], and are composed in a new way by Wenjuan et al. [34], by systemic analysis of the MPD and with the application of the Maintenance Steering Group (MSG) theory, in order to reduce the disadvantages of aircraft regular overhauling mode. In [35], it is shown that delays and disruptions are not limited to heavy aircraft maintenance and can be frequently found in almost every complex project. It is also stated that aircraft maintenance costs comprise three main elements: the expenses of labour and staff involved in maintenance activities (18% of the maintenance costs), the expenses related to the utilization of materials and spare parts for the aircraft (17% of the costs), and the cost of subcontracting maintenance to other companies (65% of the costs). Dupuy [36] estimates that direct maintenance cost, which is composed of the cost of maintenance crews, materials, and parts repair and replacement, accounts for about 11% of the total operating cost of an aircraft.

Papakostas et al. [37] observe that the contribution of the maintenance costs to the average direct operating costs has not been reduced significantly over the last two decades, and describe a short-term planning methodology of the line maintenance activities of an airline operator, at airports, during turn-around times. Based on health assessment and additional information regarding operational and economical constraints at the operator's fleet level, a multi-criteria mechanism (based on cost, remaining useful life, operational risk and flight delay) evaluates a set of generated maintenance plan alternatives. An alternative is defined as the possible allocation of all deferred maintenance tasks to a set of suitable airport resources.

2.1.2 Maintenance Planning

Structural airframe maintenance is part of scheduled maintenance, performed at regular intervals to detect/repair cracks that could otherwise affect the airplane's safety. Pattabhiraman et al. [38] observe that only a small part of planes undergo said maintenance at earlier times; nevertheless, detailed inspection of all panels on the aircraft must be performed at the time of scheduled maintenance to access the presence/absence of large cracks (threatful to safety). Since commercial airplanes are designed for low probabilities of failure (10^{-7}), there are high possibilities of no critical cracks being detected during a scheduled maintenance. In the study, two maintenance philosophies are developed: scheduled structural health monitoring and condition-based maintenance skip, and a cost model is developed to quantify the savings of said philosophies over the current scheduled maintenance.

Samaranayake and Kiridena [39] examine how certain limitations of the current approaches to aircraft maintenance planning and scheduling can be addressed using a single integrated framework supported by unified data structures that integrate multiple types of data elements over a large spectrum of maintenance types.

Humaira et al. [40] discuss the maintenance costs that an operator must bear, and develop a model to estimate the cost of a scheduled airframe maintenance check, given by equation (2.1):

$$MTC = LBR*(MEF*(MTL+EOL+NFL*(NRL+CIL)))+MTM+EOM+NFM*(NRM+CIM) \tag{2.1}$$

The hypothetical variables taken into account are the Labor Rate (LBR), the MRO Efficiency Factor (MEF) – which represents the ratio of the average M/H required by a MRO to complete a maintenance task and the M/H suggested by the MPD –, the MPD Tasks Labor (MTL), the Engineering Order Labor (EOL), the Nonroutine Labor Factor (NFL), the Nonroutine Labor (NRL), the Cosmetic Items Labor (CIL), the MPD Tasks Material (MTM), the Engineering Order Material (EOM), the Nonroutine Material Factor

(NFM), the Nonroutine Material (NRM) and the Cosmetic Items Material (CIM).

Regarding the MEF, this value is expected to be low when the delivery performance is high, which consequently results in higher values of LBR. The MEF is a value above 1, where 1 can only be achieved in ideal conditions – personnel training and experience, tool and material availability, as well as hangar conditions can affect this parameter.

However, the Turnaround Time (TAT) is a crucial element that, as can be observed, doesn't appear in the above equation. In aviation, the term turnaround refers to the period comprised between the arriving of a flight at the airport and the posterior taking off, and while it doesn't contribute directly to maintenance costs, it influences the downtime cost of the aircraft, and can be calculated from equation (2.2):

$$TAT = MEF * \frac{MTL + EOL + NFL * (NRL + CIL)}{(MLC)} \tag{2.2}$$

Where the MRO Labor Capacity (MLC) is the maintenance facility's daily labor production capacity (that depends on the shift patterns of the technicians).

In the process of scheduling maintenance, operators estimate the maintenance costs that they will incur in, and as stated in [40], this calculation typically only includes costs that are directly related to the maintenance process such as cost of labor, material, and equipment. In some cases, overhead cost is also included and some of previous works even discuss the existence of another cost throughout aircraft downtime, which is defined as cost of revenue loss. Eurocontrol [41] explains that age can be a crucial element in determining maintenance costs for an aircraft, because as it gets older the aging systems and structures can require extra maintenance work.

Bazargan [42] offers a mathematical model to help airlines identify which types of heavy aircraft maintenance checks should be outsourced, and which should be performed in-house. The achieved results suggest that more expensive and labor intensive checks should be outsourced. Due to the fact that aircraft require more expensive checks as they age, the cost of in-house heavy maintenance checks grows faster than outsourced for ageing aircraft.

With an ageing fleet, flight safety can only be assured through high fleet reliability levels. Because maintenance depends on inspections to be effective, the reliability of aircraft inspection is of utmost importance to safety. A task analysis methodology is developed by Drury et al. [43] to provide baseline data on the inspection activities of commercial aircraft. Considering that the time an aircraft spends in maintenance represents a large loss in revenue, the inspection system must combine effectiveness with efficiency if both public and the airline are to be protected.

Similarly to other industries, aviation is being impacted by the move to digitalisation, from the advent of advanced technologies such as distributed ledgers, or blockchains, to big data and artificial intelligence. Technological advancements can increase an aircraft's useful life. According to KPMG [5], depending on their business models, airlines either operate aircraft for their full life (25 to 30 years) or tend to depreciate owned aircraft over 20 years to 10%. Regarding periodic preventive maintenance of systems with deteriorated components, Tsai et al. [44] incorporates genetic algorithms in planning periodical preventive maintenance for a system based on maximizing its unit-cost life. A case study is presented in [45] to demonstrate the Structural Health Monitoring (SHM) operational concept and how an optimal maintenance strategy can be determined using this methodology that aims to reduce long term maintenance costs and increase availability. Wang et al. [46] accentuate the fact that SHM systems are progressively being considered in the aviation industry due to their ability to track the aircraft health state continuously, leading to the chance of planning maintenance based on an actual state of the components rather than on a fixed schedule.

Rajamani et al. [47] introduce the term Integrated Vehicle Health Management (IVHM), that describes a set of capabilities that enable sustainable and safe operation of components and subsystems within aerospace platforms – hence, the system satisfies the sustainability needs of an aircraft. While IVHM is typically focused on a particular vehicle, fleet level constraints can impact the operations and maintenance decisions of individual aircraft.

The study by Regattieri et al. [48] discusses maintenance policies optimization – because the initial Maintenance Review Board (MRB) for new aircraft is developed with little or no actual in-service data, the tendency is to get conservative in the decision-making process; therefore, the authors show how significant improvements regarding availability and cost reduction can be achieved using a systematic model of data analysis based on Reliability, Availability, Maintainability (RAM) principles. For the implementation of the method, the modelling of the reliability function $R(t)$ and probability density function of time to failure $f(t)$ follow a *Weibull-3 Parameters* distribution, as written in equations (2.3) and (2.4), respectively:

$$R(t) = e^{\left[-\left(\frac{t-\gamma}{\eta}\right)\right]^{\beta}} \tag{2.3}$$

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} e^{\left[-\left(\frac{t-\gamma}{\eta}\right)\right]^{\beta}} \tag{2.4}$$

where η is the scale parameter ($\eta > 0$), β is the shape parameter ($\beta > 0$), and γ is the location parameter ($\gamma \in R$).

Considering the importance of determining of an effective set of maintenance policies in the literature, the authors propose this new methodology and demonstrate its application in a real case, managing to achieve an annual cost reduction of 20%. Under the same subject, Crocker and Kumar [49] present another way to find the optimal maintenance policy for a case of military aero-engines, using Monte Carlo simulation in which the components are modelled using a Weibull distribution as well. The case study returns potential benefits from setting soft lives on cheap components that can cause expensive engine rejections. Sachon and Patè-Cornell [50] point that flight delays can even affect safety if the signals of technical problems get missed or misinterpreted; hence, a probabilistic risk analysis model is used to quantify the effect of an airline's maintenance policy on the critical measures of service quality: delays, cancellations and in-flight safety.

The scheduling of aircraft maintenance has been relying on a manual planning approach since the introduction of commercialized wide-body aircraft – in the early 70s –, and due to emphasis on efficiency and lack of accurate and timely maintenance scheduling tools, it has become an increasingly difficult task. An attempt to minimize the wasted interval between checks is made by [4], and the outcomes have shown that, when compared with the current methods, the number of maintenance checks can be reduced by around 7% over a 4 years period.

Maintenance scheduling has potential for cost savings despite coming as an end stage in airline operation, and it is an easy to understand but hard to solve problem; Gopalan and Talluri [51] present a model for the maintenance routing problem. Given a flight schedule with aircraft assigned to it, the aircraft maintenance scheduling problem is to determine which aircraft should fly which segment and when and where said aircraft should undergo different stages of maintenance checks required by the FAA. Objectively, the goal is to minimize the maintenance cost and Sriram and Haghani [52] also provide a formulation for maintenance scheduling and a heuristic approach to solve the problem, that returns good solutions within a reasonable computation time.

Under the premise that aircraft operators incur significant costs when an aircraft is taken out of service for maintenance, Kulkarni et al. [53] present a method for reducing time duration of aircraft maintenance heavy checks by using the Critical Chain Project Management (CCPM) principle. According to the article, an efficient maintenance management is not only about cutting costs, but it also reduces negative impacts on a maintenance worker and contributes to flight safety. The authors conducted a survey on a group of licensed aircraft engineers and planners focused around project tasks, activities, planning documentation and durations, and not only did 100% of the inquired admitted to never having reported an early finish of a task, regarding performing additional work in more than 40% of the executed tasks, 80% answered affirmatively. It is also suggested that in heavy maintenance, tasks are usually interdependent.

Senturk et al. [54] highlight the importance of optimizing the utilization of aircraft, given that by accumulating more FH, the direct operating costs the airline faces per FH can be reduced. Considering aircraft are designed with the intent of being flown for the majority of their useful life, every ground time can be faced as a loss for the airline. Hence, one of the ways to increase aircraft usage is reducing ground time spent in maintenance, which is rather difficult through classical maintenance approaches means. The authors consider the rigidity of the current method of performing maintenance checks and tasks (in predetermined intervals) subjects the airlines to significant losses of material and Man Hours, and that it is a very static approach that presents some disadvantages. A method that focuses on single task-oriented maintenance is proposed, and the estimations suggest that for a fleet of 30 aircraft, the savings brought by the innovation could add up to the equivalent of acquiring a new aircraft every five years. The procedure defines that instead of following a strict system in which aircraft are either *under maintenance* or *in operation*, everytime an aircraft is grounded is faced as a *maintenance opportunity* – when it is not being operated, wherever it may be, maintenance can be performed. On the aforementioned study, for a period of 10 years, a given aircraft from a real airline is estimated to be grounded for maintenance reasons for about 87 days (accumulated total); however, under the proposed method, the same aircraft would only be unavailable for 15 days over the same timeline, due to the utilization of every moment the aircraft is on the ground (for any reason) as a maintenance opportunity. It results in a 72 days savings over 10 years. To accomplish this, airlines must operate a flexible maintenance program instead of one dominated by rigid letter checks.

2.1.3 Human Factors

With the growth of air traffic, the pressures on maintenance operations for on-time performance will also continue to escalate, as predicted by the Civil Aviation Authority (CAA) [55], which ends up opening further windows of opportunity for human error. Manda and Chaitanya [56] summarize various maintenance problems associated with aircraft and report that human lapses are the main reason for incomplete and imperfect maintenance, that can go from not tightening pipes or screws at the end of a task to leaving a few rotables without checking for snags.

Human factors are crucial in the success of aircraft maintenance. Mitigating the risk of human error requires proper training and consolidate good maintenance practices habits as well as proper planning work, namely on completion of critical tasks. For example, if a maintenance team does the same task on different components/systems of the same type during the same maintenance event, there is a risk that, making an error, that same error and the same failure will occur on all these components/systems at the same time. Thus, HiFly's Internal Procedures [57] recommend not to do maintenance on different engines or redundant components installed on the same aircraft at the same time unless it is not possible to do differently; that, if it is necessary to do maintenance on more than one engine or on redundant components at the same time, different maintenance teams do the work on each engine or component; and that, if an engine run is necessary to perform a maintenance task, make sure that only the related (one) engine is in operation at the time unless the task gives other specific instructions.

Maintenance personnel frequently work under considerable time pressures to meet the scheduled departure times, which is why Dickety [58] declares that 80% of maintenance errors involve human factors. Shanmugam and Robert [59] estimate that the root cause for $30-90\%$ of aircraft accidents is related to human factors, and although the elimination of human errors in aircraft maintenance is a myth, these errors can be contained within a limit through continuous process of improvement in maintenance standards and methods. The research mentions a few technical reports that support ergonomic design of aircraft maintenance facilities (maintenance hangars, workshops, storage spaces) for enhanced human performance, which is largely influenced by physical environment. Latorella and Prabhu [60] review current approaches to the identification, report and management of human error in aviation maintenance and inspection, and it is stated that 50% of all engine-related flight delays and cancellations are due to improper maintenance.

In [61], human error is cited as a major casual factor in most aviation mishaps, and two approaches to human error reduction are given: incident based and task analysis based. Each approach provides data on performance shaping factors, i.e. situation variables that affect the probability of error occurrences. Examples are given of interventions derived from analysis of incidents and from task analysis. The human factors approach in maintenance research considers the human as the center of the system. Not only can human factors research have a significant effect on the design of new systems but it can also mitigate problems found in the sub-optimal designs of current systems. It is argued that whenever humans are part of the system, errors cannot be separated from the other two aspects of humans at work: performance (typically measured by both reliability and speed) and human well-being (health and safety of the workforce).

Johnson and Maddox [62] refer that the acronym *PEAR* is used to characterize human factors in aviation maintenance, because it prompts recall of the four most important considerations for human factors programs: **P**eople who do the job; the **E**nvironment in which they work; the **A**ctions they perform; and the **R**esources necessary to complete the job. Because you cannot apply identical strength, size, endurance, experience, motivation and certification standards to all employees, companies must ensure each person is physically capable of performing all the tasks making up the job. Incidentally, a good human factors program considers the limitations of humans and designs the job accordingly. Job Task Analysis (JTA) is the standard human factors approach to identify the knowledge, skills and attitudes necessary to perform each task in a given job. The JTA helps identify what instructions, tools and other resources are necessary. In general, the characteristics of the people, environment and actions dictate the resources. Many resources are tangible, such as lifts, tools, test equipment, computers, technical manuals and so forth, but other resources are less tangible: examples include the number and qualifications of staff to complete a job, the amount of time allocated, and the level of communication among the crew, supervisors, vendors and others.

2.1.4 Maintenance Delays

Aircraft maintenance programs have the purpose of attaining the highest availability without compromising safety and quality, so it is inferable that said programs have an imperative role in the industry in the sense that proper maintenance results in high aircraft punctuality, longer operating hours and higher revenue for operators. Hurst [63] presents an application of using in-service maintenance data to construct a risk analysis availability model that is sensitive to fleet size, aircraft flying rate and maintainability and scheduled inspection frequency and durations.

In [64], flight delays from a european airline are analyzed and it is found that longer delays of flights (over $2h$) appear primarily (near 13%) due to technical maintenance or aircraft defects, which for the same plane can cause increasing delays throughout the day (a phenomenon that [65] calls *reactionary delays*). Eurocontrol's study [41] indicates that less than 50% of the flights report to arrive on time.

For all airlines, flight delays are a fundamental source of financial and technical difficulties, and they are rather longer when it comes to technical deficiencies and servicing tasks. McCreary [66] is able to calculate a weighted average of a cost of $40\$$ per minute of delay per aircraft, and Timajo et al. [65] estimate yearly losses of about 65M$\pounds$ due to this cause. Ferguson et al. [32] notice that although airlines incur the greatest delay costs while the flights are airborne (65%), the majority of delays actually occur on the ground (87%).

IATA [67] states in that the top three ways for airlines to save money are through health monitoring, fuel cost savings and delay reductions (improved turnaround process). As it is explained in [65], turnaround operations play a very important part in aircraft flight delays, so in order for an airline to achieve maximum profit it must reduce the on-ground time of its aircraft. However, due to the maintenance tasks demanded by the manufacturer (which are directly related to the safety of the aircraft and require grounding), this represents a challenge. For this reason, [15] declares that one of the most scrutinized areas of an airline is the effectiveness of line maintenance.

Wu and Caves [68] investigate aircraft operational costs, passenger delay costs and airline schedule time-opportunity costs, and aim to investigate the relation between the punctuality of flight schedules and the efficiency of aircraft turnarounds at airports, with the intent of minimizing operational costs while maintaining the required levels of scheduled punctuality. Because the trade-off point occurs for maximum punctuality with short turnaround times, a mathematical model is applied to simulate said situation and the aggregate aircraft turnaround performance.

In [69] it is referred that the current way emergency equipment checks are carried out is an outdated time-consuming process, and its simplification could increase the revenue of airline operators. In aviation, the proverb *time is money* is key because the aircraft, which is grounded during inspections, fails to serve the purpose for which it is intended, and thus does not bring financial profits to airlines. The proposed solution is to use a Radio-Frequency Identification (RFID) system to detect and evaluate the equipment (as it is pictured in Figure 2.1) – this way, the duration of pre-flight checks of emergency equipment could be reduced by almost 90% and it could not only improve the airline's efficiency as it could also lead to increased safety, because the option of human error is eliminated.

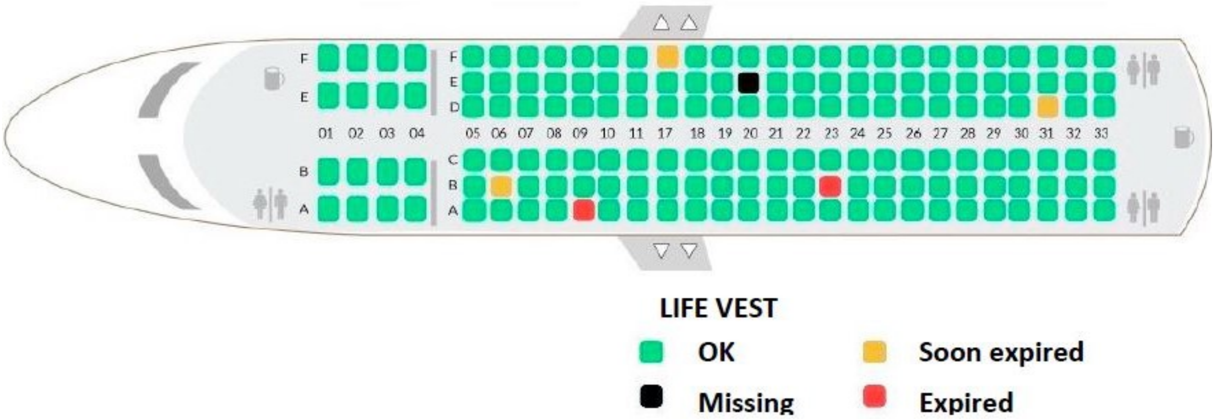


Figure 2.1: Example of RFID check visualization applied to life vests [69].

An OK vest is displayed as a green box, whereas if the vest doesn't appear on the board, the system will display the field in black. The yellow square represents a vest with an approaching expiration date (as a warning to replace it soon), and the color red is for when said date has already been reached. Adopting this method would allow for this task's duration to be reduced from approximately 45 minutes to about 30 seconds.

Cooper [1] focuses primarily on airline fleet growth and related trends affecting aftermarket demand, maintenance costs, technology and labor supply, and it is estimated that aside from said growth in fleet, the increase will be driven by more expensive maintenance visits and further technology enhancements. It is suggested that line maintenance will, therefore, become an even more attractive market, considering the growing number of new-generation aircraft in the global fleet that require less heavy-maintenance hangar work.

The long-term economical and operational benefits of adopting a more efficient approach are clear: a typical C-check of A320 family is estimated to cost $150k-350k\$$ [26], an A-check costs around $10k-15k\$$, while an additional day on operation may represent $75k - 120k\$$ of commercial revenue (depending on the utilization level of the aircraft).

Given the fact that one way to manage aircraft operation costs is by speeding up aircraft turnaround times during maintenance checks, the factors contributing to delays during aircraft A-Check maintenance are studied by Mofokeng and Marnewick [70]. According to the authors, delays during maintenance result in the loss of revenue because of potential penalties, and the identification of what aspects influence said delays can help airlines to identify the gap between best practice and current practice. By knowing the causes of delays, the maintenance company can use this knowledge to adjust their operational strategies. An A-Check is the most crucial requirement in scheduling because of the relatively short interval between the next required check. It was found that 69% of the observed delays in A-Checks were due to a poor logistics process (spares related factors), 29% were caused by unscheduled maintenance defects and pilot reports, whereas poor planning contributed to 2% of the delays. Further research was made to calculate the cost of delays to a single airline: the total of delays observed were of $8\,937$ minutes with a cost of 90.80 € per minute, resulting in a total cost of $811\,479.60$ €. Logically, the airline's revenue could be increased by minimization of these costs. It is also argued that the effectiveness of the logistics process results in reduction of turnaround time, quick overhaul rate, increase of first test pass rate and reduction of uncertainty rate.

The urge to shift the support of maintenance inspections to digital platforms is not recent; in [71], a prototype hypertext system is developed as an attempt to replace paper-based workcards with a portable computer software; due to this being set in the year of 2000, the choice of hardware for the digital-based workcard proved to be a critical issue, and the portable computer could nowadays be easily replaced for a much lighter and less expensive tablet device. The workcard is the primary job aid for aircraft maintenance and inspection, because it provides specific instructions on the tasks to be accomplished with directive information (such as which defects to look for, warnings about aircraft and personal safety, and some details of needed tools and equipment). Digital workcards can, in fact, overcome many limitations of paper-based workcards: not only feedforward (such as previous defects found in other aircraft) but also feedback (such as comparing responses with lists of possible values) data could be presented to the technician performing the maintenance work, and the accessing of detailed information in attachments or maintenance manuals would become easier – incidentally, the research proves that the computer-based system was a significant improvement over the original paper-based workcards.

Literature on maintenance management is reviewed by Deshmukh et al. [72], and important issues regarding this topic range from various optimization models, maintenance techniques, scheduling and information systems. Furthermore, within each category, gaps have been identified. The need for a shift in the maintenance paradigm is also highlighted. As stated by Arnaud Fiscel, head of transportation at the Bank of China in London [5], *with a buoyant market and ample liquidity, discipline is key*. The same principle can be applied to the maintenance field, where small discrepancies can result in big impacts on the final costs.

