

MSc Thesis

Minimising Cost by Dynamic Modelling
of Aircraft Recovery in Disrupted Operations

A Kenya Airways Case Study

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MSc THESIS

MINIMISING COST BY DYNAMIC MODELLING OF AIRCRAFT RECOVERY IN DISRUPTED OPERATIONS

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by

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Looking back over the past 9 months I am filled with a feeling with great joy and satisfaction. I feel that this project has enriched me as a person on personal, professional and academic level. On one hand it has been a very isolating experience with thousands of lines of code written and re-written and countless hours glued to the screen of my laptop, but this is not what I will remember most. I will remember most the people that have helped me to make this thesis project a success. I would like to take a moment to acknowledge a few people to whom I am grateful for the support they have given me throughout the course of my thesis work.

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Summary

Context

This research is conducted as a MSc thesis research for the Air Transport and Operations chair at the faculty of Aerospace Engineering at Delft University of Technology (TU Delft). The research project is done in collaboration with Kenya Airways (KQ) as part of an ongoing research topic between TU Delft and Kenya Airways centered around on-time performance (OTP). On-time performance is seldom achieved fully and the reason for this is because there are always disruptions that occur. Whether it be foul weather, crew illness, late passengers or technical issues; a single disruption can affect more than just the directly affected flight; it can send a ripple of reactive disruptions through an airline's network. To achieve the best on-time performance there are three areas that are of importance. (1) Mitigating the sources of disruptions where possible (e.g. preventative maintenance) (2) making sure that the schedule is set up in such a way that it can cope with disruptions (also referred to as robust scheduling) and (3) having a system in place that can quickly resolve disruptions as they occur (called recovery operations). The three are never solely applied, but are always applied in combination. The first two are proactive approaches to maximising OTP whereas the third is a reactive approach. This research is in the realm of the reactive solution to the problem; looking at recovery operations.

From an industry point of view, as airlines grow in size and fierce competition forces airlines to make optimal use of the resources at hand, the planning of their schedules becomes tighter and the effect of disruptions potentially greater. This research aims at creating a disruption management tool which can solve disruptions in a dynamic, changing environment. The ultimate goal of the model is that it can be implemented at an airline. As indicated above this research is done in collaboration with Kenya Airways and part of the goal of this research is that the model created is to be implemented at Kenya Airways. Such a tool can potentially help Kenya Airways; where the current situation is that the majority of the delays are reactionary delays. Furthermore the sources of disruptions for both primary and reactionary delays are predominantly due to aircraft related issues. The combination of many reactionary delays and aircraft as the prevalent source of disruptions has contributed to this research looking into aircraft recovery.

Literature

The literature review done for this research project has concluded that much research has been done into the topic of recovery. In the 1990's the research into optimization of recovery of aircraft, crew and passengers took flight. The early research simulated the manual approach which airline operators use, splitting the recovery of aircraft, crew and passengers into separate problems and solving them sequentially. Doing so resulted in problems which were more tractable, however still needed grave simplifications to be able to solve them within a reasonable time. In the late nineties the use of heuristics in airline recovery operations started with a research by Arguello et al. (1997) and this inspired other researchers to do the same. As the research moved forward researchers integrated the aircraft recovery problem with crew and/or passenger recovery. The research done is often tested on real life test cases, with a given set of disruptions. The disruptions found in the reviewed literature are often given as a known set for the entire disrupted scenario. The goal of this research is to develop a

recovery model which takes into account aircraft recovery problem, for which the total set of disruptions is not yet known at the beginning of the disruption scenario. The disruptions will thus be input in the program sequentially, so the model can solve a problem with the same information an operator would have. Thereby creating a more realistic approach than knowing all the disruptions beforehand. Furthermore this research makes use of a time-space network for each individual aircraft, making it possible to track and constrain individual aircraft. This approach means that a model can be created which is close to the real life situation and can be implemented.

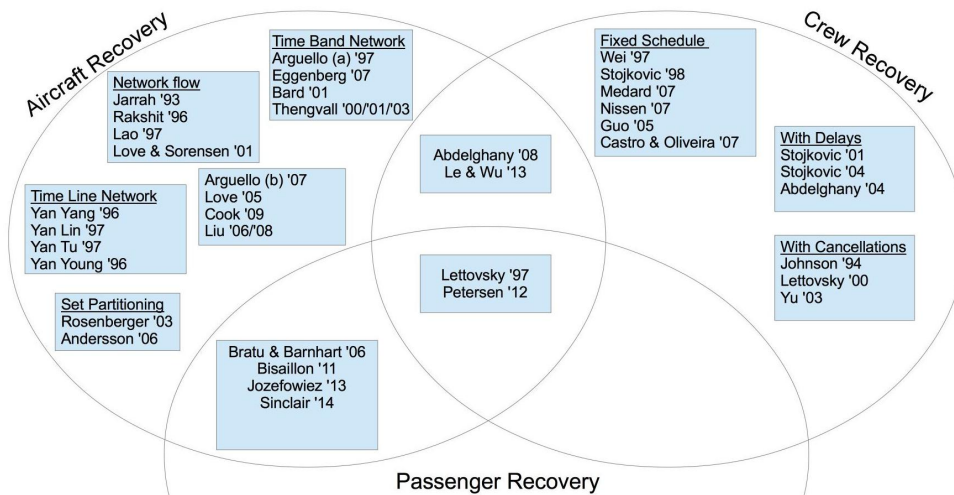


Figure 1: Venn diagram showing relevant research papers in the field of recovery operations

Research objective

This research project, being a collaboration between Delft University of Technology and Kenya Airways, has research objectives with regards to the academic goals and the industry goals. In short the academic goal is to extend the body of knowledge and the industry goal is to improve operations at Kenya Airways. These two goals will be achieved with the following research objectives:

"Create a model which solves the aircraft recovery problem in a dynamic way and demonstrate the difference between solving in a non-dynamic way."

"Demonstrate the feasibility of using a time-space network for each aircraft for solving the aircraft recovery problem in real-time operations, through developing a search algorithm testing small selections of aircraft."

The industry objective is to *"Minimise the cost of disruptions by creating a dynamic model that recovers aircraft, to be implemented at Kenya Airways"*

The goal of improving KQ operations can be achieved in this project through the implementation of the model. The model can be used as a decision support tool to the Duty Manager Operations (DMO's) providing insight into the lowest cost solution for a given set of disruptions, in sometimes already disrupted operations. The goal of extending the body of knowledge comes from a few elements. The first being the dynamic aspect of the model, which refers to a model that does not solve for one set of disruptions known at a certain point in time but that it solves for each disruption as it becomes known, whilst taking into account disruptions that have become known earlier. All the while attempting to return to the original schedule. The second novel addition in this work is the use of a time-space network for each aircraft and displaying that such an approach is feasible for a large problem in real time. The manner in which this is to be achieved is by a search is done to find the best selection of aircraft for the solution, where an optimal solution is found for a small selection and these selections

are compared. This type of heuristic search by aircraft and finding optimal solutions for each selection is a novel approach.

Dynamic Recovery Modelling

The dynamic recovery model (DReM) presented in this thesis exists of several interacting parts. Figure 2 presents a schematic representation of the dynamic recovery modelling framework presented in this work. On the outermost level of the presented model is the simulation of an actual disruption; an approach where the time that a disruption becomes known is key. The disruptions are solved for each step in time when new information becomes known.