2.2 Bayesian Networks

Weber et al. [73] make a bibliographical review over the last decades on the applications of Bayesian networks in the most various fields. The literature related to this subject shows an increasing trend, primarily due to the benefits that BNs provide, such as the ability to model complex systems and make predictions regarding the occurrence probability of events, along with the possibility to update probabilities according to evidences. In [74], the properties of the modeling framework that makes BNs particularly well suited for reliability applications are discussed; Bayesian networks present significant advantages over other frameworks, mainly the possibility of combining different sources of information to provide a global assessment.

The aviation safety sector has improved drastically over the past few years – in [75], the aim is to examine the ability of BNs to make accurate predictions on aviation risks; under this modeling technique, probabilities are combined to simulate the probabilistic behavior of the system in question.

It is commonly known that the aeronautics industry aims to come up with important changes in its maintenance strategies, because although there is an arising number of solutions, it is still a highly unpredictable field, which can pose a significant problem. Ferreiro et al. [76] develop a Bayesian network to model the case of predicting brake wear, in a study that explains the use of BNs as a prognostic technique applied to aircraft maintenance.

The use of Bayesian networks in the aircraft maintenance field is very common, and can be applied to diverse situations: Kochenderfer et al. [77] use a Markov process represented by a dynamic Bayesian network to model nominal flight (without avoidance maneuvering). A Markov process is defined by having the probability distribution over future states conditionally independent of past states (given the present state). Bayesian networks were chosen for the modelling because they compactly represent multi-variable probability distributions. The more independent parameters there are in the model, the more data one needs to properly estimate their values; however, by using dynamic Bayesian networks, conditional independence between some variables can be leveraged to reduce the number of parameters. Lee and Choi [78] assess the reliability of a starter-generator in a commercial aircraft; it is settled that the life of the component is limited by the reliability of a bearing, of which the degradation is represented by a Dynamic Bayesian Network. In [79], a Bayesian forecasting method was developed to revise engineering estimates in light of demand on new aircraft programs, and it outperforms the other methods enabling the inventory optimization model to establish stock levels that achieve higher fill rate, resulting in better initial inventory investment decisions. As it is explained, Bayes' rule provides an intelligent way of combining prior knowledge with observed data, and it is commonly expressed as the probability of prior belief *A* given new knowledge *B*, thus providing a coherent method of mathematically expressing changes in uncertainty whenever new knowledge is gained [80].

In [10] the aircraft maintenance capacity planning problem is addressed, and the applicability of BNs as a Big Data and Predictive Analytics (BDPA) tool is studied – given their probabilistic nature, BNs are a reliable technique to address the uncertainty of maintenance workload estimations, therefore improving the MRO's capacity planning decision-making process. If the available capacity is higher than required, there is underutilization of resources and financial inefficiency occurs; if, on the contrary, the available capacity is lower than required, delays will happen with potential financial penalties and damages to the reputation of the maintenance organization. In [81] it is presented a Bayesian approach to assess the efficiency of a queuing system in aircraft maintenance, where the numbers of repair crews and spare planes must be enough to meet the needed operational capacities.

Sand et al. [18] make a brief review of some of the existing mathematical models developed to evaluate maintenance on component reliability, and present the possibility of applying BNs to model maintenance strategies' impact on utility risk, as it is argued that these networks allow for an optimization of maintenance tasks. The term risk is defined as the possibility of deviation from an expected outcome or event.

In the maritime sector, several attempts have been made to develop models to characterize risks in traffic; the risk of individual ships, which is an important feature for supporting traffic supervision and control tasks to improve both the prevention and response to ship accidents and other threats is characterized through a BN model by Dinis et al. [82], using a dataset collected from the Paris Memorandum of Understanding (MoU). Its predictive validity is assessed qualitatively through a framework and quantitatively through a sensitivity analysis that proves the model's consistency. Hänninen [83] discusses the use of Bayesian networks in maritime safety modeling, and defends that BNs are able to represent complex and uncertain relationships between variables, providing the possibility of updating the model as new evidence is acquired.

Balmat et al. [84] combine static risk factors (such as the ship type, age flag and gross tonnage) with dynamic factors (related to weather conditions) in a previous model that approaches the maritime risk assessment. Yang et al. [85] present a Bayesian network model to determine vessel detention rates that includes company performance as a risk factor.

Montewka et al. [86] present a framework for risk analysis and assessment in maritime transportation systems that is systematic, proactive and transferable, utilising BNs as a medium to express and propagate the background knowledge available about the system being analysed. Discrete and continuous variables are combined, which allows for probabilistic relationships among the variables and for a fast propagation of information through the framework.

3

Methodology

Contents

3.1 A Review on Maintenance History

In the early days of aviation, when pilots and mechanics were responsible for developing maintenance programs grounded on their own personal experiences, the solutions were rather trivial and run by little or no analysis [26]. When airplanes became settled as a new means of transportation, new regulations were demanded for their maintenance requirements, with a more intense involvement of Regulatory Authorities.

De Florio [22] defines that an airworthiness authority is in charge of prescribing airworthiness requirements and procedures, informing the interested parties of said prescriptions, controlling aeronautical material, design, manufacturing organizations and aircraft operators, and certifying aeronautical material and organizations.

3.1.1 Maintenance Steering Group

The MSG was founded in 1968, with the intent of formulating a decision-logic process that could be used for creating the initial maintenance requirements for new aircraft. Later that year, the group comes up with MSG-1 – *Maintenance Evaluation and Program Development*, which was the first time that a decision-logic diagram was used to develop the scheduled maintenance program for the new Boeing 747 aircraft. Both hard time and on-condition processes are used [87].

Around 1970, MSG-1 was replaced by MSG-2, making it a suitable methodology for later generation aircraft. This update introduces a third primary maintenance process – Condition Monitoring (CM), under which no services or inspections are scheduled to determine integrity or serviceability; yet, their mechanical performance is still monitored and analyzed. On CM, a certain operating characteristic of a component is assessed and compared to the standard operating levels. As long as the trend data remains within the acceptable range, any variation is considered to be normal; if otherwise, the equipment must be removed to prevent failure in the future.

As it can be inferred, CM is not a preventive maintenance process because it allows failures to occur when the failure modes are considered not to have a direct negative effect on operating safety (i.e., when the failure modes are not critical). The main savings that can be obtained with the application of CM are the avoidance of output losses (due to the breakdown of the component) and the reduction of maintenance costs [88].

Subsequently, MSG-3 was developed, and it adopts a decision-tree methodology with the purpose of separating safety-related items from economic ones, thus defining adequate treatment of hidden functional failures. Following this new logic, activities are assessed at the system level rather than the individual component level; if the functional failure of a system has no effect on operational safety (or if it has insignificant economic repercussions), the existence of a routine maintenance activity is not justified.

MSG-3 (replacing the earlier MSG-1 and MSG-2 philosophies) allows for maintenance tasks to be grouped into packages in more efficient ways for the operator – matching work against operational requirement – rather than carrying out checks that are pre-defined by the MPD. This process results in higher safety standards, because of the greater degree of selective approach to maintenance that ends up reducing the maintenance tasks, which minimizes the infant mortality effect associated with excessive maintenance.

3.1.2 Development of Maintenance Tasks

As foreseen, MSG-3 is the actual method used for the development of the scheduled maintenance tasks and intervals that will be considered acceptable by the regulatory authorities, operators and manufacturers. Non-scheduled or non-routine maintenance consists of the remaining maintenance actions to correct discrepancies found during scheduled tasks. The generic list of tasks, also summarized on Table B.1 from appendix B, and as stated by EASA [14] is presented below:

- **Lubrication/Servicing (LU/SV or LUB/SVC)** for the purpose of maintaining inherent design capabilities.
- **Operational/Visual Check (OP/VC or OPC/VCK)** is a failure finding task to determine if an item is fulfilling its intended purpose.
- **Functional Check/Inspection (FC/IN* or */FNC)** are quantitative checks to determine if one or more functions of an item perform within specified limits. There are three levels of inspections to determine if an item is fulfilling its intended purpose, as defined in [14]:
  - General Visual Inspection (GV/GVI) made from within touching distance to an interior or exterior area, installation or assembly to detect obvious damage, failure or irregularity.
  - Detailed Inspection (DI/DET) of a specific item, installation or assembly to detect damage, failure or irregularity.
  - Special Detailed Inspection (SI/DTI) which is an intensive examination of a specific item, installation or assembly to detect damage, failure or irregularity.
- **Restoration (RS or RST)** is reworking, replacement of parts or cleaning necessary to return an item to a specified standard.
- **Discard (DS or DIS)** is the removal from service of an item at a specified life limit.

After identifying a task (through the MSG-3 process), the maintenance working groups determine the adequate interval for it, that should be based on service experience combined with engineering judgment. These intervals typically consist of a frequency and usage parameter, e.g. 600 FH, or 600 FC.

3.1.3 Applications of EASA

There are three main standards of EASA related to Continuing Airworthiness: Part 21, Part M and Part 145, that provide the requirements of certification of aircraft and components, continuing airworthiness organizations and the approval of maintenance organizations.

Continuing airworthiness is defined as *all of the processes ensuring that, at any time in its life, an aeroplane complies with the technical conditions fixed to the issue of the Certificate of Airworthiness and is in a condition for safe operation* [89].

- **Part 21** regulates the approval of aircraft design and production organisations, as well as the certification of aircraft products, parts and appliances.
- **Part M** establishes the measures to be taken to make sure airworthiness is maintained – including maintenance. It also specifies the conditions that must be met by organizations involved in continuing airworthiness management, and it shall ensure that no flight takes place unless (i) the aircraft is maintained in an airworthy condition, (ii) any operational and emergency equipment is correctly installed and serviceable (or clearly identified as otherwise), (iii) the airworthiness certificate is valid, and (iv) maintenance is performed in accordance with the Approved Maintenance Program (AMP) [90].
- **Part 145** sets the requirements and procedures necessary for the approval of maintenance organizations of aircraft – in compliance with Part M, all maintenance actions shall be undertaken by an approved maintenance organization (Part 145). An important feature of this standard is the guidance on how the smallest organizations could satisfy the intent of this part.

3.1.4 Development of Maintenance Programs

The maintenance program must ensure the realization of the inherent safety and reliability levels of the equipment at a minimum total cost, including maintenance costs and the costs of resulting failures. The initial maintenance policies schedule follow the wellknown MSG-3 process, that outlines the general organization and decision processes for determining scheduled maintenance requirements initially projected for the aircraft's life [48].

3.1.4.A Maintenance Review Board Report (MRBR)

Before the introduction of a new aircraft, its manufacturer – the Type Certificate (TC) holder – must prepare and submit for approval the initial minimum scheduled maintenance requirements in a document named Maintenance Review Board Report (MRBR). The TC is a document by which the authority states that an applicant has the compliance of a type design to all applicable requirements.

After being approved by the authorities, the MRBR is used as a framework around which each air carrier develops its own maintenance program. Although maintenance programs may vary widely, the initial requirements for a particular aircraft will remain the same, regardless, seeing as the MRBR contains the initial minimum scheduled maintenance/inspection requirements for a particular transport category [54].

Tasks from the MRBR can't be deleted or altered without approval from the appropriate national regulatory authority; however, the individual task intervals may be changed upon relevant substantiation (by the operator) and review and approval (by the regulatory authority).

3.1.4.B Maintenance Planning Document (MPD)

The MPD contains all the requirements outlined on the MRBR plus mandatory scheduled maintenance requirements that can only be altered upon the consent of the applicable airworthiness authority. Its main objective is to provide maintenance planning information necessary for each operator to develop a customized scheduled maintenance program [54]. Additional or revised tasks are notified by regular Advisory Circulars (AC) and Airworthiness Directives (AD) issued by civil aviation regulatory authorities, such as EASA and the FAA, and are detailed in the aircraft's Certification Maintenance Requirements (CMR) and Airworthiness Limitations (AL) documents.

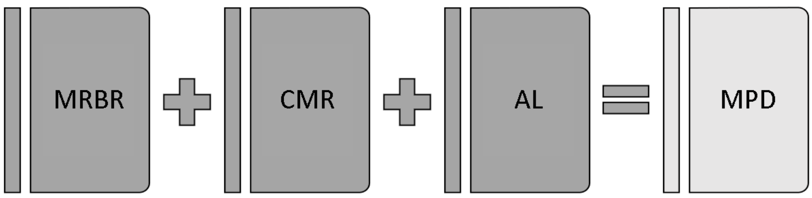


Figure 3.1: Assembly of the Maintenance Planning Document (MPD) [26].

- **Certification Maintenance Requirements (CMR)** - The CMR are required periodic tasks developed through the design certifications phase of the aircraft, resulting from formal numerical analysis conducted to prove compliance with catastrophic failure conditions. They are intended to detect safety latent failures that could result in hazardous failure conditions. *Example of a CMR task is performing a visual inspection of the elevator mechanism.*

- **Airworthiness Limitations (AL)** - The AL are a regulatory approved means of introducing inspections or maintenance practices with the intent of preventing problems with certain systems. The document can include mandatory replacement times, inspection intervals or related procedures for structural safe-life parts. *Example of an AL task is performing a detailed inspection of the fuel tank wire bundles to prevent potential wire chafing and arcing to the tank.*

It is important to settle that, as explained by [54], the MPD is neither a controlling nor an approved document – it is not required by regulation, although it is considered useful by many costumers.

3.1.4.C Operators Approved Maintenance Program (OAMP)

The abovestated MPD scheduled maintenance tasks can't be considered as all-inclusive, and it is the airline's responsibility to develop additional requirements in the form of Service Letters (SL), Service Bulletins (SB) and AD.

The OAMP outlines the air carrier's routine and the scheduled maintenance tasks required to provide instructions for continued airworthiness. Each task, in turn, shall be converted to procedures that will be used by mechanics to fulfill the intended requirement. The manual containing those procedures is denominated Aircraft Maintenance Manual (AMM) and its chapters are organized by the Air Transport Association (ATA) system, that provides a common referencing standard for all commercial aircraft documentation.

The majority of air carriers' maintenance departments generate task cards by combining the OAMP with extracted procedures from the aircraft's AMM. Task cards are used as a simple means of complying with regulations for performing maintenance – they provide detailed, concise procedural instructions that organize and control maintenance activities.

3.1.4.D Maintenance Event Letter Checks

In the process of developing a maintenance program, all the tasks are gathered into scheduled work packages – tasks with similar intervals get grouped into a number of maintenance packages, designated by an alphabetic letter, each with its own interval. The three most common letter checks are:

- **A-Check:** Consists of a general inspection of the airplane with specific target areas opened, requiring about 20 to 60 M/H to be completed. It is usually performed overnight at airport gates, and its periodicity varies by aircraft type, cycle count, or even number of hours flown since the last check [35], though it is typically performed every 800 FH. Examples of A-check tasks are checking and servicing oil, filter replacement, lubrication, operational checks and inspections.

- **C-Check:** These checks require an intensive inspection of the majority of the aircraft's components, putting the vehicle out of service until it is completed, which can take up to 2 weeks. They must be performed at maintenance bases, and usually every 20 to 24 months (although this periodicity can vary, depending on the operator's maintenance program). Examples of C-check tasks include functional and operational system checks, cleaning and servicing and attendance to minor structural inspections.

- **D-Check:** For this check, the aircraft is taken out of service for several weeks. Its exterior paint gets stripped, and large parts of the outer panelling are removed, uncovering the airframe, supporting structure and wings, for detailed inspections of the most structurally significant items. This is done every 6 to 12 years. It is common for airlines to merge a D-check into a C-check and label it as a *heavy* C-check.

B-checks are not defined above due to not being very frequent anymore, and not performed by every operator (in particular, not performed by the Part 145 organization involved in the study).

Not all A or C-checks include the same maintenance tasks, as some items are only required for every second or fourth inspection – to distinguish these differences, items are numbered so that $2A$ items are carried out in every other A-check, in an $A2$ inspection, and both $2A$ and $4A$ items are performed in every fourth inspection, called an $A4$. $1A$ items are performed in every A inspection, and after an $A4$ inspection, a new cycle of four begins (these cycles are pictured in Figures 3.2 and 3.3, and although the periodicities can vary depending on the applicable maintenance program, the presented values are the ones practiced by the airline providing data to the dissertation).

Inspection type / Items	A1	A2	A3	A4
1A	X	X	X	X
2A		X		X
4A				X

Figure 3.2: Cycles of A-checks [91].

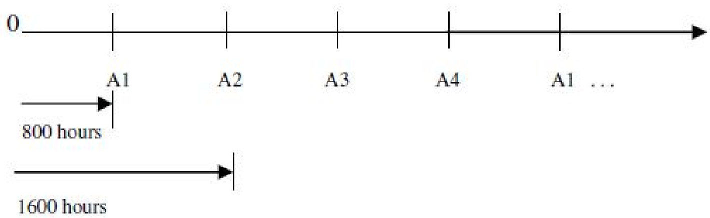


Figure 3.3: Periodicity of A-checks [91].

3.2 MPD Task Identification

This section goes over the identification and interpretation of an MPD task. On Figure 3.4 a cut of a specific task from the Airbus A330 MPD is shown (the entire page from the document is presented in Figure A.1, from appendix A.).

AIRBUS A330 MAINTENANCE PLANNING DOCUMENT

TASK NUMBER	ZONE	DESCRIPTION	SAMPLE THRESHOLD (ST) SAMPLE INTERVAL (SI) THRESHOLD (T) INTERVAL (I)	SOURCE	REFERENCE	MEN	M/H	APPLICABILITY
324000-02-1	195	BRAKE ACCUMULATORS AF FNC FUNCTIONAL CHECK OF NITROGEN CHARGE PRESSURE ON ALTERNATE PARKING BRAKE ACCUMULATORS. ACCESS: 195BB	I: 1000 FH	MRB 9	324000-210-805 MRB REFERENCE: 32.40.00/06	1 *	0.10 0.01	ALL
SYSTEMS, APU AND POWER PLANT : LANDING GEAR			REV. DATE: MAR 01/20	SECTION: 2-32			PAGE 6	

Figure 3.4: Cut from the A330 MPD page [12]

Each task is assigned with a unique identification number (the one from the Figure would be $324000-02-1$), where the first two digits represent the task's ATA number and the rest denote the maintenance sequence number. Tasks are also differentiated by zone, marked in the second column (maintenance zones are defined on Table B.2 from appendix B), description, skill and task codes (listed, respectively, on Tables B.1 and B.3 from appendix B), interval, applicable fleet type and the AMM procedures that apply.

It is important to refer that apart from the estimated task durations, in M/H, the MPD also gives an an approximate value for the workload (in M/H as well) required to create the access to the zone where the task is performed (when applicable, below the duration of its execution), due to the fact that some tasks must be performed in areas that are usually covered.

In the aviation industry, aircraft are aged by daily utilization with respect to three different usage parameters: Calendar Days (DY) – representing a full 24h period, FH – the elapsed time between a wheel lift off and subsequent touch down, and FC – a complete sequence of take off plus landing. Tasks on maintenance programs developed under MSG-3 are assigned with varying intervals (i.e. DY, FH, FC), and some tasks might even combine two of these intervals.

The MPD also includes an inspection interval tolerance; in case that tolerance is used in one maintenance cycle, the amount of DY/FH/FC used from the tolerance must be deducted from the maximum usage parameter values for the next cycle, in order to guarantee that these are met in the long term. This flexibility makes it possible for operators to group maintenance tasks into packages to create checks in the most efficient way for them (scheduling and planning maintenance around the available capacity and constraints), which ends up permitting the maximum utilization of task's intervals [92].

3.3 Workcards

Each maintenance inspection package (whether it is an A-, C- or D-check) comes with a sequenced checklist (presented in Figures A.2 and A.3, from appendix A) containing several numbered workcards with the tasks that must be performed and accordingly reported for, in order for the check to be completed. This section will scrutinize all the pertinent details from a workcard (visible in Figure A.4, from appendix A), which was, along with the MPD, the main source of the data used for the dissertation.

The document contains relevant information regarding the aircraft on which maintenance is being performed (e.g. registration/tail number, type, fleet and serial numbers), visible in Figure 3.5, and data concerning the task itself (source, its number, applicable manual and corresponding reference), presented in Figure 3.6. It has blanks to be filled in with respect to the corrective action to be taken (in accordance with the AMM), the technician(s) who executed the task (and how long it took, in M/H), along with a detailed report of which defects were found, if any.

Registration	CS-TFZ	AC Type:	A330-243
Fleet Nbr	XF_112	Serial Nbr	1008

Figure 3.5: Workcard aircraft information.

Source:	MRB 9
Task Number:	324000-02-1
Manual Type:	AMM
Manual Ref:	324000-210-805-A

Figure 3.6: Workcard task information.

Some of the tasks in an inspection check's workcards cannot be found on the MPD, either because they have been removed from more recent revisions of the document, or because the task derives from the operator's AMP, or because it involves nonroutine work.

3.4 Data Filtering

This section summarizes the criteria and methods used to filter the available data (information from the workcards), namely how it will be selected to be processed or eliminated according to how relevant it can be for the study.

All the relevant details from the workcards are registered in a spreadsheet (a section of the document is available in Figure C.1 from appendix C) that accounts for the aircraft's tail number and age (in both FH and FC), the workcard, task and ATA numbers, the zone where maintenance is being performed, the task and skill codes, the suggestions for the workloads from the MPD and the actual workloads (both in M/H) registered by the technicians (as well as their names), along with a brief analysis of the computed differences and corresponding percentages.

Additionally, tasks are differentiated by their source – when a task does not come from the MPD, the entry gets eliminated from the computations (and colored in red), due to the fact that the main objective of the study is to find a relationship between the work being done and the corresponding information on the MPD.

The location of the maintenance event is also identified – as Rosales [35] explains, the manpower and facilities at line stations are usually more limited, which is why it becomes relevant to distinguish which checks were done at a hangar or maintenance base (where all the necessary tools and equipment are nearby) and which were performed at the airport apron (where the technicians must get the tools and equipment from the line maintenance station, which can cause unexpected delays), especially because the studied inspections do not require a high number of tools and consumables to be fetched. Furthermore, because the airline only operates one maintenance base station, it is likely that it will often be more congested in terms of workload, and inconveniences such as having to wait for units or spare parts to arrive makes this situation prone to delaying the maintenance process. This distinction between base or line station maintenance will allow for a more accurate evaluation of how each facility influences the workload deviations, for this airline specifically. Table 3.1 states the IATA codes of the locations of the company's base and line maintenance stations.

Table 3.1: Base and line maintenance station locations.

Base	Line Maintenance Station
BRU	AKL, BNE, BWN, BYJ, LIS, OSL

Due to the fact that for each type of item (1A, 2A and 4A) the set of tasks to be accomplished is almost the same (with few occasional exceptions), information (i.e. its task and skill codes, how long the task took to be performed in each check and the age of the plane at the time, measured in FH and FC) is grouped with respect to task, in a spreadsheet presented in Figure C.2 from appendix C (note that each column corresponds to data from a different check, while every line stands for an individual task entry).

The goal of the dissertation is to find a probabilistic relation between a set of input parameters and the deviations on the lengths of the performed tasks and checks, which is why it becomes important to identify the outliers of the sample in order to eliminate them. According to Murteira [93], a good measure of the dispersion of a sample is given by the interquartile range, $R_{IQ} = Q_3 - Q_1$, that represents the amplitude of the interval that contains 50% of the central observations of the collection, which means that in its computation, the observations that are too big or too small aren't included.