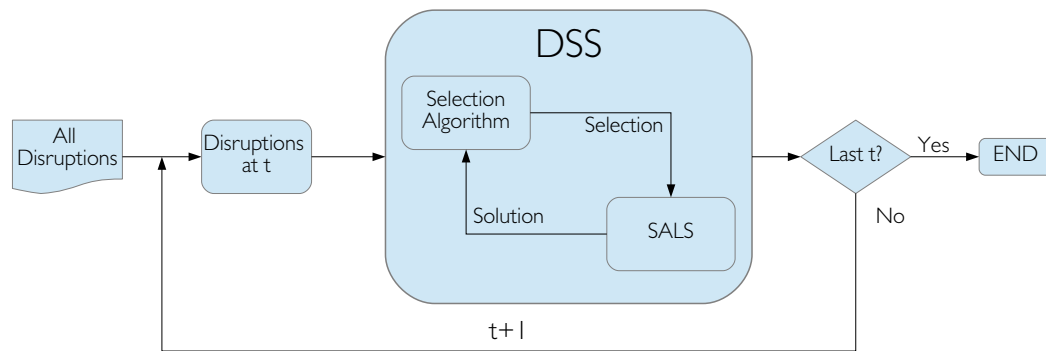


Figure 2: Schematic representation on the Dynamic Recovery Model and the modules which it makes use of.

Each time that new information becomes known regarding disruptions; i.e. each time the situation changes, the model solves to find the lowest cost solution to the disruptions at hand. The part of the model that solves a set of disruptions at each point in time is called the Disruption Set Solver (DSS). The DSS consists of two parts; the first is an algorithm which is aimed at finding the best selection of aircraft to solve a disruption. This algorithm calls upon the second part, which is called the Selected Aircraft Linear Solver (SALS). As the name suggest this module solves a linear programming problem in which a time-space network representation is used. The time-space network representation is one that consists of nodes and arc where each node represent a certain airport at a certain time. This research presents a new use of the time-space network, which is the use of a time-space network for each aircraft in the selection to be solved by SALS. This type of use of the time-space network results in a model in which there is no limitation to the aircraft specific constraints that can be implemented, thereby making the model realistic and applicable in practice.

Verification and Validation

The verification of the model is done through a series of tests on small networks to check that the model is finding the expected solutions. To validate the model firstly a face validation of the conceptual model is done, validating the relevance of the model. This is followed up by the validation of results found on true test scenarios provided by Kenya Airways. These test scenarios and solutions are discussed with Duty Operations Managers (DMO) and are found to be valid.

Results

The results from running the model in this research are analysed in two different perspectives. The first is the results the model achieves in terms of cost depending on the disruption input and the input parameters, and the second the computational performance of the model.

Dynamic vs Non-dynamic

The Dynamic Recovery Model is run for two different situations: (CASE 1) the actual time at which disruptions become known are used, this is the dynamic (changing) situation. (CASE 2) all the disruption are known at the beginning of the day, this is the non-dynamic situation. When comparing the result over four days of real scenarios provided by Kenya Airways, the total cost of in the non-dynamic situation was 69.2% of the cost in the realistic dynamic situation.

Model Performance

An important aspect in recovery operations is that the problem is not only solved, but is solved within real-time such that the disruption can be solved as quickly as possible. The measurement of performance in this research is done by the run-time of the DSS, which is the module that solves disruptions at each point in time. The DSS for the tested scenarios is run 38 instances and always achieves a solution within 15 min and in 93.3% of the DSS converges to a solution within 10 minutes. According to experts at Kenya Airways this makes the model fit for real-time use.¹

Conclusions and limitations

There are three main conclusions with respect to this research:

1. The creation of the DReM, dynamic recovery model, has provided novel insight into the difference between running recovery operations in a dynamic and non-dynamic way, showing the large effect on the cost of disruptions. Where knowing all the disruption beforehand results in a cost reduction of 30.8%.
2. This research has demonstrated the feasibility of using parallel time-space networks in combination with an aircraft search algorithm as a valid method for solving aircraft disruptions in suitable time for real-time use.
3. The DReM and more specifically the module DSS (disruption set solver) can be implemented in actual operations as decision support tool. There are many different inputs that can be adapted by the user, giving a variety of possible solutions. The solutions can be used as a basis or inspiration for a comprehensive solution. Furthermore the computation time of less than 15 minutes is suited for real-time use.

The main limitation of this research is that crew and passenger connectivity fall outside the scope of the model. This results in that the solutions found by the model proposed in this research could violate constraints regarding crew and/or passenger connectivity. Some suggestions are made in the recommendations of this report as to how the scope can be extended. However, these will have an impact on the performance of the model. This limitation affects the direct implementation of the solutions found in actual operations, but does not mean that the model cannot be used as decision support for which it is intended.

¹This information is confirmed by Thomas Omondi and Francis Musila, former and current head of operations control, respectively.

Acronyms

2

ARM	Aircraft Recovery Model
ATO	Air Transport and Operations Chair at TU Delft
CRM	Crew Recovery Model
DFS	Depth First search
DMO	Duty Manager Operations
DOC	Direct Operating Cost
DPM	Disrupted Passenger Metric
DReM	Dynamic Recovery Model
DSS	Disruption Set Solver
EUR	Euro
FAM	Fleet Assignment Model
GRASP	Greedy Randomized Adaptive Search Procedure
IOCC	Integrated Operations Control Center
JKIA	Jomo Kenyatta International Airport Nairobi
KQ	Kenya Airways
KSh	Kenyan Shilling
LP	Linear Programming
MAS	Multi-Agent System
MILP	Mixed Integer Linear Programming
NCF	new connections and flights heuristic
OCC	Operations Control Center
OTP	On-Time Performance
Pax	Passengers
Pax J	Business class passengers
Pax Y	Economy class passengers
PDM	Passenger Delay Metric
PFM	Passenger Flow Model
RCCG	Reduced Cost Column Generator
ROADEF	French Operational Research (OR) and Decision Support Society
RTW	Recovery Time Window
SALS	Selected Aircraft Linear Solver
SRM	Schedule Recovery Model
STA	Scheduled Time of Arrival
STD	Scheduled Time of Departure
TAT	Turn Around Time
TU Delft	Delft University of Technology
TW	Time Window
USD	United States Dollar

²The acronyms for airports and aircraft are given as lists in Appendix D and E

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Chapter 1

Introduction

In the airline industry the competition is fierce. The possibility for passengers to easily select their airline of choice on-line only amplifies the competition. Airlines are on a fine line between price competitiveness and being able to provide the best service. One important factor for providing top class service is the reliability of the on-time performance.

In airline operations the high investment cost of aircraft results in efficient and tight planning of resources in order to maximise the utilisation of aircraft in an airlines fleet. By utilising the fleet to the maximum, tickets can be priced competitively and profits can be maximised. High utilisation however results in a tight planning which makes the flight schedule particularly delicate in disrupted situations. In some cases a single disruption can send a ripple or even a wave of delays through an entire network. One way to overcome the delicacy of a schedule is to have successful recovery operations in place. This report is a MSc thesis work done in collaboration between Delft University of Technology and Kenya Airways titled:

"Minimising Cost by Dynamic Modelling of Aircraft Recovery in Disrupted Operations"

This research is conducted as a MSc thesis research for the Air Transport and Operations chair at the faculty of Aerospace Engineering at Delft University of Technology (TU Delft). The research project is done in collaboration with Kenya Airways (KQ) as part of an on-going research topic between TU Delft and Kenya Airways centered around on-time performance (OTP). On-time performance is seldom achieved fully and the reason for this is because there are always disruptions that occur. Whether it be foul weather, crew illness, late passengers or technical issues; a single disruption can affect more than just the directly affected flight; it can send a ripple of reactive disruptions through an airline's network. To achieve the best on-time performance there are three areas that are of importance. (1) Mitigating the sources of disruptions where possible (e.g. preventative maintenance) (2) making sure that the schedule is set up in such a way that it can cope with disruptions (also referred to as robust scheduling) and (3) having a system in place that can quickly resolve disruptions as they occur (called recovery operations). The three are never solely applied but are always applied in combination. The first two are proactive approaches to maximising OTP whereas the third is a reactive approach. This research is in the realm of the reactive solution to the problem; looking at recovery operations.

In the academic context this report aims at extending the body of knowledge in the field of airline recovery operations. In the 1990's the research into decision support and optimization of recovery of aircraft, crew and passengers took flight. The early research simulated the manual approach which airline operators use, splitting the recovery of aircraft, crew and passengers into separate problems and solving them sequentially. Doing so resulted in problems that were more tractable, however still needed grave simplifications to be able to solve them within a reasonable time. In the late nineties the use of heuristics in airline recovery operations started with a research by Arguello et al. (1997) and this inspired other researchers. Much of the research done is tested on real life test cases, with a given set of disruptions. It is found in the literature reviewed that test cases often take place on

scenarios of single disruptions or a set of disruption of a day that are all known at the beginning of the day.

In real life, disruptions become known over the course of the day. Each time a new disruption becomes known the situation changes. Solving the new disruption should not only attempt to resolve the incumbent disruption but should attempt to resolve previously solved disruption. In each case returning as close to the original schedule as possible. This research creates a model that solves disruptions in such a changing (dynamic) environment. And is aimed at displaying the difference between modelling in a dynamic and non-dynamic way.

From an industry point of view, as airlines grow in size and fierce competition forces airlines to make optimal use of the resources at hand, the planning of their schedules becomes tighter and the effect of disruptions potentially greater. This research aims at creating a disruption management tool that can solve disruptions in a dynamic, changing environment. The ultimate goal of the model is that it can be implemented at an airline. As indicated above this research is done in collaboration with Kenya Airways and part of the goal of this research is that the model which is created is to be implemented at Kenya Airways. The current situation at Kenya Airways is that the majority of the delays are reactionary delays. Furthermore the sources of disruptions for both primary and reactionary delays are predominantly due to aircraft related issues.

The objectives of the research can be summarised into two academic and one industry objectives:

"Create a model which solves the aircraft recovery problem in a dynamic way and demonstrate the difference between solving in a non-dynamic way."

"Demonstrate the feasibility of using a time-space network for each aircraft for solving the aircraft recovery problem in real-time operations, through developing a search algorithm testing small selections of aircraft."

The industry objective is to *"Minimise the cost of disruptions by creating a dynamic model that recovers aircraft, to be implemented at Kenya Airways"*

The setup of the report is done in such a way to first explain the reasoning behind the objectives that have been defined and why they are relevant, followed by how they are to be achieved and finally the results are presented along with an analysis and conclusions about the project. Chapter 2 provides the reader with a summary of the literature that has been reviewed for this thesis work. The literature review has two goals: to select the best methods in recovery operations that are applicable to this project and to define the scope of this thesis such that it can extend the body of knowledge in the field of airline recovery operations. The literature review is followed by the project plan in Chapter 3, which defines the research objectives and research framework used in this project. Chapter 3 also defines the conceptual model used. The Model is explained in detail in Chapter 4. This is followed by a description of the case study at Kenya Airways in Chapter 5. The case study is explained by giving some background information about Kenya Airways and information about the data input into the model. Chapter 6 verifies and validates the model, this is done by face validating the conceptual model and verifying the model on small test cases and validating the total model with Kenya Airways Duty Operations managers. The final chapters 7 and 8 provide the results and the conclusions and recommendations respectively.

Chapter 2

Literature

The manner in which airlines recover from disrupted operations is of critical importance to the profitability of airlines. This chapter is a literature review, which investigates the current state of the art in recovery operations with a special focus on aircraft recovery. The research that has been done in recovery operation has been traditionally separated into aircraft, crew and passenger recovery. The reason for this is two-fold; firstly because computational time necessary to solve the problems together is large and secondly because it followed from the state of the practice of solving the problems sequentially. As computational power increased, and research into heuristics progressed, several attempts have been done at integrating aircraft and/or crew and/or passenger recovery with the goal of providing optimal solution to the integrated problem. This review investigates the different approaches used and finds that there is a gap between the results found academically and how they would operate in real life. In literature the models are often tested on one of two circumstances either solving for a single disruption, or solving for a set of disruptions all of which are known in first instance. This research investigates the possibility of solving the recovery problem in a changing / dynamic environment. This literature review gives background information about the state of the art and some of the research from which inspiration is drawn for this MSc thesis

Section 2.1 expands on the research done on the recovery problems of aircraft and crew. Though the focus of this research is on aircraft recovery. A subsection of Section 2.1 will look at the recovery problem of crew as several techniques applied to crew recovery have been adopted in this aircraft recovery research. As research into recovery operations progressed researchers also started looking for integrated solutions to the problems of aircraft and crew as well as passenger recovery. The integrated approaches are described in Section 2.1.3. This is followed by a section that analyses the position of the proposed research topic within the body of research and finally Section 2.3 presents some brief conclusions and point of discussion.

2.1 Recovery

Once an airline's schedule has been generated and fixed the airline can proceed to the operations phase. In practice airlines are rarely able to operate a schedule exactly as planned. The reason this is the case is because airline operations are prone to numerous types of disruptions. When disruptions occur these can affect more than just the directly disrupted flight, and can send a shock-wave of disruptions through the network. There are two ways through which the knock-on effect of disruptions can be minimised. The first is through the creating the schedule in such a way that it is able to cope with disruption. This solution methodology is called 'robust scheduling' and aims at minimising knock-on effect by placing buffers in the schedule whilst still maximising aircraft utilisation. For example simply placing very large amount of time between flights might lead to a very robust schedule but would not be profitable for an airline, the study of robust scheduling aims at intelligently placing the buffers so that the disrupted operations can quickly return to scheduled operations. Robust scheduling always occurs in combination with the second technique in minimizing the knock-on effects of delay,

which is the schedule recovery operations. This refers to the way in which the airline deals with a disruption once it has happened. The recovery involves re-planning in real time with the resources at hand. Robust scheduling and recovery operation are always closely related and never is only one of the two used. Robust scheduling can be seen as the proactive part of the solution to a disruption and recovery operations as the reactive part of the solution. This literature review focuses on the reactive, recovery solution.

The recovery problem at large, similarly to the planning problem, consists of aircraft and crew recovery but has the additional problem of passenger recovery. In this section first the methods used to solve the problems as separate entities are treated. Section 2.1.3 investigates the attempts at integrating the recovery of different resources. Figure 2.1 provides an overview of the published research in the field of recovery operations.