The definition is given by: any value of the collection, x, is a severe outlier when: $x_i < Q_1 - 3(Q_3 - Q_1)$ or $x_i > Q_3 + 3(Q_3 - Q_1)$ and a moderate outlier when: $Q_1 - 3(Q_3 - Q_1) < x_i < Q_1 - 1.5(Q_3 - Q_1)$, $Q_3 + 1.5(Q_3 - Q_1) < x_i < Q_3 + 3(Q_3 - Q_1)$. The values given by $Q_1 - 3(Q_3 - Q_1)$ and $Q_3 + 3(Q_3 - Q_1)$ are called external lower and upper barriers, whereas the values given by $Q_1 - 1.5(Q_3 - Q_1)$ e $Q_3 + 1.5(Q_3 - Q_1)$ are the interior lower and superior barriers.

This characterization can be applied to the sample of workloads. The author defends that explanations for outliers range from human errors made when measuring the data to the nature of the phenomena in the study; since the most severe irregularities correspond to tasks in which there are reports of defects found in the equipment (that led to unscheduled extra work, falling into the nature of the circumstances), both justifications apply, and therefore the outliers must be eliminated accordingly.

3.5 Bayesian Networks

The calculus of Bayesian probabilities is based on simple and intuitive axioms that express ground statements of probability regarding the occurrence of a single event, the occurrence of mutually exclusive events, and the co-occurrence of events [94]. Naim and Condamin [17] emphasize that the probability of a future and uncertain event depends on the amount of information available to the individual attempting to assess this likelihood – this expresses that uncertainty is closer to a belief than to a frequency.

By establishing an intuitive link between data and probability (and in parallel, knowledge and uncertainty), Bayes sets the foundation for any theory of decision.

If A is a variable with states $a_1, ..., a_n$ then $P(A)$ denotes a probability distribution over the states exemplified in equation (3.1):

$$P(A) = (x_1, ...x_n); x_i \geq 0; \sum_{i=1}^{n} x_i = 1 \tag{3.1}$$

in which x_i is the probability of A being in state a_i.

If a variable B has states $b_1, ..., b_m$ then $P(A|B)$ denotes an $n * m$ table containing the values of $P(a_i|b_j)$. $P(A, B)$, the joint probability for the variables A and B is also a notation for an $n * m$ table that presents a probability for each configuration (a_i, b_j). For all states a of A and b of B there is $P(a, b) = P(a|b)P(b)$. When this rule is used on the variables A and B, the procedure is to apply it to the $n * m$ configurations (a_i, b_j).

$$P(a_i|b_j)P(b_j) = P(a_i, b_j) \tag{3.2}$$

Equation (3.2) means that in the table of $P(A|B)$, for each integer j the column of b_j gets multiplied by $P(b_j)$ to obtain the table $P(A, B)$. When applied to variables, the same notation is adopted (see equation (3.3)):

$$P(A|B)P(B) = P(A, B) \tag{3.3}$$

From a table $P(A, B)$, the probability distribution $P(A)$ can be calculated. Let a_i be a state of A. Then comes equation (3.4):

$$P(a_i) = \sum_{j=1}^{m} P(a_i, b_j) \tag{3.4}$$

Supposing now that a part of the domain is being considered, and there is a certain belief regarding the state of a particular variable, A. Next, arises the information that the state of the variable B is b, and this data is to be used to update the belief in the state of A. In the framework of probabilities, it is said that there is a prior distribution $P(A)$, and it is desired to compute the posterior $P(A|b)$. Now, assuming that the world consists of three finite variables (let them be A, B, C) and that the model of the world is the joint probability distribution $P(A, B, C)$ then equation (3.5) applies such that:

$$P(A) = \sum_{B,C} P(A, B, C) \tag{3.5}$$

which translates into equation (3.6):

$$P(A, b) = \sum_{C} P(A, b, C) \tag{3.6}$$

and equation (3.7):

$$P(A|b) = \frac{P(A, b)}{\sum_A P(A, b)} \tag{3.7}$$

This means that if there is information on the joint distribution over the relevant variables, belief updating is a rather simple task. However, if the distributions are unknown, a way of finding conditional independencies is to consider causality in the domain in focus. For example, if A has a causal impact on C and C has a causal impact on B – and this is the only relation involving B –, then B is independent of A given C. Causality can be graphically represented in networks called **Bayesian networks** [95].

A Bayesian network is a type of quantitative causal model structure based on the Bayes' theorem that represents and processes knowledge in a probabilistic way, making it an excellent tool for reasoning under uncertainty [82], seeing as it provides a quantification of consequences.

Regarding the Bayes' theorem, it works like a program that takes old probabilities along with new data as inputs, and delivers new updated probabilities as outputs; it can be easily computed using Tables [96]. Dividing a domain Ω into n mutually exclusive sets $A_1, A_2, ...A_n$ then (notice equation (3.8)):

$$P(A_k|B) = \frac{P(A_k) * P(B|A_k)}{\sum_j P(A_j) * P(B|A_j)} \tag{3.8}$$

For this instance, given a posterior probability P_m, the probability that the next observation will be C is given by equation (3.9):

$$P_m(C) = \sum_j P_m(A_j|C) = \sum_j P_m(C|A_j) * P_m(A_j) \tag{3.9}$$

A BN consists of a qualitative part, a Directed Acyclic Graph (DAG) along with a quantitative part, a Conditional Probability Table (CPT) (or a set of them). The DAG (exemplified in Figure 3.7) contains nodes representing random variables (to each state of the node is assigned a probability that is defined *a priori* for a root node and computed by inference for the others [73]) and directed arcs representing dependencies or causal relationships between variables; then, a joint probability distribution is defined

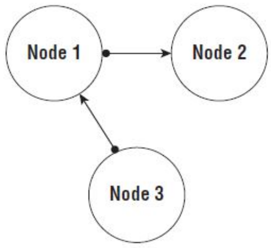


Figure 3.7: Example of a directed acyclic graph [97].

over the variables depending on the directed arcs, which makes inference through conditional probabilities possible. The directions of links between variables (directed arcs) represent the parent-child relationships, with the arrow head pointing in the direction of causality, i.e. the child [80]. The networks are acyclic, which means that for any given node, there must not be a way to loop back into it [83]. Each network node consists of a finite number of mutually exclusive states and each state has a probability of occurrence that depends on the current states of the variable's possible parent nodes.

The qualitative and quantitative parts of a BN can be defined through manual or automatic means. Manual means are the definition by a domain expert of variables and arcs (and corresponding values and directions) for the qualitative part, and of the resulting conditional probabilities for the quantitative part. Automatic means refer to the computational methods capable of defining the structure of the network and its CPT from the provided data.

There is a five-step process often mentioned in the literature [74, 82] for the development of a Bayesian network structure:

1. Delineating the objectives of the model;
2. Defining the variables;
3. Designing the network's graphical structure;
4. Building the network's CPT;
5. Validating the model.

Accordingly, after setting the goal of the network, the development of a BN requires identifying the variables to be included as nodes in the model (which is often determined by the aim of the study), and then establishing the relationships (arcs) between them [86]. To each node is assigned a CPT to express the intensity of the relationship between the variables in the systems, which contains all known information regarding the states of the variables; once this is done, the BN model is complete (fully quantified) and capable to make inference – this quantified BN represents the *prior* knowledge.

Within conditional probability distributions in a BN, different variables are combined and their values can be updated whenever new information is obtained; this information is automatically propagated through the network to produce updated probabilities for all the nodes in the model and examine the impact on the remaining nodes. These updated posterior probabilities are generated results of both prior information and new evidence; hence, the abilities of BNs fully justify their use for the purpose of this thesis.

3.5.1 BN Learning from Data

3.5.1.A Structure Learning

After defining the variables that will be used in the BNs, their dependencies must be established through directed arcs. Several computational methods based on learning algorithms can automatically estimate the structure of a BN from data, such as *Bayesian Search*, *PC*, *Essential Graph Search*, *Greedy Thick Thinning*, *Tree Augmented Naive Bayes* and *Augmented Naive Bayes*.

Prior to the run of each of the algorithms, there are three obstacles to structure learning that are tested for [98]:

- None of the algorithms allows for learning from a combination of discrete and continuous variables, so if there is even one discrete variable in the learning set, all continuous variables must be discretized.

- None of the algorithms (except the *Naive Bayes*) is capable of learning the structure of the model when its records have missing values.

- None of the algorithms allows for learning with variables (i.e. the columns from the dataset) containing the same value across all the records; this is generally considered useless in learning a model's structure, because it cannot be a predictor for any other variable.

Since the *Bayesian Search* structure learning algorithm is one of the earliest and most popular algorithms used, it is the one that will be used for the present data. It was introduced by Cooper and Herskovits [99] and refined later by Heckerman and Shachter [100]. Essentially, it follows a hill climbing procedure (guided by a scoring heuristic) with random restarts, that calculates the probability of a structure of variable relationships given a database. The algorithm has the following parameters:

- Max Parent Count: it limits the number of parents that a node can have. The size of the conditional probability tables of a node grows exponentially with the number of its parents.

- Iterations: this sets the number of restarts of the algorithm. Because the algorithm searches through a hyper-exponential search space, restarts allow for probing more areas of the search space and increase the chance of finding a structure that will better fit the data.

- Sample size: it takes part in the network's score calculation, representing the inertia of the current parameters when introducing new data.
- Seed: it is the initial random number seed used in the random number generator. Seed equal to zero makes the number generator random.
- Link Probability: it is used when generating a random starting network at the outset of each of the iterations, which influences the connectivity of the starting network.
- Prior Link Probability: influences the network's score by offering a prior over all edges.
- Max Time: sets a limit on the run time of the algorithm.
- Use Accuracy as Scoring Function: when checked, the algorithm will use the classification accuracy as the scoring function in search for the optimal graph.

This algorithm produces a DAG that achieves the highest score – this score is proportional to the probability of the data given the structure, which, assuming the same prior probability can be assigned to any structure, is proportional to the probability of the structure given the data. Given the theoretical limits to what can be identified based on data, it is possible to manually transform the DAGs of a BN.

3.5.1.B Parameter Learning

As foreseen, the quantitative part of a BN refers to the CPTs established after its structure, which are filled with parameters (i.e. conditional probabilities). Since their manual specification is a highly demanding task, an alternative to this is to use computationally implemented algorithms capable of learning parameters from data.

A widely used algorithm for parameter estimation is the Expectation-Maximization (EM) algorithm, which computes maximum-likelihood estimates for the parameters from datasets that may contain missing values [101,102]. The **E**xpectation step consists in the calculation of expectations for the missing values using the estimates of missing parameters, while in the **M**aximization step new maximum-likelihood estimates are calculated using the original dataset plus the expected missing values from the expectation step [10]. The algorithm then runs iteratively for a predetermined number of iterations (or until it converges). For this case, the used dataset does not contain missing values, therefore the maximum likelihood estimates are possible to compute by counting frequencies from the database.

This algorithm has several features, and the parameter initialization allows for choosing a starting point of the EM algorithm [98]:

- Uniformize: causes the algorithm to start with all parameters in the network taken from the uniform distribution, which is a typical option that should be used when it is intended to disregard the existing parameters.

- Randomize: allows for picking random values for parameters, which introduces some randomness in the algorithm's search for the optimal values of parameters.

- Keep Original: allows for starting with the original parameters. This option should be used when using a new data set as an additional source of information over an existing network, because keeping the original parameters and learning from the same data file that they were extracted from will lead to over-fitting the data.

For the present case study, the distributions are uniformized prior to learning as a starting point for the algorithm. Once everything is set, the EM algorithm updates the network parameters following the chosen options.

3.5.2 Sensitivity Analysis

According to Saltelli et al. [103], it is a common agreement that a model cannot be validated in the sense of be *proven* true; rather, it is more defensible to declare that it has been extensively corroborated, which means it survived a series of tests – whether formal, of internal consistency or relative to the model's capacity of explaining or predicting the outcomes in a convincing way.

Validation is a crucial aspect of any modeling methodology, since it provides confidence in the delivered results [80]; because there isn't a specific semantic to build a BN, one must validate the model according to the system's reality [73].

In the present section, it is important to make the distinction between validation – a demonstration that a predictive model within its domain of applicability possesses a satisfactory range of accuracy consistent with its intended application, and verification – a demonstration that the modeling formalisms (calculations, inputs, code) are correct [75]. Langseth and Portinale [74] defend that this should be performed both through sensitivity analysis as well as by testing how the model behaves when analysing well-known scenarios.

A sensitivity analysis studies how uncertainty in the output of a model (that is either numerical or otherwise) can be allocated to different sources of uncertainty in the model's inputs [103]. A related procedure is the uncertainty analysis, that focuses rather on quantifying the uncertainty in the output of the model. Both methods are presented in Figure 3.8, in which the observations are usually assumed to be error-free, for the sake of simplicity.

As enumerated by Saltelli et al. [104], the setting up of a sensitivity analysis generally depends on the number of uncertain factors, the characteristics of the output of interest and the scope of the analysis.

A more traditional approach to sensitivity analysis aims at assessing the impact of changes in the input parameters on a model output of interest, which is valuable for model validation, i.e. for verifying that it responds as expected. In the specific context of BN models, this analysis studies the effect on a target variable of introducing, systematically, an evidence on a state of a model variable while keeping the others unchanged, thus identifying the most important model parameters, i.e. the ones with the largest influence on the target variables of interest. This approach is called the parameter sensitivity analysis.

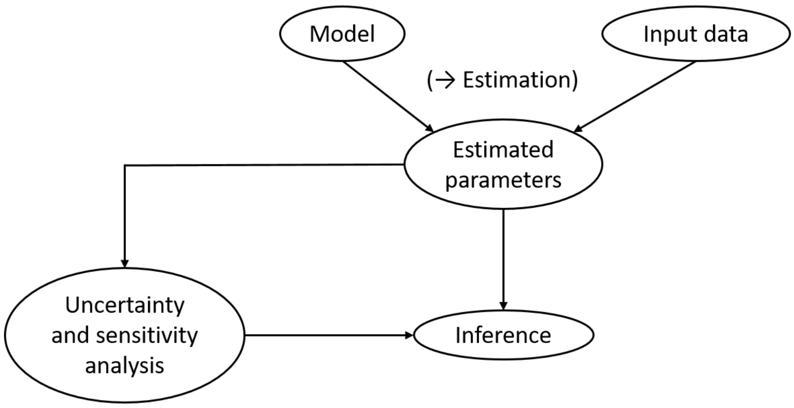


Figure 3.8: Uncertainty and sensitivity analyses [103].

Another approach to sensitivity analysis referred to as sensitivity to findings or evidence provides important insights into the properties of the models and their robustness. This method assesses the variations of the BN's posterior probability distributions under different conditions using typically two types of measures, entropy and mutual information.

Inspired by the concept of sensitivity to evidence, Dinis et al. [82] have proposed a sensitivity measure formulated in terms of the variation in the posterior distributions of the model variables resulting from introducing an evidence on a state of the model's output, as follows.

Let $X_{i,j}$ be the variable i of the BN model with $j = 1, ..., m_i$ states and $P(X_{i,j=1,...,m_i}|Y = e)$ its posterior probability distribution for a given Y, i.e. providing the evidence e to a particular state of the Y variable ($Y = e$). The variation in the posterior probability distribution of the variable $X_{i,j}$ when Y changes from state e to state f is given by equation (3.10):

$$\Delta P(X_{i,j=1,...,m}|Y) = P(X_{i,j=1,...,m}|Y = f) - P(X_{i,j=1,...,m}|Y = e) \tag{3.10}$$

A global measure of the importance of the variable X_i on the variable Y is then defined based on ΔP as equation (3.11) writes it:

$$S_{X_i} = \sqrt{\sum_{j=1}^{m} \frac{(\Delta P(X_{i,j}|Y))^2}{2}} \tag{3.11}$$

This value ranges from 0 to 100%, the former corresponding to no effect of the evidence provided in Y on the posterior probability distribution of X_i, and the latter to the maximum variation that can be produced by changing the evidence.

In addition to the global sensitivity measure S_{X_i}, a state j sensitivity measure $S_{X_{i,j}}$ of variable X_i can also be derived as visible in equation (3.12):

$$S_{X_{i,j}} = \frac{\Delta P(X_{i,j}|Y)/2}{S_{X_i}} \tag{3.12}$$

In which $\Delta P(X_{i,j=1,\ldots,m}|Y)$ is given by equation (3.10) and S_{X_i} is the global sensitivity measure of the variable X_i, given by equation (3.11), used to normalise the state variation of posterior probabilities.

The state sensitivity provides a measure of the relative variation of the state's posterior distribution, and it is defined only for variables with global sensitivity greater than zero ($S_{X_i} > 0$).

4

Results Analysis

Contents

4.1 Description of Maintenance Dataset

For the Airbus A330, a total of 67 A-checks were analyzed (see Table 4.1 for details) for the time period comprised between 2015 and 2020. Information was gathered regarding one vehicle of each of the following variants: A330-202, A330-223, A330-243, A330-322 and A330-941, summing up to a total of five aircraft of this model. Following what is said in 1.5, because the company applies the same maintenance program to the entire model (A330 range), distinctions will not be made regarding the variant.

Table 4.1: Total of analyzed checks for the Airbus A330.

	1A	2A	4A
Number of Checks	38	21	8

For the Airbus A340, a total of 60 A-checks were analyzed (see Table 4.2 for details) for the time period comprised between 2013 and 2020. The airline provided data on five A340-313 and one A340-312, which sums up to a total of six aircraft of this model.

Table 4.2: Total of analyzed checks for the Airbus A340.

	1A	2A	4A
Number of Checks	36	17	7

Breaking the dataset down in terms of variables, as it it briefly mentioned in Chapter 3, every check is classified according to:

- the aircraft's model: A330 or A340, which dictates the applicable maintenance program and the corresponding MPD version for reference;
- the aircraft's tail number: CS-TFZ, CS-TQP, CS-TKY, CS-TQW, CS-TRI, CS-TQY, CS-TQZ, 9H-FOX, 9H-JAI, 9H-SOL and 9H-SUN, which refer to the aircraft's identification number;
- the aircraft's age at the date of the inspection: the registered values range from 833 to $79\,258$ FH;
- the location in which the maintenance action takes place: Brussels (BRU) (base maintenance station), Auckland (AKL), Brisbane (BNE), Brunei (BWN), Beja (BYJ), Lisbon (LIS), Oslo (OSL) (line maintenance stations).

On the other hand, and because every check is composed by a number of unique tasks, there is a need to identify variables that assess tasks individually. A task is then defined by:

- its task code: task codes are described in 3.1.2 and listed in Table B.1 from appendix B, which is a valuable distinction due to the fact that each task code represents a different range of activities;

- its zone: from the lower fuselage to the vehicle's doors, every zone has its own coding (from 100 to 800), as it is pictured in Figure 4.1 and listed in Table B.2 from appendix B;
- its skill code: tasks might require different skills that can range from aiframe to the electrical field, as it is listed in Table B.3 from appendix B.

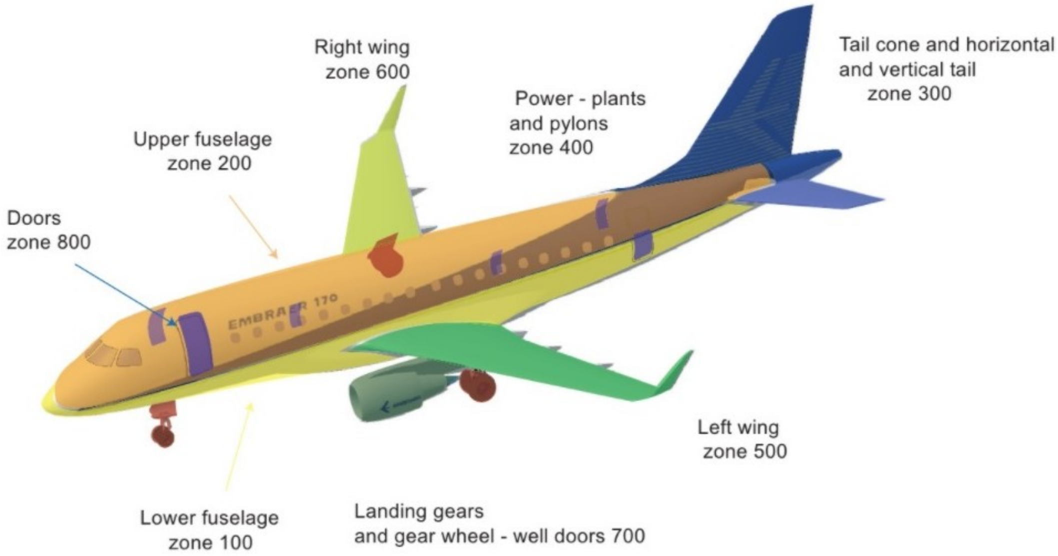


Figure 4.1: Aircraft major zones [105].

4.2 Preliminary Analysis of Maintenance Workloads

Table 4.3 presents the obtained statistics for all three 1A, 2A and 4A items for the Airbus A330, that result from the averages of the values computed for each individual check. The *# of MPD Tasks* accounts for the number of tasks from the check that state the MPD as the source; the *MPD Tasks Workload* is the sum of the registered durations of only the tasks that come from the MPD, as stated on the workcard; the *Estimated MPD Tasks Workload* is the sum of the durations of the performed tasks, as stated on the MPD (i.e. their expected required workload); the *Workload Deviation* variables (*Total* and *Per Task*) refer to the ratio between the registered deviations (in M/H) and the suggested workload from the MPD (also in M/H), applied to both check and task durations. This is formulated in equation 4.1:

$$Workload\,Deviation[\%] = \frac{Actual\,Workload(Workcard\,Value) - Planned\,Workload(MPD)}{Planned\,Workload(MPD)} * 100 \tag{4.1}$$

It is important to refer that all the performed tasks that are not from the MPD are discarded from the computations, since there is no official suggestion for their length and therefore they are not considered

Table 4.3: Average values for the Airbus A330 checks.

	1A	2A	4A
Average # of MPD Tasks	32	13	9
Average MPD Tasks Workload [M/H]	31,68	13,30	11,90
Average Estimated MPD Tasks Workload [M/H]	11,15	3,46	10,44
Average Total Workload Deviation	184,8%	298,8%	13,8%
Average Per Task Workload Deviation	412,6%	490,9%	102,8%

suitable data for the present problem, as explained in section 3.4.

The fact that the *Average Total Workload Deviation* variable represents more than 100% and 200% of the *Average Estimated MPD Tasks Workload* for 1A and 2A checks, respectively, means that, in general, these checks take at least twice and three times as long as the MPD suggests.

Out of the three analyzed check items, 2A clearly presents the highest discrepancies with regard to the estimated total workload and the actual one (registering an average total deviation of $298,8\%$). This is corroborated by the high percent deviations that the tasks register as well, with an average value of $490,9\%$.