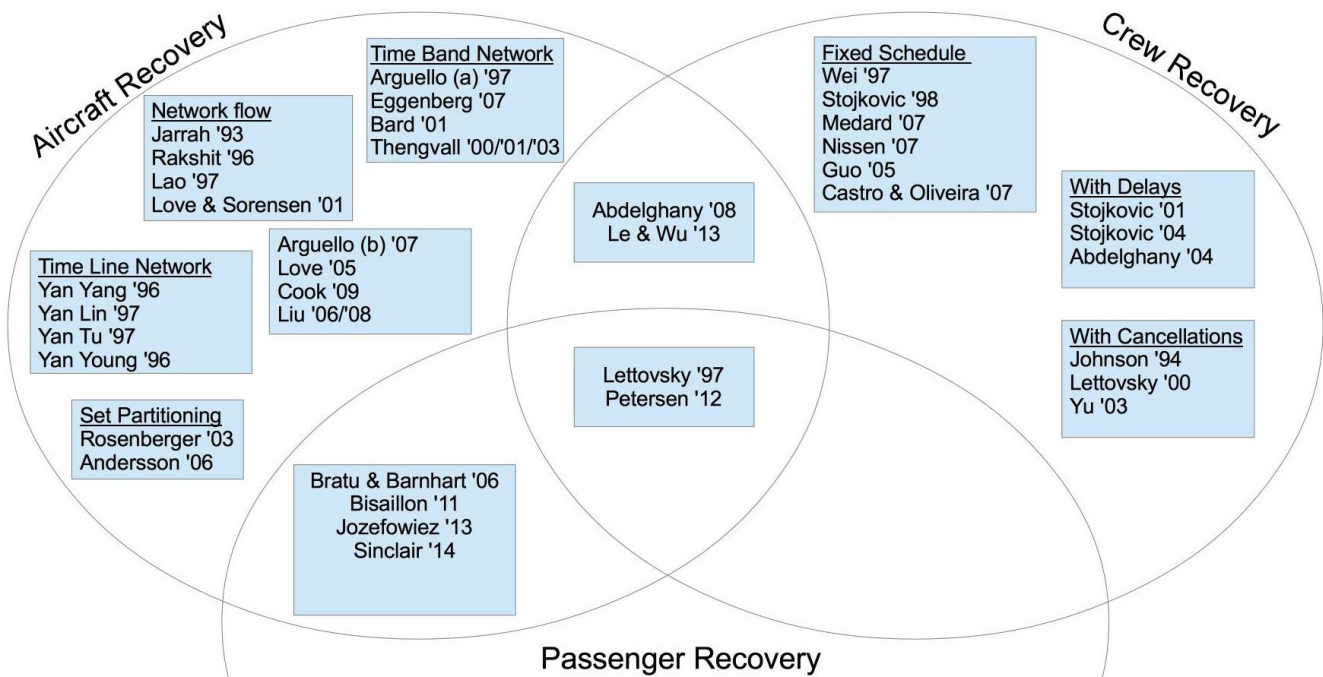


Figure 2.1: Venn diagram showing relevant research papers in the field of recovery operations

Clausen et al. (2010) is to date the most complete literature study looking at the research done on the topic of airline disruption management. It provides an insightful overview of the work done up to 2009. Up to 2009 solutions were mainly non-integrated approaches, the information in this chapter is for large part also found in Clausen et al. (2010).

2.1.1 Aircraft Recovery

Initial research on disruptions and the recovery from disruptions is focused on the recovery of aircraft. One reason might be that this is due to the fact that the number of aircraft is much smaller than the number of crew members or passengers, and the rules for aircraft scheduling are more straightforward. Clausen et al. (2010) This section looks at several papers that propose different solution approaches. The first three subsections investigate approaches using three different types of network representation that are used in literature; being network flow algorithms, time line network and time band network. The fourth subsection looks at approaches that combine a connection network with set partitioning models and the final subsection looks at some of the metaheuristic approaches used.

Flow Algorithms

In several of the papers examined network flow algorithms are used for solving the aircraft recovery problem. Jarrah et al. (1993) proposes two separate network flow models, the first for cancellation of flights and the second for re-timing of flights, however does not integrate these. This means that the model can find a re-timing solution and cancellation solution and select the best one, but does not combine re-timings and cancellations. The Network flow models used by Jarrah et al. (1993) are solved using a shortest path method which uses a disutility function to evaluate the costs of each path. This function is based on the number of passengers, the number of passengers with a connecting flight down the line, lost crew time and disruption of maintenance. The test cases are based on real data, and showed an improvement to the airline in question's operations. Rakshit et al. (1996) reports on the implementation of the model proposed by Jarrah et al. (1993) in a decision support system. In 1997 Cao and Kanafani (1997) present a two part paper which builds on the work done by Jarrah et al. (1993) and Rakshit et al. (1996). It presents a quadratic I/O programming model in where the flight revenue minus the swap and delay costs is maximized. The model allows for aircraft type swapping, ferrying as well as combining delays and cancellations. The results in this paper seem very promising, however Løve and Sørensen (2001) (p. 153) suggest that reproduction of the results using the model proposed by Cao and Kanafani (1997) was not possible and that errors were not easily resolved.

Time-line Networks

A number of the papers examined use approaches based on time-line networks. Classical time-line networks are base on the use of ground arcs, flight arcs and overnight arcs. The first to use the time-line networks for aircraft recovery are Yan and Yang (1996). Firstly arcs are added to make ferrying possible. The way in which delays are made possible, is that copies are made of flight arcs at different times. An extra constraint is added to ensure that at most one copy is selected. In the paper four variations of the model are presented, two are pure network flow problems, and two are network flow problems with several side constraints. The problem becomes of considerable size is solved near optimally within a few minutes time. Where Yan and Yang (1996) solve the problem for a single fleet, Yan and Tu (1997) extends the model to multiple fleet; Yan and Lin (1997) looks into the case of a temporary airport closure and Yan and Young (1996) extends the model with multiple stop flight. All of these papers build on the basic time-line based solution presented by Yan and Yang (1996) and although the problems are slightly different, the solution technique remains the same.

Thengvall et al. (2000) uses the model described by Yan and Yang (1996) as a basis and adds protection arcs as well as through flight arcs. These arcs make it possible to minimize the deviation from the original schedule as well as making it possible to prioritize that the same aircraft flies the continuing flights. Just as Yan and Yang (1996) the model can swap, delay and cancel flights, however does not take into account crew or maintenance considerations. Thengvall et al. (2000) uses real data from Continental Airlines with 16 B737's at 13 stations and 27 B737-100's at 30 stations. The two fleets are run separately in the model. The results show that changes in the cost function between the cost of delay, cancellations and deviation from the original schedule, result in different schedules.

Time-band Networks

Solutions based on time band are first introduced by Arguello (1997)¹ and later used by Bard et al. (2001). The time-band network is similar to the time-line network except that time is discretised along the time axis. The time-band model as used in Bard et al. (2001) makes it possible to use different time-bandwidths for the hub and the spokes, as it is desirable to have a higher resolution at the hub. Bard et al. (2001) use linear programming to solve the problem. The model is tested against a real scenario from Continental Airlines, results compare the optimal LP-solution with the lower bound

¹The PhD Thesis by Arguello was not available to the author of this literature review, thus the information that Arguello was the first to use the time-band networks is taken from Bard et al. (2001) and Clausen et al. (2010)

found by a LP-relation optimum. They show that the solutions are equal or are no further than a few percentage points from the lower bound found. Important to note is of course that as the size of the time-step increase the quality of the results decreases.

Thengvall et al. (2001) and Thengvall et al. (2003) extend the previous model from Thengvall et al. (2000) in a time-band network and consider hub closure and multiple fleets. Three mixed integer programming models are introduced: two preference models which are based on time-line networks of each subfleet and a model based on time-bands as used by Arguello (1997). Thengvall et al. (2001) shows solution times for hub closure of 2 hours never exceeding 83 seconds and hub closure for 6 hours never exceeding 810 seconds.

Eggenberg et al. (2007) proposes a column generation technique to tackle the problem based on the time-band network as generated by Bard et al. (2001). What Eggenberg et al. (2007) does, is create a time-band network for each separate aircraft, making it easy to incorporate maintenance. The model shows promising results for a small model of up to 10 aircraft, but quickly increases in run time when the amount of aircraft and recovery period increases. The model is aimed at calculating a solution with a cost for several recovery periods, so that the decision maker can make a trade-off between recovery cost and computation time. In the scope of this literature study as a preliminary study for solving the problem at Kenya Airways, this means that this technique as a sole means to solve the entire problem is not possible, but could be useful to solve a part of the problem.