Under this maintenance program, 4A inspections contain few tasks to be performed, but the suggested MPD total workload for them is higher than for 2A checks ($10,44$ [M/H] against $3,46$ [M/H]) and almost the same as for 1A items ($10,44$ [M/H] against $11,15$ [M/H]); because the former item is made up from typically longer and more thorough tasks, the possible deviations do not result in such big impacts on the *Total Workload Deviation* and *Per Task Workload Deviation* averages.

It is also relevant to comment on the fact that the deviations regarding individual tasks are higher values (when compared to the total check) because small values (such as the lengths of short tasks) are more sensitive to variations, which ends up inflating the computed average.

The graphics from Figures 4.2, 4.3 and 4.4 present all the calculated deviations (for both the total check and individual tasks) for all 1A, 2A and 4A items, as a function of the age of the aircraft (in FH). The workload deviation is represented by the term *WL_Dev*.

As it can be observed in the Figures, a linear correlation implying that overall workload deviations in performing maintenance tasks and inspections on the Airbus A330 tend to increase with aircraft age and utilization can't be inferred from the registered data.

Table 4.4 presents the obtained statistics for all three 1A, 2A and 4A items for the Airbus A340, that result from the averages of the values computed for each individual A-Check. The definitions of the variables are identical to the ones from Table 4.1.

The fact that the *Average Total Workload Deviation* variable represents more than 100% of the *Average Estimated MPD Tasks Workload* (for either the 1A, 2A or 4A) means that, in general, an A340 A-Check inspection takes at least twice as long as the MPD suggests. ´

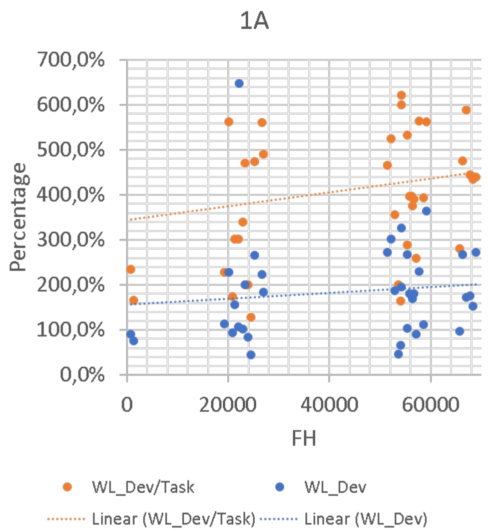


Figure 4.2: A330 1A items deviations.

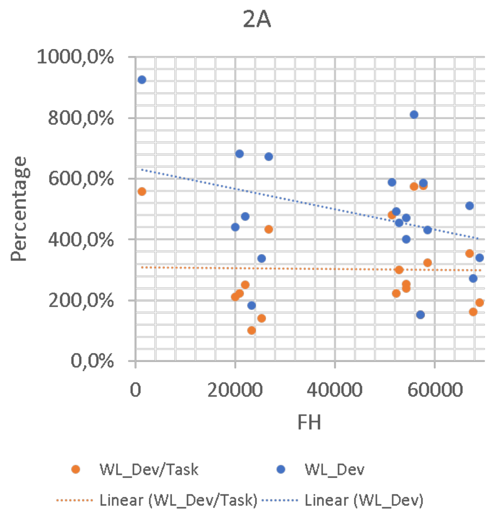


Figure 4.3: A330 2A items deviations.

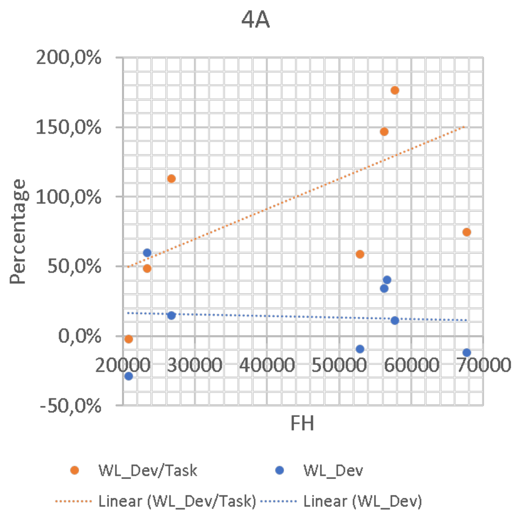


Figure 4.4: A330 4A items deviations.

Table 4.4: Average values for the Airbus A340 checks.

	1A	2A	4A
Average # of MPD Tasks	37	21	10
Average MPD Tasks Workload [M/H]	38,63	18,31	15,75
Average Estimated MPD Tasks Workload [M/H]	14,54	5,07	5,90
Average Total Workload Deviation	166,8%	260,4%	165,4%
Average Per Task Workload Deviation	327,2%	585,1%	323,5%

Regarding 1A items, the results are similar to the ones computed for the A330 with respect to their order of magnitude.

On the one hand, similarly to what happens with the previous aircraft, 2A inspections still present the highest discrepancies measured by the average total workload deviation (reaching a value of $260,4\%$) and the average per task workload deviation (of $585,1\%$), but on the other hand, for the A340, the deviations found in 4A checks have about the same order of magnitude as the ones calculated for 1A and 2A (i.e. there is not an exaggerated difference).

Note that the prediction for the length of a 4A inspection is about half of the one for the A330 for the approximate same number of tasks (9 versus 10), an indication that for the present aircraft's 4A items, tasks are rather shorter, which validates the high value that the deviation per task reaches (of $323,5\%$) – as seen before, delays on shorter tasks produce higher variations in the per task workload deviation variable.

The graphics from Figures 4.5, 4.6 and 4.7 present all the calculated deviations (for both the total check and individual tasks) for all 1A, 2A and 4A checks, as a function of the age of the aircraft (measured in FH).

Once again, the data is very dispersed and there is no evident indication that deviations in the A340 A-checks increase linearly with aircraft age and utilization.

The above-mentioned statistics for both aircraft validate the initial premise that the MPD is very optimistic with regard to the length of aircraft maintenance tasks given that, in average, the observable discrepancies don't have a negligible order of magnitude. This being said, for the considered company, the document can't be accounted for as a reliable source of the task's workloads.

At this point, it can be confirmed that the same task may present disagreeing conclusion times for distinct aircraft, or even for the same aircraft at different instances – otherwise, most checks and tasks would present similar lengths, and Figures fig. 4.2 to 4.7 prove that it is not the case (if it were, the data wouldn't be so scattered). This is another initial assumption that is corroborated by the data, namely the one made by the airline's CAMO expert, transcribed in 1.5.

Assessing check items, it can also be assumed that generally 2A items register the largest discrepancies with the highest workload deviations ($298,8\%$ and $260,4\%$ for the A330 and A340, respectively), while on the opposite end, 4A items present the smallest margins ($13,8\%$ and $165,4\%$ for the A330 and A340, respectively).

An important observation to make is that regardless of the check item or aircraft, deviations in longer tasks seem to produce a smaller effect in the final averages, due to the fact that the relative percentage of the possible discrepancies is smaller when compared to the initial large suggested value (in practical terms, this means that a $0,5$ M/H increase is more significant in a task that is expected to take $0,5$ M/H – 100% – than in one that is planned to take $2,0$ M/H – 25%).

Regarding the rest of the variables, it is not feasible to assess their influence through computed averages or linear regressions, due to their categorical nature, which is why it becomes necessary to

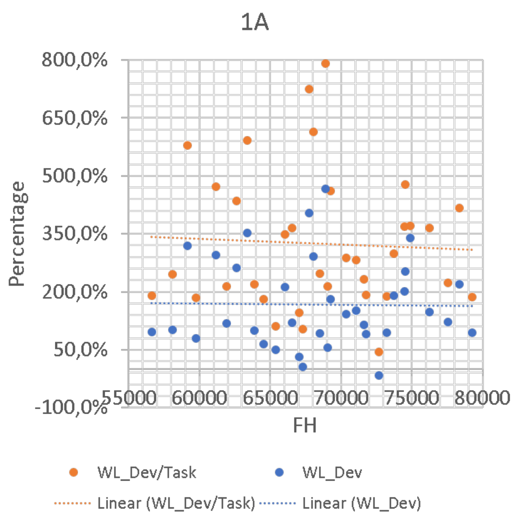


Figure 4.5: A340 1A items deviations.

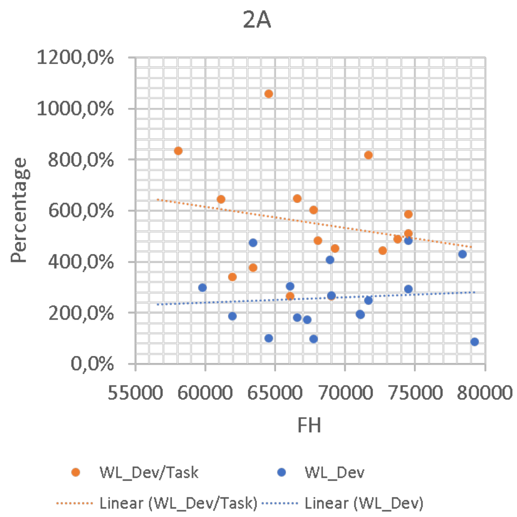


Figure 4.6: A340 2A items deviations.

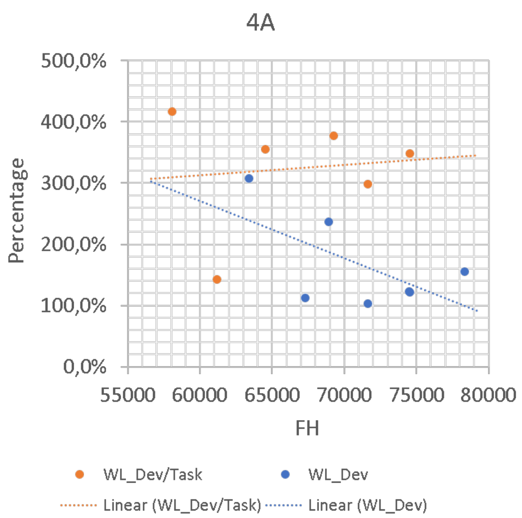


Figure 4.7: A340 4A items deviations.

adopt a new strategy to approach the data as a whole.

4.3 Probabilistic Modeling of Maintenance Workload Deviations by Bayesian Networks

This section describes the development of the Bayesian networks to model the A-checks using the computer software *GeNIe* [106], with the purpose of obtaining workload deviation predictions for maintenance checks.

Following the steps mentioned in section 3.5, the BN model is developed to get a prediction of the workload deviation for light maintenance inspections. For this reason, there is a need to build two distinct BN models: one for assessing the total workload deviation of the check (weighing in parameters such as the type of check being performed, the location of the station, the aircraft's model, tail number and age in FH) and another one for evaluating the workload deviation for a single task (taking into account the zone where maintenance is required, the aircraft's model, the job's skill and task codes). The demand for two BN models also arises from the fact that although being hierarchically related (as a check is made up from several different tasks), these two elements are not influenced by comparable variables, thus not making sense to group them in the same causal network model.

The states of each variable are presented in Tables 4.5 and 4.6. Although there are several locations in which maintenance is performed, as foreseen in 3.1, for the purpose of this work it is only relevant to make a distinction between instances when it is done at a maintenance base or line station, which is why the possible states of the location variable are reduced to two – BRU (base station in Brussels) or NO_BRU (any line station).

Table 4.5: Variables and corresponding states for the checks BN.

Variables	States
Model	A330, A340
Check	1A, 2A, 4A
Location	BRU, NO_BRU
Tail #	CS-TFZ, CS-TQP, CS-TKY, CS-TQW, CS-TRI, CS-TQY, CS-TQZ, 9H-FOX, 9H-JAI, 9H-SOL, 9H-SUN
FH	$< 30\,000$; $50\,000 - 65\,000$; $> 65\,000$
Check Workload Deviation	$< 0\%$; $0 - 100\%$; $100 - 500\%$; $> 500\%$

Table 4.6: Variables and corresponding states for the tasks BN.

Variables	States
Model	A330, A340
Check	1A, 2A, 4A
Zone	100, 200, 300, 400, 500, 600, 700, 800
Skill Code	AF, AV, EL, EN, RA
Task Code	DET, DIS, FNC, GVI, LUB, OPC, RST, SVC, VCK
Task Workload Deviation	$< 0\%$; $0 - 100\%$; $100 - 500\%$; $500 - 1\,000\%$; $> 1\,000\%$

It is important to refer that in order to get models with discrete variables only, some states are grouped into classes, namely regarding the variables FH, Task Workload Deviation and Check Workload Deviation. The intervals of the FH classes are chosen in a manner that the data is evenly distributed, for both aircraft ($30\% \pm 13\%$ of the samples in each class) – keeping in mind that data discretization methods may lead to different prediction results with respect to a given class of outcome variables (even if the model's structure remains unchanged) [80], this is an attempt to minimize the degree of imprecision that arises from variable discretization [107].

Considering that the workload deviations are given with respect to how real values exceed the theoretical suggestions, tasks and checks that present negative deviations – below 0%, stand for instances when the workloads are reduced rather than increased, while values between 0 and 100% represent increases of up to the total theoretical workload; naturally, an increase of over 100% means that the task or check is expected to require at least twice as manpower as the MPD suggests.

The BN model's graphical structure, i.e. the relationships between the variables is both forced and also assumed by the software: on the one hand, some causal relationships make theoretical sense, such as linking the aircraft's model directly to its tail number; on the other hand, the software infers the parent-child relationships between the remaining parameters.

The CPTs assigned to each variable are obtained through learning techniques from maintenance data provided to the software. The BN models are fully quantified (in terms of the *a priori* knowledge), as depicted in Figures 4.8 and 4.9 that also present the characterization of the dataset. The output variable of each model is represented in a different color for an easier identification.

With this framework it is possible to simulate scenarios with respect to future work generated by providing evidences to specific states of model variables. Starting with the check BN model, to evaluate the execution of a $4A$ item on an Airbus A330 (per example, the *CS-TFZ*) that has an age count of lower than $30\,000$ FH, in the maintenance base station, in BRU, after introducing these parameters as evidences on the states of the input variables (as pictured in Figure 4.10), the model presents the updated posterior probability distribution of the workload deviation that the check is expected to incur in. This distribution is shown in Figure 4.11, from which it is possible to conclude that for this simulation, the most likely outline is that this check's duration might exceed the manufacturers' suggestions in a range from 0% to 100%, followed by the scenario of a $< 0\%$ deviation (i.e. the check will require less workload than expected).

After obtaining this quantification, the operator gains knowledge on whether or not the check's actual workload agrees with the MPD's suggestion, and if not, how significant that deviation is, which can be a helpful insight to possess when planning said maintenance checks – there is a reduction of the uncertainty associated to the process.

Shifting to the tasks BN model, which is a more specific and detail-oriented framework, if a certain task from a $1A$ check must be performed on the Airbus A330's lower fuselage (zone 100), and if its skill

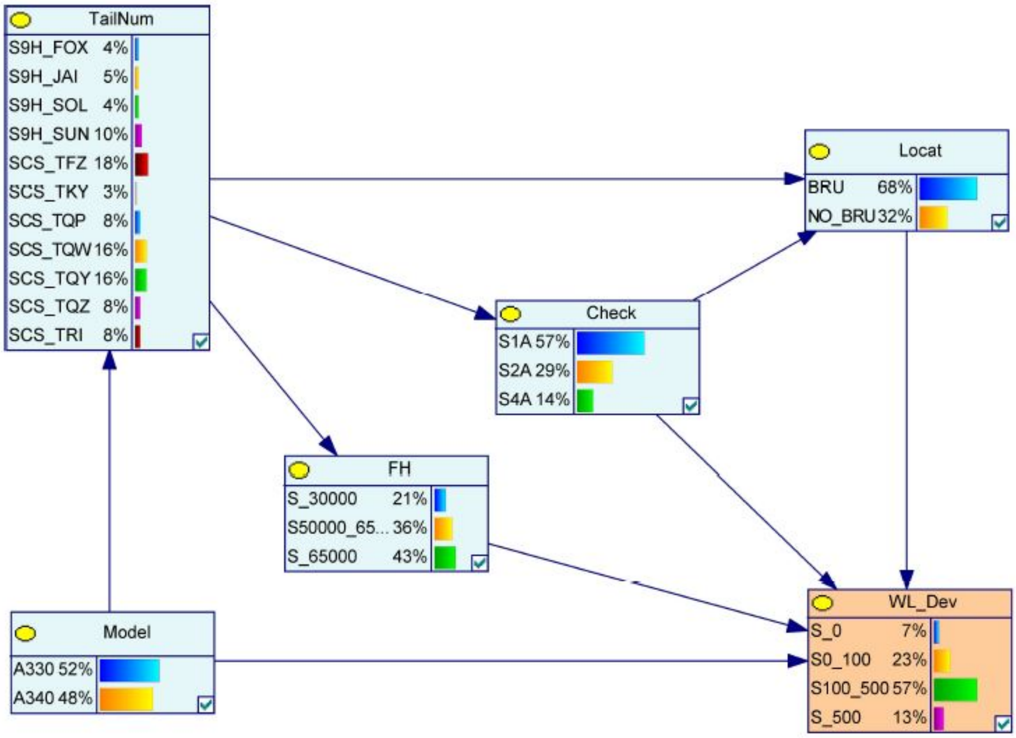


Figure 4.8: Bayesian network model for the checks.

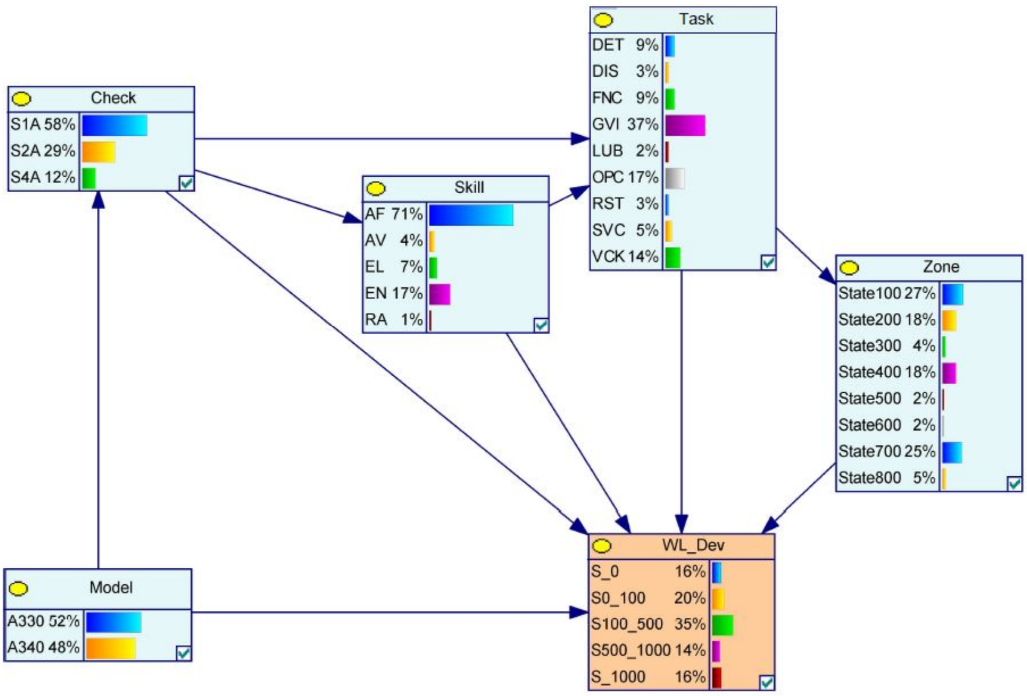


Figure 4.9: Bayesian network model for the tasks.

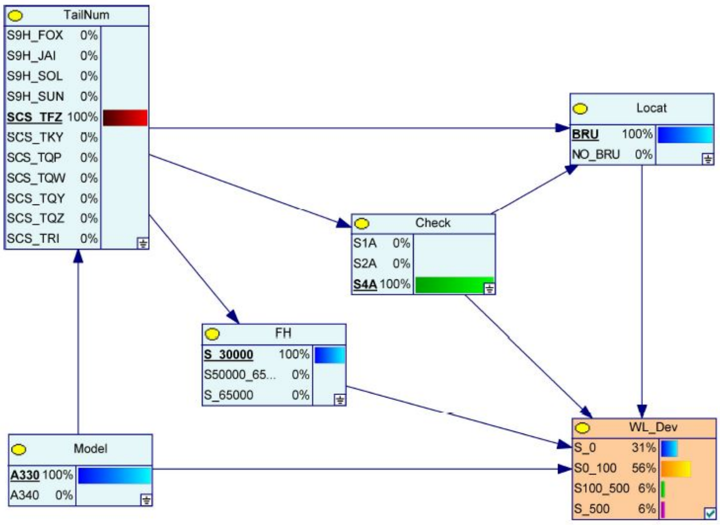


Figure 4.10: Simulated check scenario with evidences provided to variables Model=A330, TailNum=CS-TFZ, FH=< 30000, Check=4A, Locat=BRU.

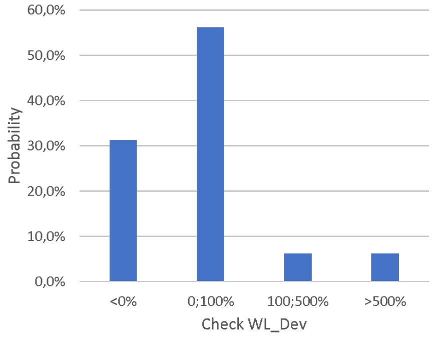


Figure 4.11: Posterior probability distribution of workload deviation for the simulated scenario.

and task codes are *AF* and *GVI* (meaning it is a general visual inspection on the aircraft's airframe), respectively, after introducing this input information as evidences on the variables' states, the model computes the posterior probability distribution for the workload deviation that the task is expected to have, with respect to the value suggested on the MPD for it. This scenario is presented in Figure 4.12, and the posterior probability distribution for this specific situation is graphed in Figure 4.13.

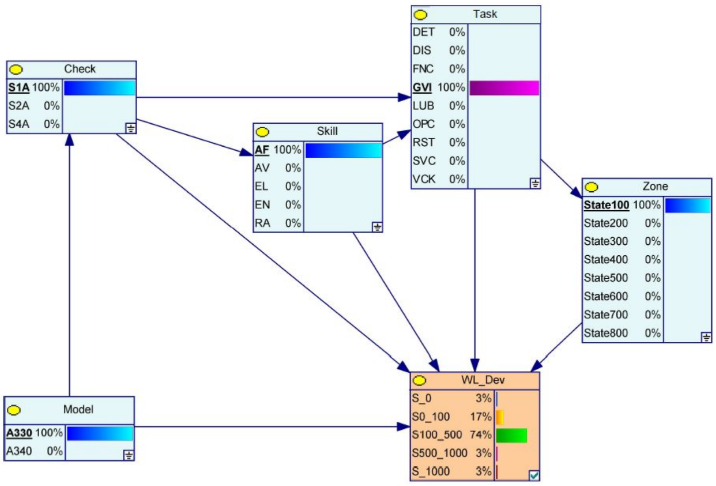


Figure 4.12: Simulated task scenario with evidences provided to variables Model=A330, Check=1A, Skill=AF, Task=GVI, Zone=100.