Set Partitioning

A different method to defining the aircraft recovery problem is to formulate it as a set partitioning model on a connection network traditionally used for tactical planning problem formulation Clausen et al. (2010). Rosenberger et al. (2003) formulate the aircraft recovery problem as a set partitioning (AKA set packing) problem. They indicate that the problem is NP-hard, which they overcome by providing an aircraft selection heuristic which efficiently determines which subset of aircraft to reroute. The rerouting set partitioning model is then solved using CPLEX. The results achieved on actual airline problems (32-96 aircraft across 3 fleet types on 139-407 flights) are impressive, with running times no more than 16 seconds.

Andersson Granberg and Värbrand (2004) also use the connection network as basis for a set packing problem combined with a Dantzig-Wolfe decomposition. The problem is solved using two separate strategies, the first being a LP-relaxation and the second a Lagrangian heuristic. The models are tested on a Swedish local carrier each tested with and without Dantzig-Wolfe decomposition. The results with column generations, both LP and Lagrangian heuristic were promising for real time use as a decision making support tool.

Heuristics in Aircraft Recovery

As the subject of aircraft recovery began to grow as did the use of different heuristics used to solve the problem. A development which is not at all surprising as the sheer size of the problem often does not allow for exhaustive techniques to look at the solution.

Arguello et al. (1997) implements a greedy randomized adaptive search procedure (GRASP) to reconstruct routings with the goal of minimizing the cost of delay and cancellations. The neighbourhood generation operations applied to route pairs and single aircraft routes are flight route augmentation, partial route exchange and simple circuit cancellations; the most promising solutions are stored in a restricted candidate list (rcl). The best neighbourhood solution becomes the incumbent, this search is repeated until one of several stopping criteria is met. To complement the GRASP Arguello et al. (1997) uses a time-band approximation scheme to obtain a lower bound to the problem under consideration. The model is tested on Boeing 757 fleet data from Continental Airlines² in which 90% of the GRASP solution were within 10% of the lower bound and never required more than 15 CPU seconds.

²The Boeing 757 fleet in question consisted of 16 aircraft

Løve and Sørensen (2001) and Løve et al. (2005) present local search heuristics based on the network formulation with nodes representing flights or aircraft. Assigning aircraft to flights is done by selecting the edge connecting the aircraft and flight for the solution. Ferrying and cancellations are implemented by using so-called "Ghost-aircraft and -flights". A heuristic search is then done identifying the best 'edges' for the solution, which is based on a weighted cost function. Cook and Tanner (2009) is a paper that investigates the cost of delay, fuel burn, etc. Results in Løve et al. (2005) are randomly generated, but are confirmed by Kohl et al. (2007) on a British airways case for 80 aircraft, 44 stations, and 340 flights.

Liu et al. (2006) use multi-objective evolutionary algorithms to construct new feasible routings. The method is limited to swapping or delaying within a single fleet. Ferrying or cancelling is not possible. The objective function is based on the cost of delay, cost of swapping and the cost of assignment of an aircraft to a flight. The model is tested on a case of 70 flights flown by 7 aircraft. Liu et al. (2008) extends the model for multi-fleet purposes, but it appears as though it simply tests the model several fleets in parallel.

2.1.2 Crew Recovery

In this section research into crew recovery is investigated, and the different methods used in literature are described. For a large part the information in this chapter is inspired by and retrieved from the literature review by Clausen et al. (2010)

The research about crew recovery can be divided into three different categories. The first is research done on crew recovery with the assumption that the flight schedule is fixed (Section 2.1.2), this results in a classical crew scheduling problem. The second category is research that extends the first view on the crew recovery by adding decision variables that make it possible to cancel flights, described in Section 2.1.2. The third category is a problem formulation where the crew recovery problem accounts for delays in the system. This problem formulation attempts to minimize the total delay of flights. Connecting flights and maximum delays are constrained and is described in Section 2.1.2. Similar to some approaches in the aircraft recovery problem many researchers limit the problem size by setting or minimizing the recovery time window (RTW) and/or limiting the number of crew taken into account in the recovery problem. The latter is achieved by only taking into account the affected crew members and selecting number of candidate crew members. This limited problem view is graphically depicted in Figure 2.2. Such a limited problem makes the computation time significantly less, but does require some pre-processing to select the time window as well as candidates to use in the solution.

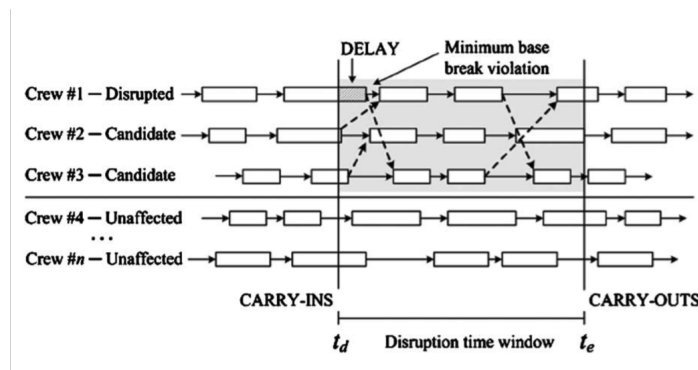


Figure 2.2: Figure showing how a recovery problem can be limited by defining a disruption time window with t_d and t_e defining beginning and end of the window as well as selecting a limited group of candidates for the solution.

Crew Recovery Given a Fixed Schedule

The papers described in this section use a fixed flight schedule and create a crew recovery model to repair broken pairings. This would in fact depict the method traditionally use by airlines in which aircraft and the schedule have been recovered and a new schedule has been formed and then crew scheduling must attempt to fit the new schedule. Wei et al. (1997) use a multicommodity network flow problem to model the crew pairing repair. The challenge and objective is to minimize operational costs as well as returning to the original schedule as soon as possible. Both papers use a limited time window to reduce the problem size and solve the problem using a depth-first branch-and-bound technique.

Stojković et al. (1998) use the time-window technique as well as candidate crew selection. Aside from defining the time window, which they call the operational period, they also define a working period. The working period extends the entire shift of a pairing. Clausen et al. (2010) describe the approach used by Stojković et al. (1998) as an integer nonlinear multicommodity network flow problem, which split into a set-partitioning problem and a shortest path problem with side constraints. To solve the problem column generation is successfully implemented within a branch-and-bound tree to obtain integer solutions. The results are promising for real time application, solving single-day scenarios within 30 seconds and seven-day scenarios between 4–20 minutes. The authors do comment that the set partitioning model should be extended to find ‘all’ of the personal requirements in a pairing.

Medard and Sawhney (2007) integrate the pairing and assignment of crew into one problem. This because on the day of operations, contrary to the planning phase the two become the same problem, because the crew members are already in place. The solution techniques they provide are simple tree searches and more sophisticated column generation and shortest-path algorithm. For the column generation two separate techniques are applied and tested the first being a depth first search (DFS) and the second a reduced cost column generator (RCCG). Results on several different single and multibase cases show that the DFS usually out performs the RCCG in computing time, but that the RCCG often comes with a more optimal solution. Especially when the problem size increases it seems that RCCG is providing better results, and sometimes better computation time.

Nissen and Haase (2006) have presented a duty-period-based formulation of the crew recovery problem tailored to the needs of European airline. This because airlines in Europe predominantly pay crew fixed salaries. This approach results in a shorter recovery horizon and in a smaller problem. The solution technique applied is a branch-and-price algorithm, which is in effect a hybrid technique between column generation and branch-and-bound algorithm. The approach is tested on several different scenarios and the result are achieved in adequate running time for operational use.