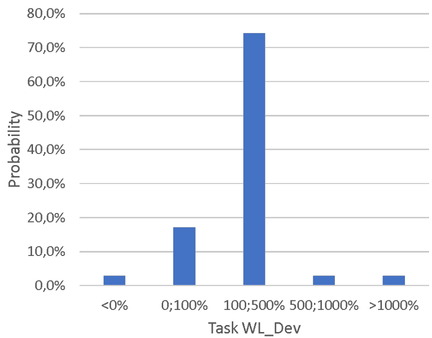


Figure 4.13: Posterior probability distribution of workload deviation for the simulated scenario.

By observing the distribution, it is possible to deduce that the conclusion of this task is highly expected to take two to six times as long as it is suggested on the MPD (corresponding to an increase falling in the $100 - 500\%$ range). This ability of the software to experiment possible scenarios can be a valuable tool for the airline, provided it becomes possible to see the category that the planned work falls into, and therefore get reliable information on the most likely output event.

Another characteristic of this framework is the possibility of updating it as new knowledge becomes available, as described in 3.5. If information on future checks and tasks is to be introduced in the BN model, its accuracy (regarding the delivered results) will be continuously improved.

4.3.1 Sensitivity Analyses

The values computed from the sensitivity analyses performed on the check and task models (following the procedures described in 3.5.2) are presented in Figures D.1 and D.2 of appendix D. For this validation, the several states of the *Workload Deviation* variable are quantitatively described as presented in Table 4.7. The *Very High* classification only applies to the *Task Workload Deviation* variable.

Table 4.7: Qualitative classification of workload deviations.

Deviation Range	Classification
$< 0\%$	Negative
$0 - 100\%$	Low
$100 - 500\%$	Moderate
$500 - 1000\%$	High
$> 1000\%$	Very High

This classification provides an easier understanding and representation of the possible consequences (negative to moderate deviations are not considered as critical as moderate to high), and it makes it possible to evaluate the ideal settings that take place in each chosen range.

4.3.1.A Global Sensitivity Analysis

A global sensitivity analysis allows for a quantification of how each variable affects the model's outcome. This analysis is conducted in both models in order to find the most relevant variables in the model, and as a criteria for selecting the most appropriate ones to conduct local sensitivity analysis.

Figure 4.14 presents the global sensitivities S_{X_i} of the check BN model variables calculated through equation 3.11, when changing the evidence in the *Workload Deviation* from negative to low, low to moderate and moderate to high.

The aircraft's *Model* is the variable that evaluates how the deviations affect the A330 or the A340 individually. In the negative to low range of deviation this parameter presents a higher global sensitivity

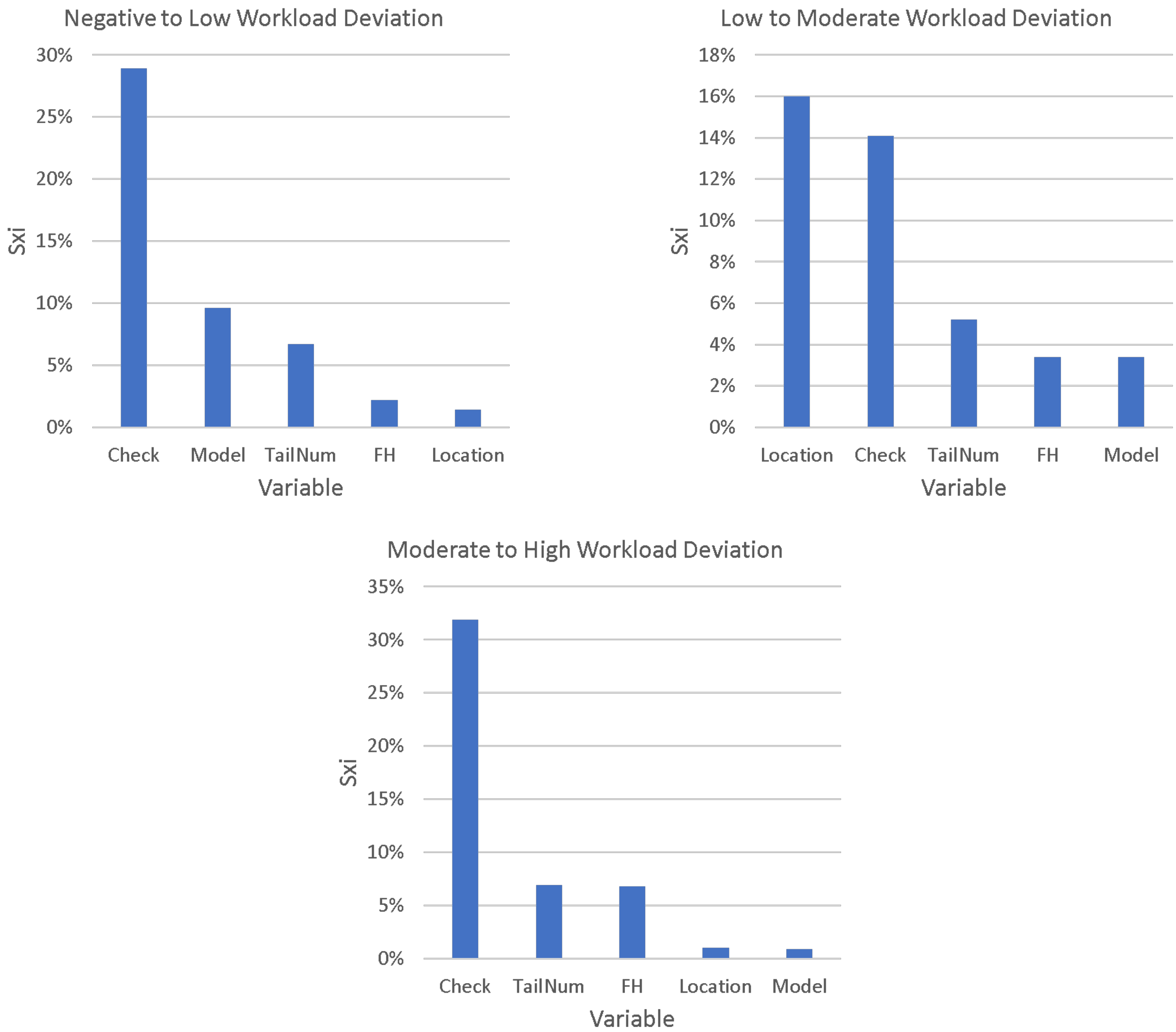


Figure 4.14: Global sensitivities S_{x_i} of check model variables when the check workload deviation changes from negative to low, low to moderate and moderate to high.

value, which means that for this category, both models behave differently, but for classes of larger deviations they show a similar pattern (this is suggested by the low sensitivity that this parameter presents for the higher ranges). This result is corroborated by the statistics of Tables 4.3 and 4.4 in section 4.2: given the fact that for the Airbus A330 the average total workload deviation of a 4A check would fall within the low: $0 - 100\%$ category (with a value of $13,8\%$), while on the other hand, for the A340 it would belong in the moderate: $100 - 500\%$ range (with a value of $165,4\%$), it only makes sense that both aircraft behave differently when the output category is a negative to low workload deviation. As it was discussed in section 4.2, for 1A and 2A items the two aircraft present averages that belong in similar categories of deviation. Although the aforementioned tables only gather information with respect to computed averages, the model takes into account the whole dataset.

It is quite evident that the variable with a consistently strong impact on the total workload deviation is the *Check* being performed. This finding makes sense due to the fact that different checks require different sets of tasks, thus the type of workload is the most relevant variable in the model.

The *Location* proves to be a somewhat relevant input when assessing low to moderate deviations. This is a parameter that definitely requires further investigation (namely, a local sensitivity analysis) in order to figure out if this global sensitivity is more reactive to the evidence being on the line or base maintenance station.

The influence of the parameter *Tail Number* is approximately constant throughout the classes provided it is only a measure of how wide the sample was with respect to different aircraft. The fact that its sensitivity is not very high indicates that most aircraft (within their model) present a similar behavior.

Regarding the aircraft's age, the *FH* appears to gain impact as the workload deviations increase, which favors the initial idea that could not be corroborated by Figures 4.2 to 4.7 from the previous section (due to the graphs not taking all variables into account): that delays can in fact be potentiated by the aircraft's usage parameter.

Figure 4.15 presents the results of the global sensitivities S_{X_i} of the task BN model variables calculated with equation 3.11, when changing the evidence in the *Workload Deviation* from negative to low, low to moderate, moderate to high, and finally, from high to very high. Note that the *Task* variable refers to the Task Code.

Analysing these graphs and beginning with the *Model* variable, its influence is consistently low throughout the deviation classes (indicating that both models behave similarly) except for the last one: when registered workload deviations are high to very high, the two aircraft models present a different pattern. This is corroborated by the evidence from Tables 4.3 and 4.4 in section 4.2. For example, a 2A item for the A330 presents an average per task workload deviation of $490,9\%$, categorizing this as a moderate deviation, while the same item for the A340 averages a $585,1\%$ of deviation per task, which belongs to the superior category of high deviation.

The reason for why the *Check* variable presents an inconstant pattern of impact has to do with the high dispersedness of the data visible in Figures 4.2 to 4.7. Because this BN model is focused on all the tasks and not on checks as packages, this is not a very important parameter.

The *Zone* where the maintenance work is being performed is undoubtedly one of the most important parameters (and this is confirmed by the Figures), as some zones require the technician to be more careful and thorough than others (one can suppose that engine maintenance tasks will be the case), meaning tasks in these zones are more prone to delays.

Although not as perceptible as the zone, the required *Skill* also has a relevant impact on the output of the model. This is another variable that demands a local sensitivity analysis, in order to identify which states potentiate this contribution.

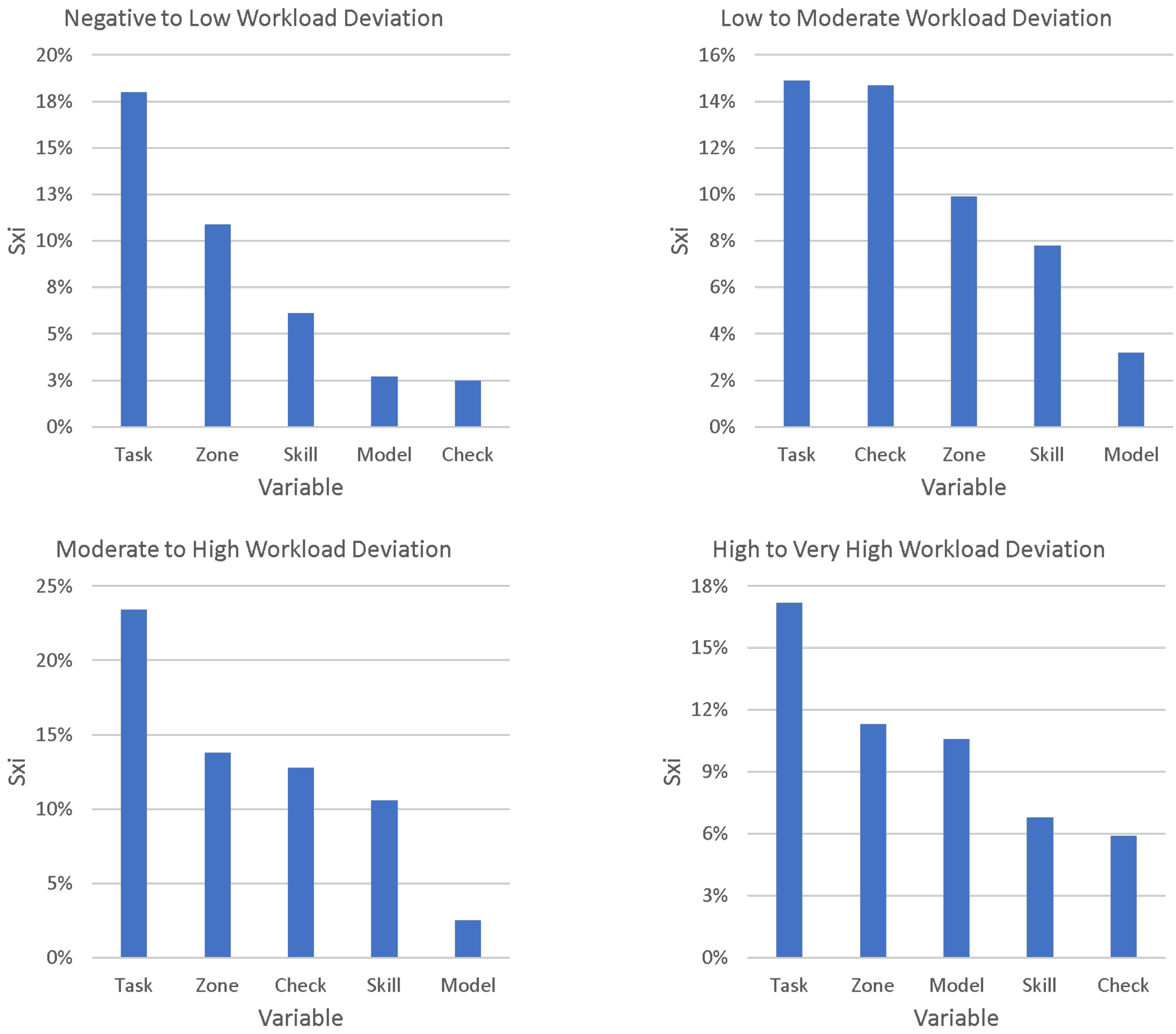


Figure 4.15: Global sensitivities S_{x_i} of task model variables when the task workload deviation changes from negative to low, low to moderate, moderate to high and high to very high.

At last, the most dominant parameter in the model is the *Task* code. Since the task code classifies the type of work that must be done, it is more than acceptable that this is the input with the largest influence on the task's workload deviation.

4.3.1.B Local Sensitivity Analysis

The local sensitivity analysis allows for a quantitative understanding, on a deeper level, of how each variable's state influences the model outcome. A few variables are considered in this analysis, and it is performed for each class of deviation and for every state of the chosen variables.

Regarding the check BN model, the parameters chosen to perform a local sensitivity analysis are the *Check* and *Location*, which are the ones that the Check *Workload Deviation* proved to be more sensitive to.

Figure 4.16 represents the posterior probability distribution of the *Check* variable for the negative, low, moderate and high ranges of check workload deviation $P(X_{i,j=1,\dots,m_i}|WL\_Dev)$ along with the graphical representation of the state sensitivities for the variable.

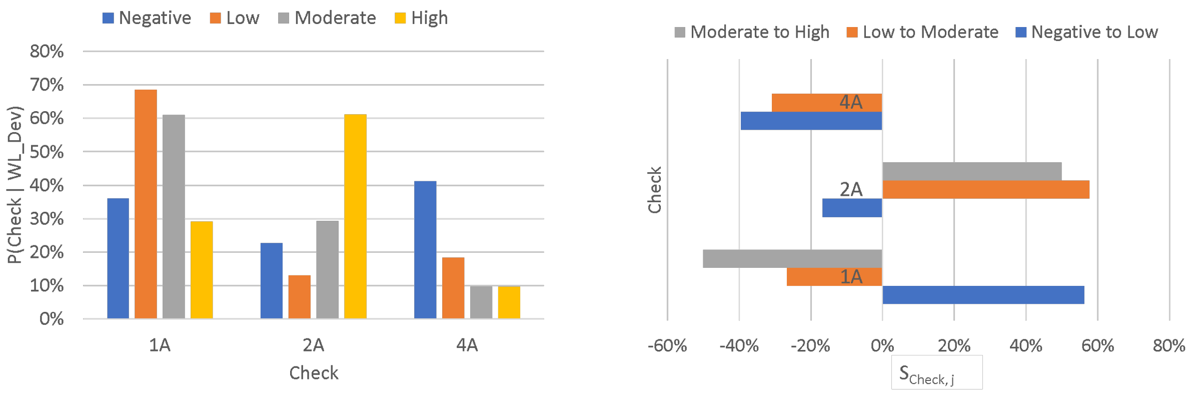


Figure 4.16: Posterior probability distribution of the *Check* variable given negative, low, moderate and high check workload deviations (left); State sensitivities $S_{x_{i,j}}$ of the *Check* variable (right).

From observation of the Figure, one can conclude that 1A are not very critical items and present the highest contributions to the negative to low ranges of deviation – these are checks with a lot of trivial tasks evened out by only some thorough tasks. The Figures confirm that 2A items have the highest weight when assessing moderate and high deviations, and a negative contribution on the negative to low range – this check is undoubtedly the most critical one in terms of overtimes. The fact that 4A items present only negative or null (for the moderate to high category) sensitivities is in accordance with what the previous data analyses had been pointing out: that these tasks are the least prone to incur in duration discrepancies. In fact, the posterior probability distribution graph suggests that the most likely outcome for this item is a negative deviation in its completion.

Figure 4.17 represents the posterior probability distribution of the *Location* variable for all the ranges of check workload deviation along with the graphical representation of the variable's state sensitivities.

This analysis confirms that the maintenance base station (BRU) tends to be more prone to deviations of higher magnitude: note the positive sensitivity on the low to moderate and moderate to high states, while line stations (NO_BRU) show a positive sensitivity for the negative to low range of deviation. This finding is supported by the suggestion made in 3.4, that maintenance works at this base station are prone to incur in overtimes due to the high levels of simultaneous work done there.

Shifting the focus to the task BN model, the parameters submitted to a local sensitivity analysis are the ones that provided the largest impacts on the *Task Workload Deviation* upon performing the global sensitivity analysis: *Task* (Code), *Zone* and *Skill*.

Starting with the *Task*, Figure 4.18 presents its posterior probability distribution alongside the vari-

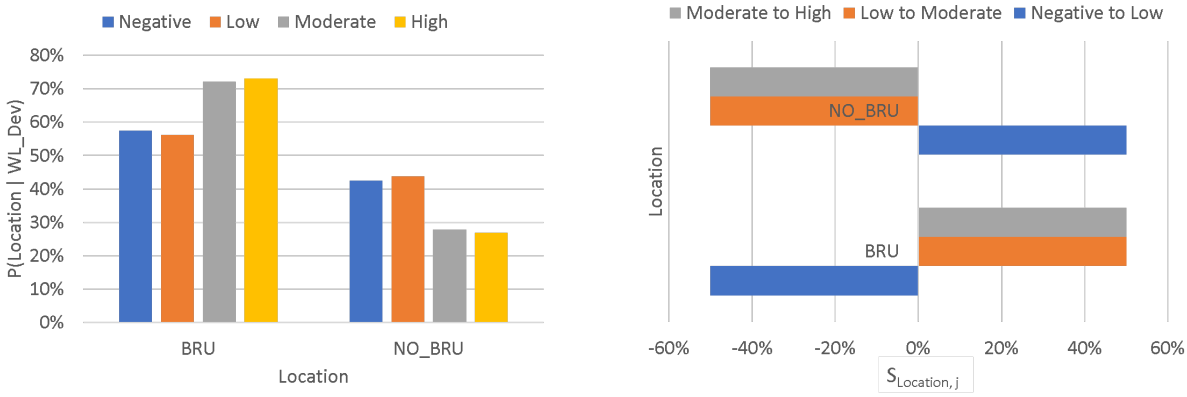


Figure 4.17: Posterior probability distribution of the *Location* variable given negative, low, moderate and high check workload deviations (left); State sensitivities $S_{x_{i,j}}$ of the *Location* variable (right).

able's state sensitivities.

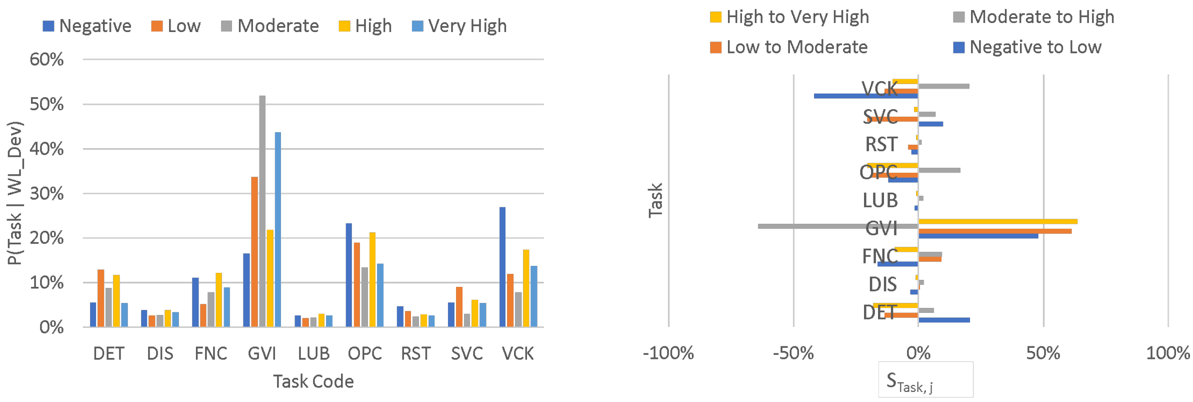


Figure 4.18: Posterior probability distribution of the *Task* (Code) variable given negative, low, moderate, high and very high task workload deviations (left); State sensitivities $S_{x_{i,j}}$ of the *Task* (Code) variable (right).

The hypothesis laid out in 1.5 defending that Lubrication (LUB) and Discard (DIS) tasks do not tend to vary much with respect to their suggested workloads is corroborated by the data – these two states, along with Restoration (RST) present nearly negligible sensitivities, which indicates that in general the workloads for these types of task agree with their respective predicted values.

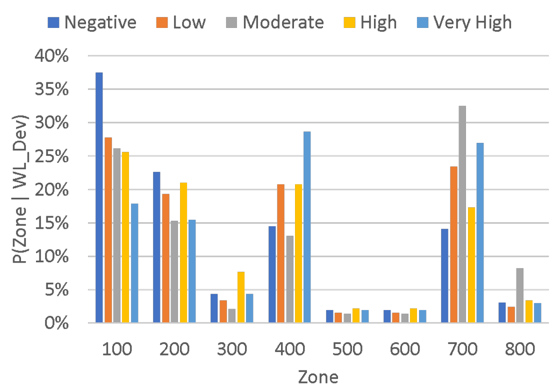
Servicing (SVC), Functional Check (FNC) and Detailed Inspection (DET) are also not very critical states – these tasks have the purpose of maintaining inherent design capabilities or determining if an item performs within specified limits, and because inspections have such low intervals it is not often for the components to require extra work that might cause a surge in overtime.

An Operational Check (OPC) consists of operating the aircraft to make sure all systems function accordingly – this task can be delayed because although each system has its own function, said function is not independent from other systems of the aircraft, hence the strong sensitivity of this state on the moderate to high class.

On the other hand, the General Visual Inspection (GVI) state is undoubtedly the one that presents the greatest impacts on all classes of deviation, except for moderate to high – as it can be seen on the posterior probability distribution graph, although the probability of performing a GVI with a high deviation is still higher than for the rest of the states (more than 20%), this range covers most of the Task Code possible states in an almost uniform manner, while other ranges are more focused on specific states.

GVI tasks are supposed to be performed at a maximum of an arm's length of distance when examining the components, which means that the inspection can be rather quick if the component is visible (which explains the low deviations) or very long if the component requires the opening (and closing) of some areas to get to it – hence the strong sensitivity registered on the high to very high deviations.

Now moving on to the *Zone*, Figure 4.19 shows the posterior probability distribution alongside the variable's state sensitivities.



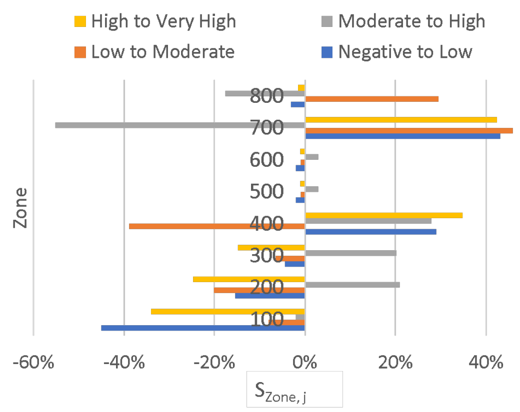


Figure 4.19: Posterior probability distribution of the *Zone* variable given negative, low, moderate, high and very high task workload deviations (left); State sensitivities $S_{x_{i,j}}$ of the *Zone* variable (right).

The maintenance zones that present the largest impacts on the highest class of discrepancy (High to Very High) are 400 – Nacelle/Pylons, and 700 – Landing Gear Compartment. This is definitely an expected result, as the engines and landing gears require the technicians to be more thorough with their work in these zones due to their fundamental role in the aircraft. The engines are crucial elements of an aircraft, and the landing gears are components that get worn off between cycles, unlike many other aircraft zones that require a less detailed inspection.

The Figure suggests that zones 500 and 600 present equal behavior in the model, which is explained by the fact that these zones are the left and right wings, respectively, and that the impact of these states is practically negligible in the model.

Zone 100, the lower part of the aircraft's fuselage, has a higher probability of presenting a negative workload deviation rather than low, and this likelihood reduces throughout the output states (as shown in the posterior probability distribution Figure). This explains why all the variable's state sensitivities are negative – maintenance tasks in this zone should not be very critical.

Zone 800, the vehicle's doors, presents a high state sensitivity in the low to moderate range, which is acceptable because inspections in this zone do not require the same level of detail as, per example, zones 200 and 300 (Fuselage Top and Stabilizers/Empennage, respectively) that are settled in the moderate to high category, meaning they might be prone to deviations (although still not as intensely as zones 400 and 700). This has to do with the fact that doors do not suffer from tearing or wear off between cycles as much as the remaining zones.

The same procedures are applied to the *Skill* variable, and the results are presented in Figure 4.20.

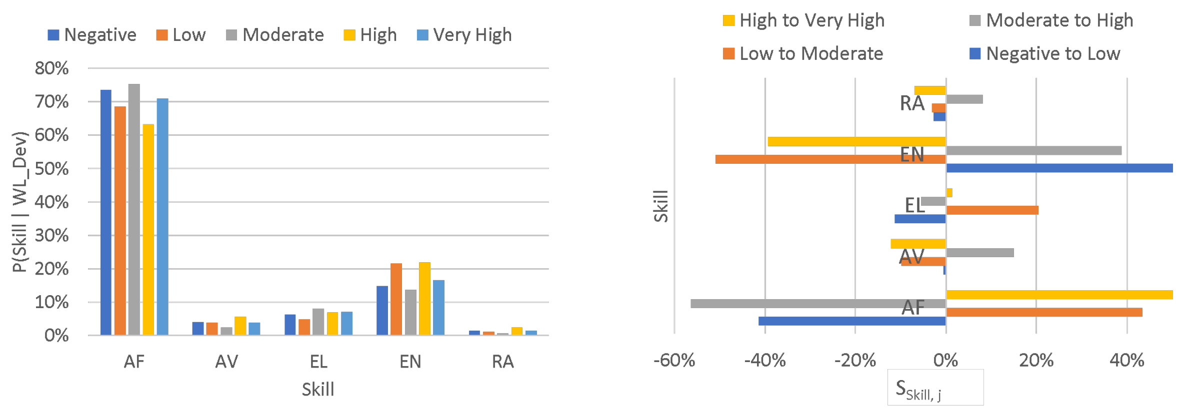


Figure 4.20: Posterior probability distribution of the *Skill* variable given negative, low, moderate, high and very high task workload deviations (left); State sensitivities $S_{x_{i},j}$ of the *Skill* variable (right).

Without a doubt, the Airframe (AF) and Powerplant (EN) are the most relevant skills. This is an expected result, as AF skills comprise flaps/slats and landing gear, and EN skills include engines and Auxiliary Power Unit (APU) accessories (which is in line with the results obtained for the zones).

Because Radio (RA) skills are only required in 4A items, and seeing as these items present the lowest workload deviations in the model, it makes sense that the influence of this state is practically negligible.

The term Electrical (EL) refers to electrical generation and distribution and Instrument (AV) represents the autopilot, instruments, digital equipment and fire protection. These skills are mainly found in 1A items, which have proved not to be highly susceptible to deviations (in comparison with 2A) – hence the seemingly uniform distribution of the posterior probabilities and sensitivities of these variables.

4.4 Application Examples – Capacity Planning

The examples provided below serve the purpose of demonstrating the practical benefits of applying BNs to aircraft maintenance capacity planning. As Dinis et al. [10] state, capacity planning balances the expected workload with the available manpower, thus being responsible for the management of uncertainty between the tactical and operational decision levels. These examples are based on the average workloads calculated from past maintenance checks of the same types as the ones being simulated.

4.4.1 Example 1 - Check BN

The maintenance services provider receives a request to perform an intervention at its maintenance base station, specifically a $2A$ check, on an Airbus A330 (tail number CS-TFZ) with $70\,000$ FH, for which the MPD predicts a total required workload of 3 M/H.

As presented in Figure 4.21, by instantiating the aforementioned states for each variable on the check BN, the operator gains knowledge on the probabilities of incurring in each of the states of workload deviation, as represented in Table 4.8.

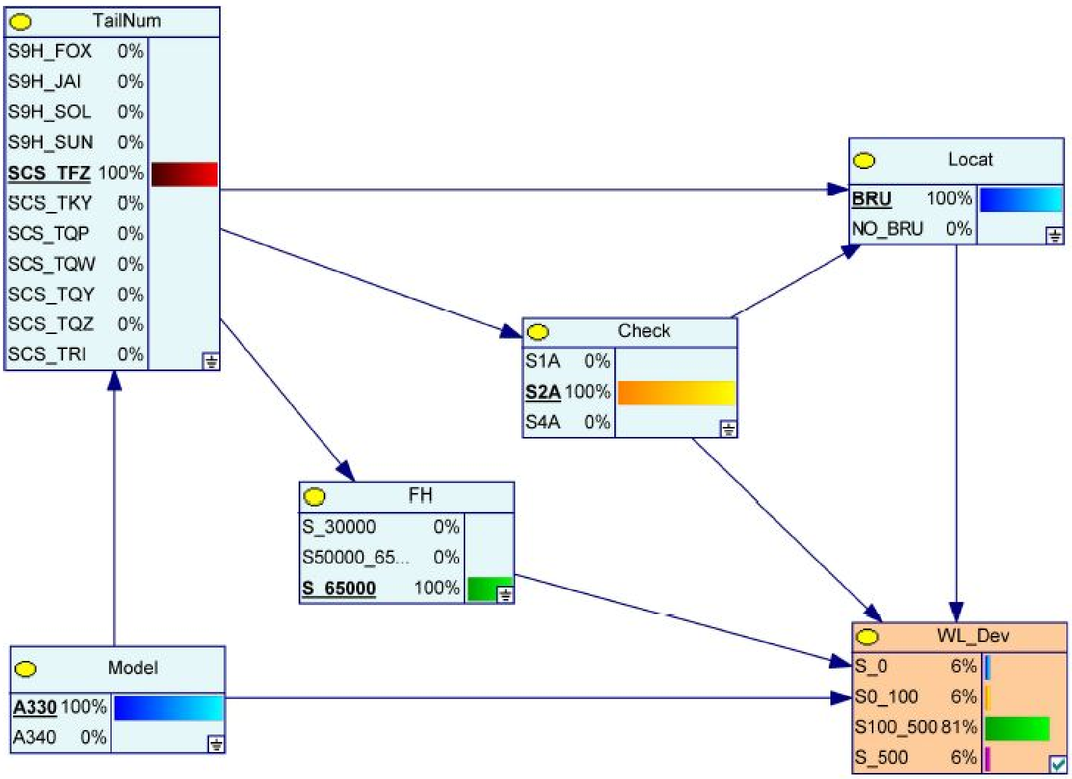


Figure 4.21: Capacity planning example 1.

Table 4.8: Probabilities of example 1 workload deviations.

Workload Deviation	Resulting Workload [M/H]	Probability	Cumulative Probability
$<$0%	$[0, 3]$	6,25%	6,25%
0-100%	$]3, 6]$	6,25%	12,50%
100-500%	$]6, 18]$	81,25%	93,75%
$>$500%	$]18, +\infty)$	6,25%	100,00%

Based on the distribution of the workload deviation probabilities, there is a probability of $81,25\%$ that the check will be delayed $100-500\%$, which corresponds to a required workload in the $]6,18]$ M/H range, and a probability of $6,25\%$ of the required workload surpassing the 18 M/H, a deviation of $>500\%$.

It is important to refer that the definition of these variables, in terms of possible states, can be increased for broader samples.

4.4.2 Example 2 - Tasks BN

The maintenance services provider is planning the $2A$ check from the previous example, in the Airbus A330, and desires to gain knowledge on the distribution of workload deviations regarding the required skills, in order to allocate the technicians and plan their schedules accordingly (at a maintenance base, technicians are differentiated by teams of skills).

Table 4.9 presents the distribution of skills per check.

Table 4.9: Skills distribution per check.

Check \ Skill	AF	AV	EL	EN	RA
1A	82,70%	2,97%	2,97%	11,08%	0,28%
2A	46,49%	3,24%	11,35%	35,68%	3,24%
4A	76,25%	7,50%	13,75%	1,25%	1,25%

From the BN model it is also possible to build Table 4.10 with the probabilities of occurrence of each class of workload deviation for each skill in A330 $2A$ checks. Although Figure 4.22 only presents one case, with the toggling of the AF state, it is required to instantiate each skill separately and register the posterior probability distribution for the classes of workload deviation, keeping the other known states for the other variables toggled (A330 model and $2A$ check).

In practical terms, when the operator computes the predicted M/H for the group of tasks of a certain skill in the check to allocate the manpower to the available teams, the BN model presents the probabilities for each class of deviation for this value (regardless of the states of the other variables).

Table 4.10: Skills workload deviations in A330 2A checks.

WL_Dev / Skill	<0%	0-100%	100-500%	>500%
AF	18,86%	16,42%	30,47%	34,25%
AV	20,00%	30,00%	25,00%	25,00%
EL	11,51%	11,51%	53,96%	23,02%
EN	12,61%	49,56%	12,61%	25,22%
RA	15,70%	15,70%	15,70%	52,90%

As the table lists, for this example the most critical skill would be RA, due to the fact that it registers the highest probability of presenting a high workload deviation $P(WL\_Dev{>}500\%) = 52,90\%$.

Note that the last two classes of workload deviation (High, $500 - 1000\%$ and Very High, $>1000\%$) are grouped in the $>500\%$ range for the sake of evaluation simplicity in this example.

On the other hand, if the check being performed were a $1A$ instead, following the same procedure and maintaining all the other variables unchanged, the BN model from figure 4.23 with the evidence on the $1A$ check state delivers the results presented in Table 4.11.

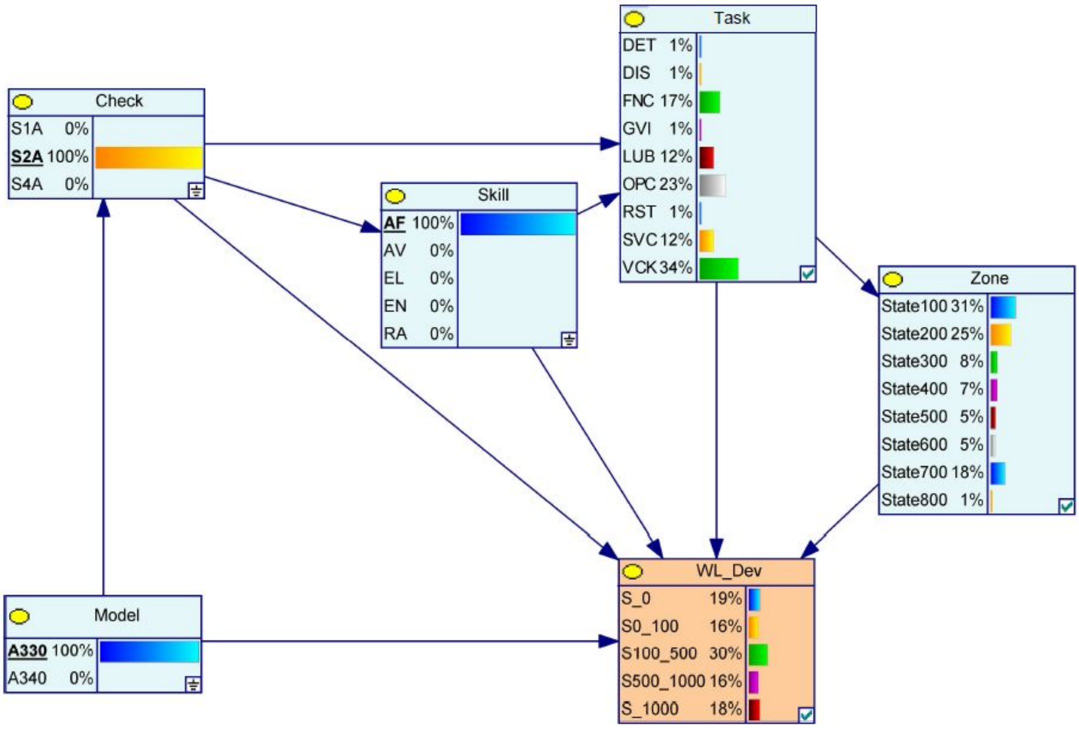


Figure 4.22: Capacity planning example 2.1.

Table 4.11: Skills workload deviations in A330 1A checks.

Skill \ WL_Dev	<0%	0-100%	100-500%	>500%
AF	13,07%	13,00%	44,96%	28,97%
AV	12,74%	30,89%	12,74%	43,46%
EL	14,25%	14,25%	43,00%	28,50%
EN	12,61%	49,56%	12,61%	25,22%
RA	25,00%	25,00%	25,00%	25,00%

As it can be seen, for this check the critical skill would be AV, because it registers a probability of $P(WL\_Dev{>}500\%) = 43,46\%$ of presenting a high workload deviation. Note that for this case the even distribution of the RA skill comes from the skill's low representation in $1A$ checks (as Table 4.9 presents, only $0,28\%$).

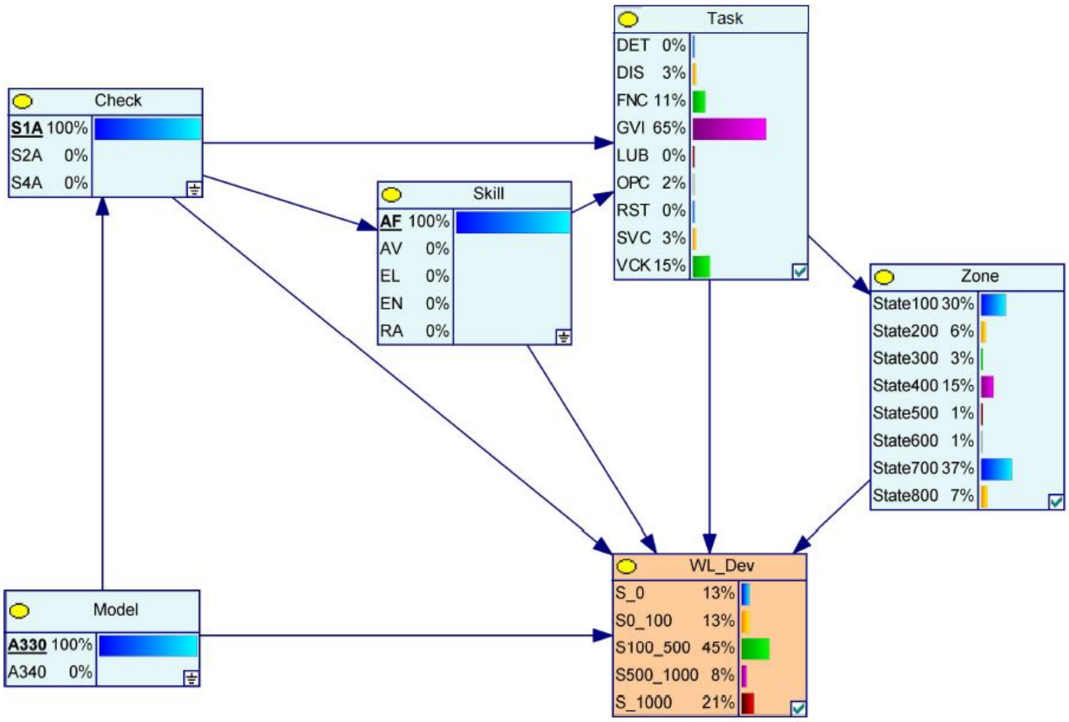


Figure 4.23: Capacity planning example 2.2.

5

Conclusions

Contents

For a leading wet lease specialist and charter airline, it is fundamental that time deviations are estimated, given that they can result in possible losses of clients and increases in financial costs.

The goal of this thesis is to find out if the predictions for the workloads of light periodic maintenance tasks in the aircraft's MPD are in line with those observed in practice. It is also intended to get an understanding of what variables are relevant for predicting workload deviations in maintenance checks, due to the high uncertainty on the maintenance reports.

For this, a framework able to analyze a problem of probabilistic nature – workload deviations in light maintenance checks – and reduce the level of uncertainty on the workload predictions is developed.

Data on maintenance light inspections (A-checks) from an EASA certified Part 145 is gathered and several variables taking part in the checks are grouped, with the main objective of evaluating how they influenced the overload, in M/H, to complete the checks' tasks, and how that time deviates from the value suggested in the aircraft's MPD.

In order to assess the variables and their importance in the workload deviations, two Bayesian networks are developed: one for analyzing checks as a whole, and one for treating more specific data about tasks.

The validation of the models is made through global and local sensitivity analyses, that aim respectively at identifying which parameters are of greater importance, and which of their states provide the greatest changes in the outputs.

Two practical examples of the application of the developed BN models are also presented to demonstrate their benefits for maintenance capacity planning – on the one hand, the check BN allows for estimating the check's workload while on the other hand, the tasks BN allows for allocating teams and scheduling shifts accordingly.

Bayesian networks prove to be a useful tool for addressing this problem, and their ability of updating the network as new knowledge becomes available makes it possible for the model to be improved as new data is observed (i.e. as more aircraft undergo maintenance inspections).

5.1 Conclusions

With respect to question 1 [*To what extent does the MPD provide reliable predictions for the tasks' workload?*], it can be concluded that for this specific maintenance operator the MPD manpower recommendations fail to deliver precise values, in M/H, for most of the reported tasks, with discrepancies that have a non-negligible order of magnitude. For the Airbus A330 and A340, respectively, tasks performed in 1A checks present average deviations of $412,6\%$ and $327,2\%$, tasks from 2A checks present average deviations of $490,9\%$ and $585,1\%$, and for 4A checks the average task deviations are of $102,8\%$ and $323,5\%$.

In regard to question 2 [*Does the age of the aircraft have a direct impact on the deviations of light periodic inspections?*], if the only parameter being considered is the aircraft's FH, a linear correlation cannot imply that workload deviations show an increasing trend as function of the usage parameter. However, the BN model shows that when taking into account more variables from the dataset, the aircraft's age gains influence as the observed deviations tend to higher classes, thus proving that there is a relationship between the age of the aircraft and the likelihood to require longer light maintenance inspections.

Concerning question 3 [*Which other factors can be considered to have an impact on the observed deviations?*], which is considered the main driver of the research, it is assessed through Bayesian network models. Overall, the item of check being performed has a decisive role over the check's workload deviation, with 2A items presenting the higher probabilities of being severely delayed, and on the opposite end, with 4A items registering high probabilities of taking less time than expected to be completed. Still under the check's workload deviation umbrella, inspections performed at the maintenance base (in Brussels) have a higher tendency of taking longer than those performed at line stations, due to the possibility of the base being overflowed in terms of workload, requiring longer waiting times for the arrival of units or spare parts. Shifting to the factors that affect the duration of individual tasks, the task code is predominantly the one of greater importance, with the *General Visual Inspection* state presenting the higher state sensitivities for most ranges of delay. Regarding the maintenance zone, nacelle/pylons and the landing gear compartment (zones 400 and 700, respectively) prove to be the ones that require more thorough work, being accountable for the data in the high to very high category of task workload deviations. At last, assessing the required skills, negative to low and moderate to high workload deviations are sensitive to the *Powerplant* state that stands for engines and Auxiliary Power Unit accessories, while the low to moderate and high to very high ranges are vulnerable to the *Airframe* skill, that includes the landing gears. Engines and landing gears are components that can get very worn off between checks, hence requiring longer inspections to ensure the equipment is working accordingly.

5.2 Suggestions

Senturk et. al [54] explain that although operators are interested in increasing aircraft utilization, they must always meet the regulatory requirements for safety and reliability reasons, which is why the only changes that can actually be done are regarding the *philosophy* of performing maintenance.

Attending to this train of thought, some recommendations that could potentially improve the process of aircraft maintenance are laid out.

The use of the proposed BN models could be implemented in the maintenance planning process by the maintenance services provider whose data was analyzed – compared to the traditional estimation methods, the proposed BNs weigh in information about the skill, task and zone codes, as well as FH, location and tail number, which increases the accuracy of the workload estimations, as corroborated by Dinis [108]. This would reduce the common practice by EASA Part 145 and MROs to overplan the total required workloads as a means of overcoming the uncertainty of estimations.

Concerning the actual execution of the task, and following what is suggested by Drury et al. [71] (and discussed in chapter 2), a digital platform could be implemented such that technicians could sign in/out of tasks and fill out workcards in an electronic device. This would eliminate the need for paper and enhance the accuracy of the registering of the actual tasks' lengths (reducing the influence of human factors in the registration of the actual workloads), which could contribute to an improvement of the company's reliability levels if further studies were to be made using data of such sort. However, because the aviation safety standards must be met, all technologies shall be certified according to the regulations, and on that account it might take a while before electronic devices play a relevant role in accelerating maintenance inspections.

5.3 Limitations and Future Work

It becomes now relevant to outline a few aspects that might have had a negative contribution on the conducted research.