Guo et al. (2005) presents a decision support framework for airline crew schedule disruption. The problem is set up as a set-partitioning problem with the goal of minimising the deviation from the current schedule. Two solutions techniques are proposed in the book chapter, the first is a column generation based method solved with a LP relaxation and the second is GA-based heuristic combined with a local search algorithm. The main focus of the author is on a step that selects the right solution strategy which is a so called strategy mapping. The strategy mapping is bases the choice for a method on five factors: the number of delays, cancellations, new flights, available crew members and daily flights in average. The strategy map then selects the better of the two methods depending on the problem. The model is tested on a case of reasonable size with significant disruption, in this case the genetic algorithm is preferred and achieves an acceptable solution within 3 minutes.

The last of the fixed schedule research papers two papers by Castro and Oliveira (2007a) Castro and Oliveira (2007b) that propose a multi-agent system (MAS) representing the OCC of an airline. The MAS has a crew recovery agent, an aircraft recovery agent, and a passenger recovery agent. The focus of the work is on the crew recovery agent. A monitoring agent class of the crew recovery agent monitors crew events and reports to the crew finder agent class. In turn the crew finder creates a list of solutions to the problem from the algorithmic agent classes and chooses the best one based on minimum payroll costs. The model’s performance is tested against a human operator and achieves a less costly solution in 25 seconds compared to a 90 seconds by the human operator. Only one test

case is reported.

Crew Recovery with Cancellations

Crew recovery with the option to cancel flights is taken into account by several authors. The first paper to be published about the subject is Johnson et al. (1994). This research laid the groundwork for three of the authors to continue research done by Lettovský et al. (2000). The authors preprocess by selecting candidates for the solution to limit the problem size and exploit the fact that an original schedule is a near optimal one and thus they try to limit the deviation from it. Once candidate crews have been selected a crew-pairing generator is used that generates feasible continuations for partially flown crew trips. A few branching strategies are presented that allow for fast generation of integer solutions. The model is solved with a branch and bound and LP relaxation. Results presented on a test case of a major US Carrier for medium size disruptions and computation times vary from a few seconds to several minutes. Authors conclude that further research is necessary to extend the problem to larger disruptions. In 2003 Yu et al. (2003) describe a decision support tool called CrewSolver created for Continental Airlines. The tool uses a depth-first search and generates several different valid recovery options. An operator can then select the most suitable solution. Continental Airlines estimate that the use of this system in 2001 saved US \$40 million in recovery cost.

Crew Recovery with Delays

Several researches make it possible for the crew recovery problem to delay a flight. The earlier describe crew recovery model with fixed schedule by Stojković et al. (1998) is extended by Stojković and Soumis (2001) to incorporate the possibility to delay flights. The model is made for only pilots, and is formulated as a multi-commodity network flow with additional constraints. The problem is solved with a column generation with a master and sub-problem for each pilot. The possibility exists to call a reserve pilot by creating a ghost commodity. The model is then tested on three different scenarios which show promising result for both quality and computation time. The authors continue research with others in Stojković and Soumis (2004) and extend the problem beyond just pilots to multiple crew types. The extension is done by creating copies of the flights for the different crew members. Constraints are added to ensure that the copied flights all have the same departure time. The results of this model tested on three scenarios show good results in terms of quality (shows cost reductions) but in larger problems show very large computation times, in excess of 1 hour. Stojkovic, Soumis and Derossiers continue their research in the field and later also investigate integrated recovery, which is described in section 2.1.3.

Another decision support tool is created by Abdelghany et al. (2004). The model suggested has an extensive preprocessing phase to find the candidate crew list, and limit the problem size. The assignment of crew is formulated as a mixed integer problem, with an objective of minimizing delay and crew cost. Finally the model solves the problem by splitting the recovery horizon (input by the user) into three chronological parts such that the problem is solved separately for each part. The model is tested on a case with 18 disrupted crew and 121 candidate crew members, a solution is found in 111 seconds. The solution did leave 4 flights unattended to. The authors conclude that the model is satisfactory for the recovery of pilots, but should be extended to cabin crew and aircraft for an integrated solution.

2.1.3 Integrated recovery

In the problem of aircraft, crew and passenger recovery, the size of the problem has always been a relevant limitation to being able to solve the problem properly for real time use. For this reason initial research into recovery has mostly been split up into separate sequential parts. As research has developed and computational power has increased there have been numerous researches that have integrating the different parts of the recovery problem.

This chapter will give a literature review of the research done in the subject of integrated recovery. The chapter will be split into several different parts, the first looking into the integrated recovery of crew and aircraft, the second investigating research about aircraft and passenger integrated recovery and the third and final section will investigate the work done on aircraft, crew and passenger integrated recovery.

Integrated Aircraft and Crew Recovery

Abdelghany et al. (2008) investigates the integrated recovery of aircraft and crew. The recovery is split into separate stages of independent flights, i.e. in a stage all the flight legs are overlapping in time, so there is no possibility for sharing resources (in the form of crew or aircraft) between flights in the same stage. Figure 2.3 illustrates the different stages. At each of the stages a simulation model makes the list of disrupted flights for the time horizon, and an optimization solver creates the resource assignments as to minimize costs. The solver has the possibility to both cancel and delay flights and the problem formulated as a mixed integer program. The results of testing the model are promising, on average savings of about 5 percent in recovery cost are achieved, and computing times of about 30 seconds, and never exceeding 50 seconds. The model is tested on an actual schedule with generated disruption scenarios (up to 25 disruptions) for an airline serving 112 cities.

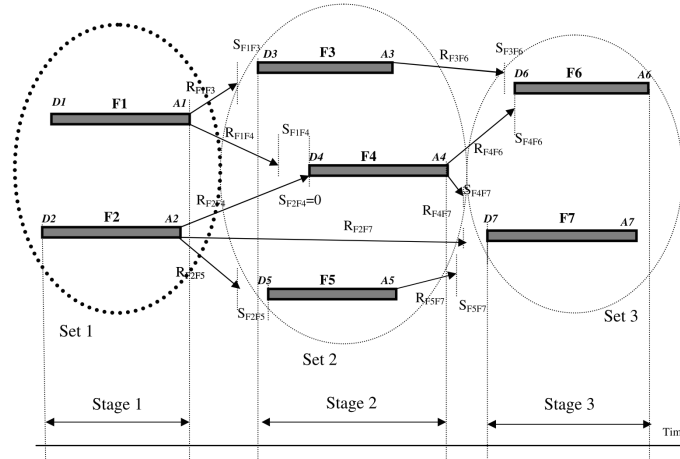
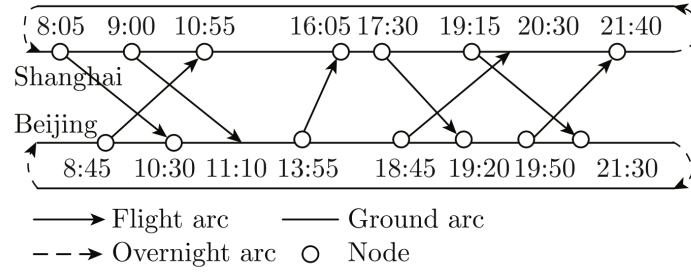
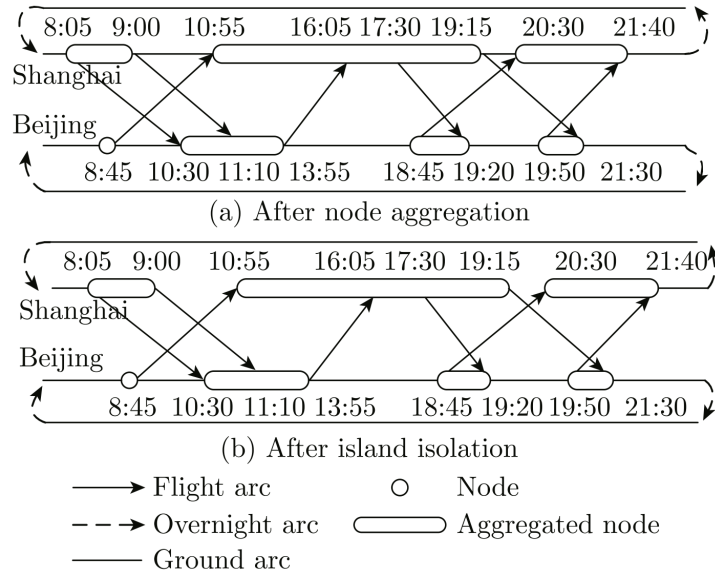


Figure 2.3: An example from Abdelghany et al. (2008) illustrating the use of stages within each stage there is a set of independent flights.