Foremost, it is not feasible to quantify the direct impact of human factors on the generated results; thus, it is possible that some of the reported workloads (in M/H) of the performed tasks might not be accurate, which is external to the process of data filtering (due to the impossibility of assessing which workloads are exact and which are not). A lot of the work done in line stations only accounts for the execution of the task while the work performed at maintenance bases accounts for the preparation of the task as well, which can originate discrepancies in the registrations. Still regarding human factors, it is impractical to evaluate the extent of experience of each technician, namely regarding expertise, technical knowledge, professional background or even the level of acquaintance and familiarity with the general operating methods of the company.

Moving on to the used data, the available M/H (in terms of manpower) are not considered as an input for the sensitivity analysis, because the information is not available. On the report of the studied airline's Maintenance & Engineering Director, maintenance checks are planned according to the available M/H, available tools and equipment, and the check's size.

Another possible limitation of the research arises from the discretization methods applied to some of the network's variables. Borsuk [107] defends that discretizing variables that are inherently continuous might introduce a degree of imprecision into the model that would otherwise not exist. Hänninen [83] states that maintaining a relatively high number of probability parameters in a rather simple model can be a drawback on a BN, which is why the discretization was an essential step for the conceptualization of the network.

In the future, it would be extremely relevant to perform a similar study on the financial aspects, to investigate the economical consequences of workload deviations to maintenance companies (in regards to loss of revenue due to extra ground times or even risk analysis of possible losses of clients).

A project focused on the airline's maintenance base capacity planning would also be important, because it could allow for a reduction of the delays that light inspections tend to incur.

Because the evaluation of workload deviations with aircraft age and utilization is conducted with respect to either the entire check or the average task, it is not possible to infer which tasks are affected by the increasing of this parameter. It would be interesting to study in a future work the influence of the aircraft age at the task level. This would provide insight on some disadvantages of maintaining an ageing fleet.

As Saltelli [104] states, what makes modelling and scientific inquiry in general so painful is uncertainty. Uncertainty is not an accident of the scientific method, but its substance.

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A

Technical Documents

AIRBUS A330 **MAINTENANCE PLANNING DOCUMENT**

TASK NUMBER	ZONE	DESCRIPTION	[illegible]	SOURCE	REFERENCE	MEN	M/H	APPLICABILITY
323100-03-1		* * * * * C O N T I N U E * * * * * VALVE. PREP.: APU RUNNING;			32.30.00/11	 *	 0.60	
323300-03-1	700	FREE FALL EXTENSION AF OPC OPERATIONAL CHECK OF LANDING GEAR FREE-FALL SYSTEM.	I: 3400 FH	CMR* MRB 8	323300-710-809 CMR REFERENCE: 323000-00001-1-C MRB REFERENCE: 32.30.00/08	2	1.20	ALL
323300-04-1	700	FREE FALL EXTENSION AF FNC FUNCTIONAL CHECK OF LANDING GEAR FREE-FALL EXTENSION. PREP.: AIRCRAFT JACKING;	I: 6 YE	MRB 8	323300-720-804 MRB REFERENCE: 32.11.00/14 32.21.00/09 32.30.00/12	1 *	0.76 2.50	ALL
324000-02-1	195	BRAKE ACCUMULATORS AF FNC FUNCTIONAL CHECK OF NITROGEN CHARGE PRESSURE ON ALTERNATE PARKING BRAKE ACCUMULATORS. ACCESS: 195BB	I: 1000 FH	MRB 9	324000-210-805 MRB REFERENCE: 32.40.00/06	1 *	0.10 0.01	ALL
324000-03-1	731 741	BRAKE ACCUMULATORS AF FNC FUNCTIONAL CHECK OF NORMAL AND ALTERNATE BRAKE RETURN ACCUMULATORS NITROGEN PRESSURES BY READING GAUGES.	I: 2000 FH	MRB 6,9	324000-210-804 MRB REFERENCE: 32.40.00/04	1 1	0.05 0.05	ALL
324000-04-1	210	BRAKES AND WHEELS AF OPC OPERATIONAL CHECK OF EMERGENCY BRAKE SHUT-OFF VALVE.	I: 4000 FH	CMP MRB 9	324400-710-802 CMP REFERENCE: 32-2-0000-001 MRB REFERENCE: 32.40.00/10	2	1.00	POST 46231 (32-3083)

SYSTEMS, APU AND POWER PLANT : LANDING GEAR REV. DATE: MAR 01/20 SECTION: 2-32 PAGE 6

Figure A.1: Page from the A330 MPD [12].

Hifly

Maintenance Schedule Check-list

CS-TFZ/016188

Check-list Revision 0 | **Workcards Issued By Schedule**

Maint Schedule Reference	Card	Trade/ Zone	Description	Completed Stamp	Check-List Index Number	NRC No(s)
216000-04-1	0139 1315	AF/200	COCKPIT & CABIN TEMP CONTROL		1	
216000-05-1	0140 1316	AF/200	COCKPIT & CABIN TEMP CONTROL		2	
255100-21-1	3282 13694	AF/100	LOWER DECK CARGO LOADING SYS		3	
255200-03-1	0215 7579	AF/100	LWR DECK FWD CARGO COMPARTMENT		4	
255300-03-1	0218 7580	AF/100	LWR DECK AFT CARGO COMPARTMENT		5	
262100-04-1	0237 1404	AV/200	ENGINE FIRE EXTINGUISHING		6	
2200-01-3	0244 9205	AV/200	APU FIRE EXTINGUISHING		7	
282200-07-4	0361 7582	AF/300	APU FUEL PUMP SYSTEM		8	
291000-07-1	0381 1536	AF/001	MAIN HYDRAULIC POWER		9	
321100-14-1-731	2774 13261	AF/700	MAIN GEAR LH		10	
321100-14-1-741	2908 12733	AF/700	MAIN GEAR RH		11	
324000-02-1	0469 1594	AF/100	BRAKE ACCUMULATORS		12	
324900-02-1	0481 10700	AF/001	TYRE PRESSURE SYSTEM		13	
325300-02-1	0484 1608	EL/001	STEERING ANGLE PROTECTION		14	
9100-03-1	0557 9202	EN/300	APU OIL SYSTEM		15	
499100-05-1	0558 9203	EN/300	APU OIL SYSTEM		16	
561000-01-1	0905 1704	AF/200	COCKPIT WINDOWS		17	
561200-HF-1	2336 4020	AF/200	COCKPIT SLIDING WINDOWS		18	
801100-R2-1-410	1283 10744	EN/400	(LH) PNEUMATIC STARTING		19	
801100-R2-1-420	1284 11169	EN/400	(RH) PNEUMATIC STARTING		20	
ZL-131-01-1	1299 1751	AF/100	FORWARD CARGO COMPARTMENT		21	
ZL-147-01-1-147	1307 3923	AF/100	(LH)MLG WELL & HYD COMPARTMENT		22	
ZL-147-01-1-148	1308 1759	AF/100	(RH)MLG WELL & HYD COMPARTMENT		23	

Figure A.2: A330 maintenance schedule check list.

Hifly

Maintenance Schedule Check-list

CS-TFZ/016188

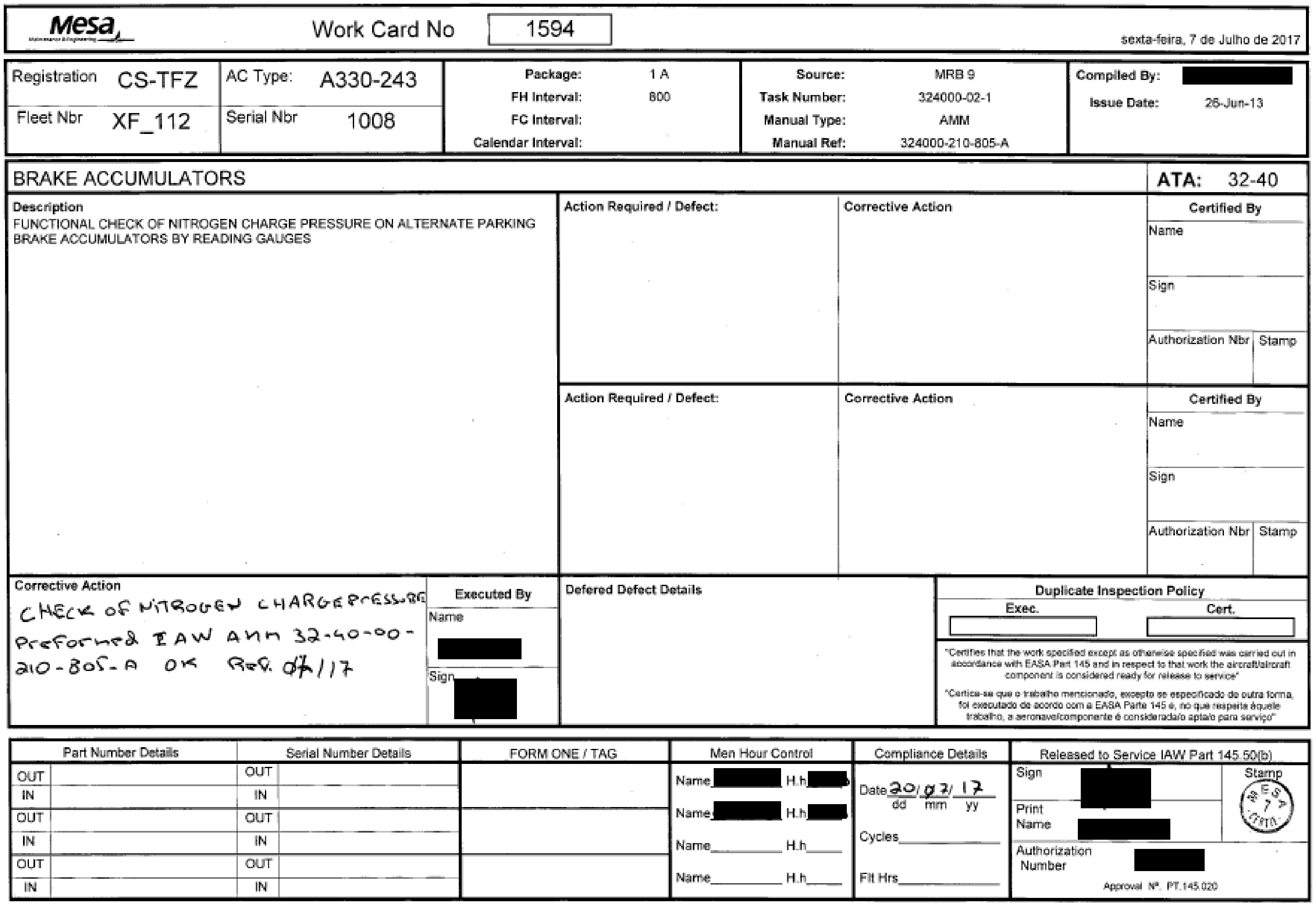
Check-list Revision 0

Workcards Issued By Schedule

Maint Schedule Reference	Card	Trade/ Zone	Description	Completed Stamp	Check-List Index Number	NRC No(s)
ZL-151-01-1	1310 1761	AF/100	AFT CARGO COMPARTMENT		24	
ZL-161-01-1	1315 1765	AF/100	BULK CARGO COMPARTMENT		25	
ZL-195-01-1	1325 1775	AF/100	HYD COMPARTMENT & FAIRINGS		26	
ZL-197-01-1	1327 1777	AF/100	REAR FAIRINGS		27	
ZL-400-01-1-410	1367 3924	AF/400	(LH) PWR PLANT,NACELLES&PYLONS		28	
ZL-400-01-1-420	1368 1817	AF/400	(RH) PWR PLANT,NACELLES&PYLONS		29	
-711-01-1	1399 1850	AF/700	NOSE LANDING GEAR		30	
ZL-713-01-1	1400 1851	AF/700	NOSE LANDING GEAR MAIN DOORS		31	
ZL-715-01-1	1401 1852	AF/700	NOSE LANDING GEAR AFT DOORS		32	
ZL-731-01-1-731	1402 3926	AF/700	(LH) MAIN LANDING GEAR		33	
ZL-731-01-1-741	1403 1853	AF/700	(RH) MAIN LANDING GEAR		34	
ZL-732-01-1-732	1404 3927	AF/700	(LH) MLG - LEG DOORS		35	
ZL-732-01-1-742	1405 1854	AF/700	(RH) MLG - LEG DOORS		36	
ZL-733-01-1-733	1406 3928	AF/700	(LH) MLG - HINGE DOOR		37	
-733-01-1-743	1407 1855	AF/700	(RH) MLG - HINGE DOOR		38	
ZL-734-01-1-734	1408 3929	AF/700	(LH) MLG MAIN DOOR		39	
ZL-734-01-1-744	1409 1856	AF/700	(RH) MLG MAIN DOOR		40	
ZL-821-01-1	1412 1859	AF/800	FORWARD CARGO COMPARTMENT DOOR		41	
ZL-822-01-1	1415 1862	AF/800	AFT CARGO COMPARTMENT DOOR		42	
ZL-823-01-1	1418 1865	AF/800	BULK CARGO COMPARTMENT DOOR		43	

Total of 43 Tasks

Figure A.3: A330 maintenance schedule check list (cont.).



Mesa

Work Card No 1594

sexta-feira, 7 de Julho de 2017

Registration CS-TFZ	AC Type: A330-243	Package:	1 A	Source:	MRB 9	Compiled By:	[redacted]
Fleet Nbr XF_112	Serial Nbr 1008	FH Interval:	800	Task Number:	324000-02-1	Issue Date:	26-Jun-13
		FC Interval:		Manual Type:	AMM		
		Calendar Interval:		Manual Ref:	324000-210-805-A		

BRAKE ACCUMULATORS

ATA: 32-40

Description
FUNCTIONAL CHECK OF NITROGEN CHARGE PRESSURE ON ALTERNATE PARKING BRAKE ACCUMULATORS BY READING GAUGES

Action Required / Defect:	Corrective Action	Certified By
		Name
		Sign
		Authorization Nbr | Stamp

Action Required / Defect:	Corrective Action	Certified By
		Name
		Sign
		Authorization Nbr | Stamp

Corrective Action
CHECK OF NITROGEN CHARGE PRESSURE PREFORMED IAW AMM 32-40-00-210-805-A OK REF. 07/17

Executed By
Name [redacted]
Sign [redacted]

Defered Defect Details

Duplicate Inspection Policy
Exec. Cert.

"Certifies that the work specified except as otherwise specified was carried out in accordance with EASA Part 145 and in respect to that work the aircraft/aircraft component is considered ready for release to service"

"Certica-se que o trabalho mencionado, excepto se especificado de outra forma, foi executado de acordo com a EASA Parte 145 e, no que respeita àquele trabalho, a aeronave/componente é considerada/o apta/o para serviço"

Part Number Details		Serial Number Details		FORM ONE / TAG	Men Hour Control	Compliance Details	Released to Service IAW Part 145.50(b)
OUT		OUT			Name [redacted] H.h [redacted]	Date 20/07/17 (dd mm yy)	Sign [redacted]
IN		IN					Stamp
OUT		OUT			Name [redacted] H.h [redacted]		Print Name [redacted]
IN		IN			Name___ H.h___	Cycles___	
OUT		OUT					Authorization Number [redacted]
IN		IN			Name___ H.h___	Flt Hrs___	Approval Nº. PT.145.020

Figure A.4: A330 Work Card #1594.

B

Technical Definitions

Table B.1: Task codes list.

Task Code	Definition
DET	Detailed inspection
DIS	Discard
FNC	Functional check/test
GVI	General visual inspection
LUB	Lubrication
OPC	Operational check/test
RST	Restoration
SDI	Special detailed inspection
SVC	Drain, servicing, replenishment
VCK	Visual check

Table B.2: Major zones list.

Zones	Description
100	Fuselage Lower
200	Fuselage Top
300	Stabilizers/Empennage
400	Nacelles-Pylons
500	Left Wing
600	Right Wing
700	Landing Gear Compartment
800	Doors
900	Lavatories & Galleys

Table B.3: Skill codes list.

Skill Code	Definition	Scope
AF	Airframe	Hydro-mechanical, environmental, fuel, oxygen, cargo systems.
AV	Instrument	Autopilot instruments, digital equipment and fire protection.
CA	Cabin Utility	Furnishing, galleys.
EL	Electrical	Electrical generation, distribution and associated services.
EN	Powerplant	Engines and APU accessories.
NDT	Non-Destructive Test	All non-destructive test and borescope inspections.
RA	Radio	Radio and radio navigation.
UT	Utility	Toilets water, wastewater.

C

Spreadsheets

Workcard #	Task #	ATA	Source	Zone	Interval	Task/Skill	Title	Description	Durat	Access	Total (MPD)	Technician	Durat(Wc)	Total(Wc)	DIF	%	Date	LOC
1315	216000-04-1	21-60			800FH	COOLING TEMPERA	F CABIN TEMPERATURE SENSORS					Tech A	2	2			28/01/2016	BRU
1316	216000-05-1	21-60	MRB 7	200	800FH	AF DIS	MPER/	PERATURE SEI	0,25	0	0,25	Tech A	1	1	0,75	300,0%	26/01/2016	
13694	255100-21-1	25-50	MRB 9	130, 150	1000FH	AF FNC	CARGC	F DOOR SILL A	1	0,2	1,2	Tech B	1	1	-0,2	-16,7%	27/01/2016	
7579	255200-03-1	25-50	MRB 9	130	800FH	AF VCK	ARD CA	F DRAINAGE S	1	0	1	Tech B	1	1	0	0,0%	27/01/2016	
7580	255300-03-1	25-50	MRB 9	150	1000FH	AF VCK	CARG	F DRAINAGE S	1	0	1	Tech B	1	1	0	0,0%	27/01/2016	
1404	262100-04-1	26-20	MRB 9	210	800FH	AV OPC	E EXTI	K OF FIRE EXT	0,05	0	0,05	Tech B	0,1	0,1	0,05	100,0%	26/01/2016	
9205	262200-01-3	26-20	MRB 9	210	800FH	AV OPC	EXTINI	K OF FIRE EXT	0,2	0	0,2	Tech B	0,1	0,1	-0,1	-50,0%	26/01/2016	
7582	282200-07-4	28-20	MRB 9	311	800FH	AF OPC	L PUMP	AIR SEPARAT	0,2	0,01	0,21	Tech B	1	1	0,79	376,2%	27/01/2016	
1536	291000-07-1	29-10	MRB 9	7, 197, 4	800FH	AF VCK	DRAUL	DRIVEN PUMPS	0,3	0,51	0,81	Tech C Tech D	0,5 1	1,5	0,69	85,2%	26/01/2016	
13261	321100-14-1-73	32	MRB 6	731	2000FH	AF GVI	GEAR LH	MLG BOGIE F	0,05	0	0,05	Tech H	0,1	0,1	0,05	100,0%	26/01/2016	
12733	321100-14-1-74	32	MRB 6	741	2000FH	AF GVI	GEAR RH	MLG BOGIE F	0,05	0	0,05	Tech H	0,16	0,16	0,11	220,0%	25/01/2016	
1594	324000-02-1	32-40	MRB 9	195	800FH	AF FNC	CCUMU	N ALTERNATE	0,1	0,01	0,11	Tech B	0,5	0,5	0,39	354,5%	26/01/2016	
10700	324900-02-1	32	MRB 9	10, 700	800FH	AF FNC	SSURI	TPIS AND TYRI	0,3	0	0,3	Tech B	0,5	0,5	0,2	66,7%	26/01/2016	
1608	325300-02-1	32-50	MRB 9	210, 710	800FH	EL OPC	NGLE F	COCKPIT ANI	0,2	0	0,2	Tech B	0,1	0,1	-0,1	-50,0%	26/01/2016	
9202	499100-03-1	49-90			800FH	APU OIL SY	OR DRAIN PLUG FOR DETECTION OF METALLI					Tech E	1	1			27/01/2016	
9203	499100-05-1	49-90			800FH	APU OIL SY	TER ELEMENT AND HOUSING FOR DETECTION					Tech E	2	2			27/01/2016	
1704	561000-01-1	56 10			800FH	COCKPIT WIN	F ALL COCKPIT WINDOWS FROM INSIDE					Tech F	0,5	0,5			26/01/2016	
4020	561200-HF-1	56 10			800FH	COCKPIT SLIDING	OF THE SLIDING WINDOWS					Tech F	0,5	0,5			26/01/2016	
10744	01100-R2-1-41	80	MRB 6,9	410	800FH	EN SVC	TIC ST	ECTION OF ST	0,5	0,1	0,6	Tech C Tech G Tech D	0,5 0,5 0,5	1,5	0,9	150,0%	27/01/2016	
11169	01100-R2-1-42	80	MRB 6,9	420	800FH	EN SVC	TIC ST	ECTION OF ST	0,5	0,1	0,6	Tech C Tech G	0,5 0,5	1	0,4	66,7%	27/01/2016	
1751	ZL-131-01-1	ZL100	MRB	131, 132	800FH	AF GVI	RGO C	ON OF FORWA	0,4	0,1	0,5	Tech A	1	1	0,5	100,0%	28/01/2016	
3923	L-147-01-1-14	ZL100	MRB	147	800FH	AF GVI	YDRAU	ING GEARS W	0,1	0,15	0,25	Tech H	0,5	0,5	0,25	100,0%	26/01/2016	
1759	L-147-01-1-14	ZL100	MRB	148	800FH	AF GVI	YDRAU	ING GEARS W	0,1	0,15	0,25	Tech H	0,5	0,5	0,25	100,0%	26/01/2016	
1761	ZL-151-01-1	ZL100	MRB	151, 152	800FH	AF GVI	O COM	CTION OF AFT	0,4	0,1	0,5	Tech A	1	1	0,5	100,0%	27/01/2016	
1765	ZL-161-01-1	ZL100	MRB	161, 162	800FH	AF GVI	O CON	TION OF BULK	0,3	0,1	0,4	Tech A	1	1	0,6	150,0%	26/01/2016	
1775	ZL-195-01-1	ZL100	MRB	195, 196	800FH	AF GVI	ARTM	OF HYDRAULIC	0,2	0,3	0,5	Tech H	0,5	0,5	0	0,0%	26/01/2016	
1777	ZL-197-01-1	ZL100			800FH	REAR FAIR	PECTION OF REAR FAIRINGS (EWIS)					Tech H	0,25	0,25			26/01/2016	
3924	L-400-01-1-41	ZL400	MRB	400	800FH	AF GVI	, NACE	OF POWER PL	0,1	0	0,1	Tech I	2,5	2,5	2,4	2400,0%	28/01/2016	
1817	L-400-01-1-42	ZL400	MRB	400	800FH	AF GVI	, NACE	OF POWER PL	0,1	0	0,1	Tech I	2,5	2,5	2,4	2400,0%	28/01/2016	
1850	ZL-711-01-1	ZL700	MRB	711	800FH	AF GVI	ANDIN	CTION OF NOS	0,15	0,2	0,35	Tech H	0,5	0,5	0,15	42,9%	26/01/2016	
1851	ZL-713-01-1	ZL700	MRB	713, 714	800FH	AF GVI	G GEA	OF NOSE LANI	0,2	0,2	0,4	Tech H	0,25	0,25	-0,2	-37,5%	26/01/2016	
1852	ZL-715-01-1	ZL700	MRB	715, 716	800FH	AF GVI	G GEA	ON OF NOSE L	0,1	0	0,1	Tech H	0,25	0,25	0,15	150,0%	26/01/2016	
3926	L-731-01-1-73	ZL700	MRB	731	800FH	AF GVI	LANDI	SPECTION OF	0,25	0	0,25	Tech H	0,83	0,83	0,58	232,0%	26/01/2016	
1853	L-731-01-1-74	ZL700	MRB	741	800FH	AF GVI	LANDI	SPECTION OF	0,25	0	0,25	Tech H	0,83	0,83	0,58	232,0%	26/01/2016	
3927	L-732-01-1-73	ZL700	ted from MPD		800FH	MAIN LANDING GEA	ON OF MAIN LANDING GEAR - LEG DOORS					Tech H	0,25	0,25			26/01/2016	
1854	L-732-01-1-74	ZL700	ted from MPD		800FH	MAIN LANDING GEA	ON OF MAIN LANDING GEAR - LEG DOORS					Tech H	0,25	0,25			26/01/2016	
3928	L-733-01-1-73	ZL700	ted from MPD		800FH	MLG HINGE D	ION OF MAIN LANDING GEAR HINGE DOOR					Tech H	0,16	0,16			26/01/2016	
1855	L-733-01-1-74	ZL700	ted from MPD		800FH	MAIN LANDING GEA	ON OF MAIN LANDING GEAR - HINGE DOOR					Tech H	0,16	0,16			26/01/2016	
3929	L-734-01-1-73	ZL700	MRB	734	800FH	AF GVI	NG GE	ON OF MAIN L	0,1	0,15	0,25	Tech H	1	1	0,75	300,0%	26/01/2016	
1856	L-734-01-1-74	ZL700	MRB	744	800FH	AF GVI	NG GE	ON OF MAIN L	0,1	0,15	0,25	Tech H	0,25	0,25	0	0,0%	26/01/2016	
1859	ZL-821-01-1	ZL800	MRB	821	800FH	AF GVI	O COM	CK FITTINGS A	0,2	0,1	0,3	Tech A Tech J	1 1	2	1,7	566,7%	27/01/2016	
1862	ZL-822-01-1	ZL800	MRB	822	800FH	AF GVI	OMPA	FITTINGS AT D	0,2	0,1	0,3	Tech A Tech J	1 1	2	1,7	566,7%	27/01/2016	
1865	ZL-823-01-1	ZL800	MRB	823	800FH	AF GVI	COMPA	FITTINGS AT D	0,2	0,05	0,25	Tech A	1	2	1,75	700,0%	27/01/2016	

Figure C.1: Spreadsheets built for 1A items.