Le and Wu (2013) create a model that solves the aircraft and crew recovery problems simultaneously. The authors describe an objective function and constraints that are very similar to the basic FAM and the crew planning model presented in Bazargan (2010) and Belobaba et al. (2009), with several additional constraints associated with recovery such as cancellation or deadheading. The solution methodology used by Le and Wu they call iterative tree growing with node aggregation. In fact they do two different things; the first is a preprocessing preprocessing technique to limit the amount of groundarcs and nodes in a time space network. This consists of node aggregation in which arrivals and departures that are near on and other are aggregated as one node, and the second is island isolation where unused ground arcs are deleted. Both can be seen schematically in Figures 2.4 and 2.5.

Figure 2.4: Example of a time space network *source:Le and Wu (2013)*Figure 2.5: Example of a time space network with node aggregation and island isolation *source:Le and Wu (2013)*

The iterative tree growing with node combination makes use of the time-space network, and grows flight arcs from a starting node and draws all parallel copy arcs of the original flight arc. If a copy arc is created and selected most probably a new node will be created from this new node copy arcs and delay flight arcs can be created and connected again. The lowest cost total path is selected and all surplus arcs are deleted from the network to give the solution.

Le and Wu (2013) test the proposed model on real data from a medium-size Chinese airline (170 flight, 4 fleets, 35 aircraft and 51 airports). The model is tested for aircraft recovery and integrated aircraft and crew recovery, in these two cases the model decrease cost by about half and three quarters compared to the trivial solution of cancelling or simple delay propagation. Authors do not state how results compares to current operations at the airline, nor do they present computation times. This makes it very difficult to asses the quality of the solution and whether is is applicable in real-time operations.

Integrated Aircraft and Passenger Recovery

In Clausen et al. (2010) the authors describe two papers in which a more passenger focused integrated recovery is attempted. The first being Bratu and Barnhart (2006) which describes two different models with particular focus on passenger recovery whilst taking into account the rules surrounding aircraft and crew. The authors use a time line network representation, with copies of each flight are created to make it possible to re-time flights, this method is described in section 2.1.1 and is used

by among others Yan and Yang (1996). The first model proposed by Bratu and Barnhart (2006) is the so called PDM model (Passenger Delay Metric), in which passenger delay cost are accurately calculated by modelling passenger disruptions and the recovery options. The second is called DPM model (Disrupted Passenger Metric) only uses an approximation of the passenger costs. This reduces the computation time for a real life scenario vastly. Running times of the two models vary greatly 3.33 to 83.33 minutes . The PDM is considered unfit for real time use, where the DPM could be used in real time.

In the 2009 ROADEF Challenge, a competition organized by the French Operational Research (OR) and Decision Support Society (ROADEF), is done on the subject of disruption management in the airline industry. The goal of the competition is to create a tool which re-plans aircraft routes and passenger itineraries such that the cost for the airline is minimized. Part of the challenge is that computation times may not exceed 10 minutes as the goal is to be able to implement the results in real time. The winner Bisaillon et al. (2011) and runner-up Jozefowicz et al. (2013) have published their results and models.

The winner of the challenge Bisaillon et al. (2011) in short uses a three phase neighborhood search heuristic method. Given an initial schedule, list of disruptions and a recovery period the heuristic alternates between construction, repair and improvement phases, which iteratively destroy and repair parts of the solution. The first two of the phases aim to produce a solution that is at least feasible or satisfactory. The third phase attempts to improve the solution through large schedule changes whilst still remaining feasible. An overview of the method is presented schematically in Figure 2.6, for a more detailed design of the phases see Bisaillon et al. (2011) pg. 146 – 148. The result achieved by the model reach feasible scenarios quickly even with large problems (45 airports, 256 aircraft and 1423 flights; disruptions varying from 34 airports to 230 flights to 4 aircraft). Computation times in each instance is set to 10 minutes.

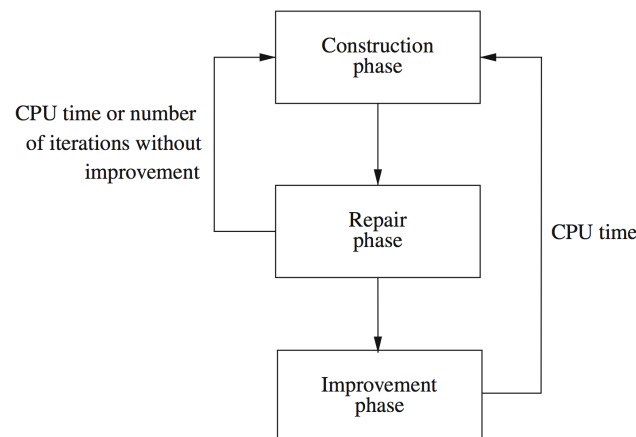


Figure 2.6: Solution method as given by Bisaillon et al. (2011) *source: Bisaillon et al. (2011)*

More recently in 2013 Sinclair et al. (2014) have presented a research which suggest improvements to the model created by Bisaillon et al. (2011). The research for the large part explains the model created by Bisaillon et al. (2011) and makes several adjustment to the the algorithms used so that the solution technique becomes more time efficient and cost effective. The changes made are depicted in Figure 2.7. The results of the improvements are tested on the same scenarios as the original competition. Of the 22 scenarios the improved model found 17 best solution cost within 5 minutes and 21 best solution cost within 10 minutes. In the case with high number of cancelled flights it has been shown to be advantageous to run the model for longer than 10 minutes. Improvements suggested by Sinclair et al. (2014) are among others a better understanding of the relation between cancellation cost and cost of delay, as the authors comment that in this model cancellation cost overshadow the

effect of delays.

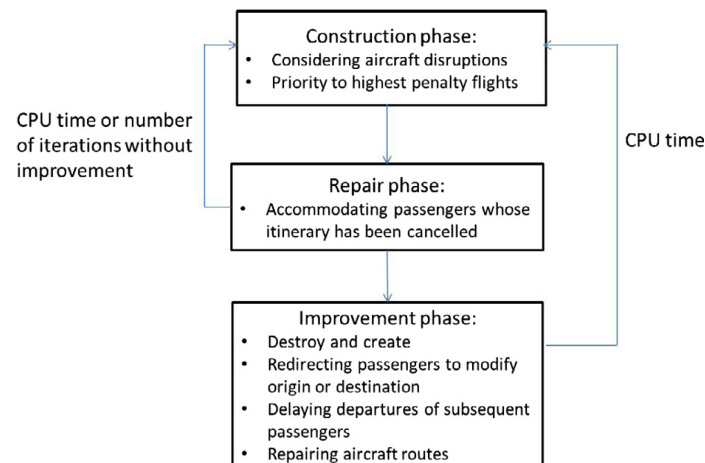


Figure 2.7: Solution method as given by Sinclair et al. (2014) *source:Sinclair et al. (2014)*