Workcard #	Task #	Skill	Task	ATA	Zone	#	MPD	AVG	MED	STD	DIF	DISP	Q1	Q3	IQ_R	LB	UB	AVG	STD	DIF	%
1316	216000-05-1	AF	DIS	1-60	200	37	0,25	1,19	1	0,72	0,94	3,2	0,6	1,5	0,9	-0,8	2,85	1,13	0,61	0,88	351%
13694	255100-21-1	AF	FNC	25	100	27	1,2	0,96	0,7	0,79	-0,2	2,8	0,5	1	0,5	-0,3	1,75	0,7	0,44	-0,5	-42%
7579	255200-03-1	AF	VCK	5-50	100	38	1	1,1	1	0,99	0,1	4,06	0,5	1	0,5	-0,3	1,75	0,74	0,33	-0,3	-26%
7580	255300-03-1	AF	VCK	5-50	100	38	1	0,99	0,77	1,27	-0	7,9	0,5	1	0,5	-0,3	1,75	0,69	0,34	-0,3	-31%
1404	262100-04-1	AV	OPC	5-20	200	38	0,05	0,52	0,4	0,42	0,47	1,9	0,25	0,88	0,63	-0,7	1,83	0,48	0,34	0,43	868%
9205	262200-01-3	AV	OPC	5-20	200	38	0,2	0,52	0,4	0,4	0,32	1,9	0,3	0,58	0,28	-0,1	0,99	0,36	0,17	0,16	80%
7582	282200-07-4	AF	OPC	3-20	300	38	0,21	0,78	0,6	0,5	0,57	1,9	0,5	1	0,5	-0,3	1,75	0,68	0,35	0,47	222%
1536	291000-07-1	AF	VCK	9-10	, 400	38	0,81	1	1	0,94	0,19	5,75	0,5	1	0,5	-0,3	1,75	0,81	0,36	-0	-1%
1537	291000-08-1	AF	SVC	9-10	100	23	0,4	0,69	0,6	0,34	0,29	1,46	0,5	1	0,5	-0,3	1,75	0,69	0,34	0,29	72%
13261/1349	321100-14-1-	AF	GVI	32	700	37	0,05	0,88	0,83	0,7	0,83	3,9	0,5	1	0,5	-0,3	1,75	0,73	0,38	0,68	1350%
12733/1349	321100-14-1-	AF	GVI	32	700	37	0,05	0,83	0,83	0,54	0,78	1,9	0,4	1	0,6	-0,5	1,9	0,73	0,43	0,68	1359%
1594	324000-02-1	AF	FNC	2-40	100	38	0,11	0,96	0,9	0,7	0,85	3,7	0,5	1	0,5	-0,3	1,75	0,74	0,3	0,63	576%
1751	ZL-131-01-1	AF	GVI	.100	100	38	0,5	1,42	1	1,27	0,92	5,8	0,7	2	1,3	-1,2	3,95	1,06	0,65	0,56	112%
3923	ZL-147-01-1-:	AF	GVI	.100	100	38	0,25	0,85	0,55	0,73	0,6	3,85	0,5	1	0,5	-0,3	1,75	0,66	0,36	0,41	164%
1759	ZL-147-01-1-:	AF	GVI	.100	100	38	0,25	0,88	0,55	0,74	0,63	3,85	0,5	1	0,5	-0,3	1,75	0,69	0,42	0,44	178%
1761	ZL-151-01-1	AF	GVI	.100	100	38	0,5	1,3	1	1,35	0,8	7,8	0,5	2	1,5	-1,8	4,25	1,12	0,77	0,62	124%
1765	ZL-161-01-1	AF	GVI	.100	100	38	0,4	1,06	1	0,76	0,66	2,9	0,5	1,43	0,93	-0,9	2,81	0,95	0,61	0,55	138%
1775	ZL-195-01-1	AF	GVI	.100	100	38	0,5	0,86	0,7	0,66	0,36	3,8	0,5	1	0,5	-0,3	1,75	0,74	0,35	0,24	48%
3924	ZL-400-01-1-	AF	GVI	.400	400	37	0,1	1,56	1	0,89	1,46	3,8	1	2	1	-0,5	3,5	1,41	0,82	1,31	1307%
1817	ZL-400-01-1-	AF	GVI	.400	400	38	0,1	1,81	2	1	1,71	3,9	1	2,24	1,24	-0,9	4,09	1,68	0,94	1,58	1579%
1850	ZL-711-01-1	AF	GVI	.700	700	38	0,35	0,94	0,83	0,5	0,59	1,7	0,5	1	0,5	-0,3	1,75	0,82	0,36	0,47	133%
1851	ZL-713-01-1	AF	GVI	.700	700	38	0,4	0,77	0,5	0,54	0,37	1,8	0,43	1	0,58	-0,4	1,86	0,66	0,41	0,26	66%
1852	ZL-715-01-1	AF	GVI	.700	700	38	0,1	0,57	0,5	0,37	0,47	1,84	0,3	0,77	0,47	-0,4	1,48	0,55	0,3	0,45	450%
3926	ZL-731-01-1-	AF	GVI	.700	700	37	0,25	1	0,83	0,76	0,75	3,9	0,5	1,5	1	-1	3	0,92	0,57	0,67	267%
1853	ZL-731-01-1-	AF	GVI	.700	700	37	0,25	1,03	0,83	0,99	0,78	5,9	0,5	1,2	0,7	-0,6	2,25	0,9	0,53	0,65	258%
3929	ZL-734-01-1-	AF	GVI	.700	700	38	0,25	0,7	0,6	0,37	0,45	1,8	0,5	1	0,5	-0,3	1,75	0,67	0,31	0,42	167%
1856	ZL-734-01-1-	AF	GVI	.700	700	38	0,25	0,75	0,55	0,47	0,5	1,8	0,5	0,96	0,46	-0,2	1,64	0,61	0,26	0,36	145%
1859	ZL-821-01-1	AF	GVI	.800	800	38	0,3	1,11	1	1,04	0,81	5,8	0,5	1,15	0,65	-0,5	2,13	0,92	0,55	0,62	208%
1862	ZL-822-01-1	AF	GVI	.800	800	38	0,3	1,13	1	1,08	0,83	5,8	0,5	1,2	0,7	-0,6	2,25	0,88	0,54	0,58	193%
1865	ZL-823-01-1	AF	GVI	.800	800	38	0,25	1,02	0,92	0,86	0,77	3,8	0,5	1	0,5	-0,3	1,75	0,7	0,34	0,45	181%
12218	493100-01-3	EN	VCK	49	300	11	0,18	0,8	1	0,52	0,62	1,8	0,4	1	0,6	-0,5	1,9	0,8	0,52	0,62	344%
10700	324900-02-1	AF	FNC	32	, 700	25	0,3	1,29	1	1,19	0,99	5,9	0,5	2	1,5	-1,8	4,25	1,09	0,68	0,79	264%
1608	325300-02-1	EL	OPC	2-50	. 700	31	0.2	0.57	0.4	0.48	0.37	1.9	0.2	1	0.8	-1	2.2	0.57	0.48	0.37	185%

Workcard #	FC 3813 FH 22895 13195	FC 3869 FH 23354 13673	FC 3975 FH 23998 15162	FC 4104 FH 24548 16188	FC 4177 FH 25258 16984	FC 4435 FH 26733 18678	FC 4492 FH 26961 19581	FC 14347 FH 52223 9303	FC 14697 FH 52869 10229	FC 14843 FH 53605 11931	FC 15032 FH 54261 13202	FC 15272 FH 55330 15451	FC 15375 FH 55815 16222	FC 15494 FH 56347 17058	FC 1563 FH 5707 1798
1316	0,3	1,16	0,5	1	0,5		1,1	2	1,25	1	1	1	0,75	1,5	0,
13694	0,2	0,6	0,5	0,4	1	0,5	0,7			0,5	0,5	1	0,3	1	0,
7579	0,5	0,6	1	1	1,2	1	0,4	2	0,83	0,5	1	1	0,3	1	0,
7580	0,5	0,6	0,5	1	1	1	0,7	2	0,83	0,5	0,5	1	0,3	1	0,
1404	1	0,26	0,5	0,5	0,1	0,5	0,2	1	0,83	0,4	2	0,25	0,3	0,16	0,
9205	0,36	0,16	0,5	1	0,1	0,5	0,4	2	0,5	0,4	0,32	0,25	0,5	0,5	0,
7582	0,3	1	0,5	0,3	0,3	0,75	1,5	2	0,25	0,4	1	1	1,5	0,2	0,8
1536	0,3	0,5	1	0,4	0,4	1	1	1	0,5	1	1	1	1	0,5	0,2
1537								1,66	0,5	0,4	1	0,5	1	0,8	0,2
13261/1349	0,3	1,33	0,5	0,3	1	1	1	0,83	0,5	0,3	2	1	1	1	0,
12733/1349	0,3	1,33	0,16	0,3	0,8	1	1,7	1	0,1	0,4	2	1	1	1	0,
1594	0,75	0,3	0,5	0,4	0,7	1	1	1	1	1	0,6	0,5	1	1	0,
1751	0,5	2	1	1	3	1	1	2	1	0,4	1	1	1	1	1,
3923	0,8	0,5	0,5	0,3	0,5	2	1	0,83	1	0,3	1	0,5	2	1	0,
1759	0,5	0,5	0,5	0,4	0,5	1	1,5	0,83	2	0,3	1	0,5	2	1	0,
1761	1	2	0,5	1	3	0,5	0,7	2	1	0,3	0,5	1	1	1	0,
1765	0,5	2	0,5	1	3,1	1	0,4	2	1	0,3	0,5	0,8	1	1	0,
1775	0,5	0,5	0,5	0,3	0,7	1	1	0,83	1	0,3	1	0,5	1	1	0,
3924	2,5	2	1	0,2	1	3,2	2,2	1	1	2	1	1	0,5	0,75	
1817	3,33	2	1	0,5	2	3,2	2,2	1	1	1	1	1	0,5	1	1,8
1850	0,5	1,66	0,5	0,3	2	1	1	0,83	1	0,3	1	0,5	2	1	0,
1851	0,5	1,66	0,5	0,3	2	1	0,6	1,66	0,5	0,2	1	0,5	2	1	0,
1852	0,2	1	0,5	0,3	0,5	1	0,6	0,83	0,5	0,2	1	0,5	1	1	0,
3926	0,5	1,66	0,5	0,1	2	1,5		0,83	2	0,4	1,5	0,5	1	1	0,
1853	0,7	1,66	0,5	0,1	2	1	1,5	0,83	2	0,4	1,5	0,5	1	1	0,
3929	0,3	0,75	0,5	0,3	1	1,5	1	0,83	1	0,2	1	0,5	1	1	0,
1856	0,5	0,75	0,5	0,3	0,7	1	2	0,83	1	0,2	0,5	0,5	1	1	0,
1859	0,5	1	1	0,4	3,1	1	0,4	1	0,5	0,2	0,5	0,5	1	1	1,
1862	0,2	1	0,5	0,4	3,1	0,5	0,7	1	0,5	0,2	0,5	0,5	1	1	1,
1865	0,2	1	0,5	0,4	3,1	1	0,7	1	0,5	0,2	0,5	0,3	1	1	0,
12218								1	1	1					
10700	1,83	0,1	0,5	0,3	2,2	2	0,6	2	1	1	2	1	1	2	0,7
1608	1	0.16	0.2	0.5	0.5	0.4	0.2	1	0.5	0.4	2	1	0.3	0.5	0.

Figure C.2: Spreadsheets built for 1A tasks.

D

Sensitivity Analyses

Output:		Model		TailNum											FH			Check			Locat	
Deviation per Check		A330	A340	9H-FOX	9H-JAI	9H-SOL	9H-SUN	CS-TFZ	CS-TKY	CS-TQP	CS-TQW	CS-TQY	CS-TQZ	CS-TRI	<30000	50000;65000	>65000	1A	2A	4A	BRU	NO_BRU
State nº	No Evidence	0,524	0,476	0,041	0,049	0,041	0,105	0,176	0,025	0,081	0,160	0,160	0,081	0,081	0,214	0,355	0,431	0,568	0,294	0,138	0,676	0,324
1	<0%	0,589	0,411	0,041	0,035	0,042	0,068	0,184	0,035	0,099	0,132	0,146	0,082	0,135	0,263	0,331	0,406	0,361	0,227	0,412	0,575	0,425
2	0;100%	0,492	0,508	0,045	0,043	0,048	0,090	0,177	0,047	0,087	0,126	0,181	0,100	0,055	0,241	0,331	0,428	0,686	0,130	0,184	0,561	0,439
3	100;500%	0,526	0,474	0,039	0,050	0,041	0,112	0,182	0,015	0,076	0,159	0,157	0,075	0,092	0,202	0,352	0,446	0,611	0,293	0,096	0,721	0,279
4	>500%	0,535	0,465	0,042	0,063	0,029	0,116	0,147	0,024	0,080	0,236	0,143	0,073	0,048	0,194	0,424	0,382	0,292	0,612	0,097	0,731	0,269
	ΔP 2→1	-0,096	0,096	0,003	0,008	0,006	0,022	-0,007	0,012	-0,012	-0,005	0,036	0,018	-0,080	-0,023	0,001	0,022	0,325	-0,097	-0,228	-0,014	0,014
	ΔP 3→2	0,034	-0,034	-0,005	0,006	-0,007	0,022	0,005	-0,032	-0,010	0,033	-0,024	-0,025	0,037	-0,039	0,020	0,018	-0,076	0,163	-0,087	0,160	-0,160
	ΔP 4→3	0,009	-0,009	0,003	0,013	-0,012	0,003	-0,035	0,009	0,004	0,076	-0,014	-0,002	-0,044	-0,008	0,072	-0,064	-0,319	0,318	0,000	0,010	-0,010
	S 2→1	9,6%		6,7%											2,2%			28,9%			1,4%	
	S 3→2	3,4%		5,2%											3,4%			14,1%			16,0%	
	S 4→3	0,9%		6,9%											6,8%			31,9%			1,0%	
	State S 2→1	-50,0%	50,0%	2,4%	5,9%	4,3%	16,4%	-5,3%	9,1%	-9,3%	-4,0%	26,6%	13,5%	-59,7%	-50,8%	1,7%	49,1%	56,2%	-16,8%	-39,5%	-50,0%	50,0%
	State S 3→2	50,0%	-50,0%	-4,9%	6,2%	-7,0%	21,2%	4,6%	-30,7%	-10,0%	31,6%	-23,1%	-23,6%	35,9%	-57,7%	30,5%	27,2%	-26,7%	57,7%	-30,9%	50,0%	-50,0%
	State S 4→3	50,0%	-50,0%	2,1%	9,4%	-8,7%	2,4%	-25,0%	6,2%	2,5%	55,0%	-10,3%	-1,8%	-31,9%	-6,0%	52,7%	-46,7%	-50,0%	50,0%	0,0%	50,0%	-50,0%

Figure D.1: Global and local sensitivity analyses performed for checks.

Output:		Model		Check			Task									
	Deviation per Task	A330	A340	1A	2A	4A	DET	DIS	FNC	GVI	LUB	OPC	RST	SVC	VCK
State nº	No Evidence	0,524	0,476	0,585	0,291	0,124	0,090	0,032	0,086	0,373	0,024	0,173	0,031	0,054	0,139
1	<0%	0,512	0,488	0,509	0,297	0,194	0,055	0,038	0,111	0,165	0,027	0,233	0,046	0,055	0,269
2	0;100%	0,539	0,461	0,509	0,322	0,169	0,129	0,027	0,051	0,337	0,021	0,190	0,036	0,090	0,119
3	100;500%	0,508	0,492	0,678	0,256	0,066	0,088	0,028	0,079	0,519	0,021	0,134	0,024	0,029	0,078
4	500;1000%	0,483	0,517	0,531	0,322	0,147	0,117	0,038	0,122	0,218	0,030	0,212	0,029	0,061	0,173
5	>1000%	0,589	0,411	0,599	0,295	0,106	0,054	0,034	0,089	0,437	0,026	0,142	0,026	0,054	0,138
	ΔP 2→1	0,027	-0,03	3E-04	0,025	-0,02	0,074	-0,01	-0,06	0,172	-0,01	-0,04	-0,010	0,035	-0,150
	ΔP 3→2	-0,03	0,032	0,169	-0,07	-0,1	-0,04	0,001	0,027	0,182	3E-04	-0,06	-0,01	-0,06	-0,04
	ΔP 4→3	-0,03	0,025	-0,15	0,066	0,081	0,029	0,010	0,043	-0,3	0,008	0,078	0,005	0,031	0,095
	ΔP 5→4	0,106	-0,11	0,068	-0,03	-0,04	-0,06	-0	-0,03	0,218	-0	-0,070	-0	-0,01	-0,04
	S 2→1	2,7%		2,5%			18,0%								
	S 3→2	3,2%		14,7%			14,9%								
	S 4→3	2,5%		12,8%			23,4%								
	S 5→4	10,6%		5,9%			17,2%								
	State S 2→1	50,0%	-50,0%	0,6%	49,7%	-50,3%	20,5%	-3,2%	-16,6%	47,9%	-1,7%	-12,1%	-2,9%	9,8%	-41,8%
	State S 3→2	-50,0%	50,0%	57,2%	-22,1%	-35,1%	-13,7%	0,4%	9,2%	61,2%	0,1%	-18,8%	-4,1%	-20,5%	-13,7%
	State S 4→3	-50,0%	50,0%	-57,6%	25,8%	31,8%	6,1%	2,1%	9,3%	-64,2%	1,8%	16,8%	1,1%	6,7%	20,3%
	State S 5→4	50,0%	-50,0%	57,4%	-23,2%	-34,1%	-18,2%	-1,2%	-9,6%	63,6%	-0,9%	-20,5%	-0,9%	-1,9%	-10,3%

Output:		Skill					Zone							
	Deviation per Task	AF	AV	EL	EN	RA	100	200	300	400	500	600	700	800
State nº	No Evidence	0,714	0,036	0,068	0,170	0,013	0,269	0,181	0,038	0,184	0,017	0,017	0,248	0,047
1	<0%	0,736	0,040	0,062	0,148	0,015	0,375	0,227	0,044	0,145	0,019	0,019	0,14	0,03
2	0;100%	0,686	0,039	0,048	0,216	0,012	0,278	0,193	0,034	0,208	0,015	0,015	0,234	0,024
3	100;500%	0,754	0,024	0,080	0,136	0,007	0,262	0,153	0,021	0,131	0,013	0,013	0,325	0,082
4	500;1000%	0,634	0,055	0,068	0,219	0,024	0,256	0,210	0,076	0,208	0,021	0,021	0,173	0,034
5	>1000%	0,711	0,039	0,070	0,166	0,015	0,179	0,154	0,043	0,286	0,019	0,019	0,270	0,030
	ΔP 2→1	-0,050	-0	-0,01	0,068	-0	-0,1	-0,03	-0,010	0,063	-0	-0	0,094	-0,01
	ΔP 3→2	0,068	-0,02	0,032	-0,08	-0	-0,02	-0,040	-0,01	-0,08	-0	-0	0,091	0,059
	ΔP 4→3	-0,120	0,032	-0,01	0,083	0,017	-0,01	0,058	0,056	0,077	0,008	0,008	-0,15	-0,05
	ΔP 5→4	0,077	-0,02	0,002	-0,05	-0,01	-0,08	-0,06	-0,03	0,079	-0	-0	0,096	-0
	S 2→1	6,1%					10,9%							
	S 3→2	7,8%					9,9%							
	S 4→3	10,6%					13,8%							
	S 5→4	6,8%					11,3%							
	State S 2→1	-41,4%	-0,6%	-11,4%	56,1%	-2,7%	-45,0%	-15,5%	-4,5%	29,0%	-2,0%	-2,0%	43,1%	-3,1%
	State S 3→2	43,4%	-9,8%	20,5%	-50,9%	-3,1%	-8,1%	-20,1%	-6,5%	-38,8%	-0,9%	-0,9%	45,9%	29,4%
	State S 4→3	-56,3%	14,9%	-5,5%	38,8%	8,1%	-2,1%	20,9%	20,2%	28,0%	2,9%	2,9%	-55,2%	-17,6%
	State S 5→4	57,1%	-12,2%	1,3%	-39,3%	-6,9%	-34,0%	-24,7%	-14,8%	34,8%	-1,0%	-1,0%	42,4%	-1,6%

Figure D.2: Global and local sensitivity analyses performed for tasks.