Jozefowicz et al. (2013) present a heuristic method which they divide into three phases and they call the new connections and flights heuristic (NCF). The first phase is the integration of the disruptions which considers the set of disruptions sequentially in the following order: (i) cancelled flights; (ii) delayed flights; (iii) aircraft breakdowns; (iv) airport capacity drops; (v) airport capacity overflow repair; (vi) connectivity repair. Each of which is solved by a separate proposed algorithm, cancelling or retiming flights. For a detailed description of the algorithms the reader is referred to Jozefowicz et al. (2013) p387–388. The second phase attempts to assign passenger with same origin and destination to itineraries in which they can reach their destination. Each are assigned to existing rotations where possible through a shortest path problem. If passengers cannot yet be accommodated they are stored for the third phase. The third phase is the flight leg creation, in this phase new sub-rotations are inserted into existing aircraft rotations to allow for the transportation of passengers from the group unable to be accommodated, the groups are prioritize by size. The complete algorithm is presented in Jozefowicz et al. (2013) p. 290. The result achieved by Jozefowicz et al. (2013) model are equally impressive as those by the winner of the competition. Though they do not reach a total score better than Bisailon et al. (2011) they do outperform them in many of the scenarios in the competition. Furthermore the model proposed by Jozefowicz et al. (2013) does not keep iterating for the full 10 minutes allowed, but it reaches a solution within a minute for the majority of the cases and never surpasses 4 minutes.

Integrated Aircraft, Crew and Passenger Recovery

In 1997 Lettovsky presents his PhD thesis work on the subject of integrated recovery; combining the recovery of passengers, crew and aircraft. The problem is presented as a linear mixed integer problem, with the goal of maximizing the airline profits. Lettovsky (1997) presents the problem as a master problem which is the Schedule Recovery Model (SRM) that finds a feasible plan schedule incorporating cancellation and retimings. This is done using a Benders decomposition algorithm. This SRM then controls the sub-problem, which are three sequential problems to be solved. The first is the Aircraft Recovery Model (ARM), the second the Crew Recovery Model (CRM) and the third the Passenger Flow Model (PFM). This sequential solving of the problems make that model represents the manual technique used by many airline OCC's. ³

³The PhD thesis of Lettovsky (1997) was not available to the author of this review, this information is retrieved from Clausen et al. (2010) and Lettovský et al. (2000)

Petersen et al. (2012) is the first research to attempt a truly integrated approach across aircraft, crew and passengers. Many papers that have integrated approaches have models that solve the problems sequentially, and even though this comes with a solution to the integrated problem, the approach does not integrate the sub-problems. Petersen et al. (2012) integrate the different kinds of recovery by applying Bender's decomposition to decompose the model in a master problem (the schedule recovery problem) and three different subproblems (aircraft, crew and passenger recovery problems). The tested case on a US based airline with approximately 800 flight and 2 fleet types. To be able to compare, results are generated for sequential recovery and integrated recovery. The integrated recovery approach show significant improvements in cost across all the scenarios tested (4 disruptions, with 50%, 75% and 100% flow reduction for a period of time), as well as that the sequential in contrary to the integrated approach did not always reach feasible solutions. The largest reductions in cost occur for the larger (more complex) problems. With respect to computation times, the integrated model still should be improved for real-time use. In the tests the majority of the cases are between 25 and 35 minutes.

2.2 This Project within the Academic Scope

This section describes the link between the literature review and the relevance of the chosen thesis topic. Which can be paraphrased into creating a dynamic decision support model aimed at aircraft recovery. It is important to understand what is meant with 'dynamic'. In this topic dynamic refers to a model that solve disruptions as they come, thus a ever changing set of circumstances for which is being solved. The model will always attempts to return to the planned operations, rather than returning to the schedule that is loaded in, which might already be a disrupted situation. All of the literature examined do one of the following two; the take in a total set of disruptions during the day and then solve the entire set or they solve for a single set of disruptions as it becomes known. The limiting factor in the former is that it is not realistic to assume all disruption over a day to be know, disruptions are dynamic and often change through the course of the day. The limiting factor in the latter is that the solution always attempt to return to the schedule that is loaded into the solver. This is not a limiting factor for solving the first set of disruption in on a given day, as returning to the loaded, in this case planned, schedule is the most desirable. However this does become a limiting factor when already disrupted situation are further disrupted. In that case it is more desirable to return to the original planned schedule rather than returning to the loaded (disrupted) situation.

The novelty of this thesis topic comes from being able to see the effect of solving disruptions in real time and seeing the effect of this on solution quality⁴. Furthermore the model in this research attempt not only to solve the disruption at hand but also finding a better solution to disruption that have arisen and been solved earlier.

Within each separate disruption the best solver should be chosen. When investigating the different techniques that can be used several could be applied and would provide feasible solution but the use of a time-band network (as used by Arguello (1997) Bard et al. (2001) Thengvall et al. (2001) Thengvall et al. (2003) Thengvall et al. (2000) Eggenberg et al. (2007)) provides computation times that can be used in real-time as well as being a robust network representation that can be easily adapted. Furthermore the use of a time-band network is one which is conceptually simple. One aspect which will be further explored in Chapter 3.4 is the use of parallel time-space networks, as used by Thengvall et al. (2003). The best heuristic method cannot be concluded from the literature but promising inspiration is drawn from the ROADEF challenge which integrate aircraft and passengers, where Bisailon et al. (2011) solve for a feasible solution and then use remaining time to improve the solution. This type of approach, regardless of which exact heuristic is chosen, could be useful in decision support, as decision support can be seen as 'ideas' for an operator. So as soon as a feasible solution is found it is given to the operator and as better solutions come along those are made known.

⁴Solution quality is in this problem defined as cost and duration of the disruption

2.3 Concluding Remarks Literature

The literature review done for this research project has concluded that much research has been done into the topic of recovery. In the 1990's the research into decision support and optimization of recovery of aircraft, crew and passengers took flight. The early research simulated the manual approach which airline operators use, splitting the recovery of aircraft, crew and passengers into separate problems and solving them sequentially. Doing so resulted in problems that were more tractable, however still needed grave simplifications to be able to solve them within a reasonable time. In the late nineties the use of heuristics in airline recovery operations started with a research by Arguello et al. (1997) and this inspired other researchers to do the same. As the research moved forward researchers integrated the aircraft recovery problem with crew and/or passenger recovery. The research done is often tested on real life test cases, with a given set of disruptions. The disruption found in the literature reviewed are given as a known set for the entire disrupted scenario. This last given fact is where this master research attempts to extend the body of knowledge on airline operations. The goal of this research is to develop a recovery model which takes into account aircraft and crew, for which the total set of disruptions is not yet known at the beginning of the disruption scenario. The disruptions will thus be input in the program sequentially. Thus a novel topic is found for the MSc thesis: *Decrease the cost and duration of disruptions by creating a dynamic decision support model aimed at aircraft recovery*

The novelty of the topic comes from the dynamic aspect of the model, which attempts to provide solutions to the recovery problem as disruption becomes known, rather than solving for an entire set of disruptions or a single disruption. It may also be concluded that from the academic research the use of a time-band network appears to be the best choice for this particular topic.

Chapter 3

Project Plan

This chapter lays out the research plan that has been used in this MSc thesis. This thesis project aims at extending the body of knowledge in recovery operations by applying a dynamic model that solves disruptions as they become known to an operator. This simulation will provide insight in the difference between this approach and the approach where set of disruption over a day with all disruption known at the start.

The research objectives are explained in Section 3.1. This is followed by an explanation of the research framework in Section 3.1. The methodology and hypothesis is explained in Section 3.3 and the last Section of this chapter presents the conceptual model.

3.1 Research Objective

In short the goal of the research is to improve the recovery operations at Kenya Airways and to expand the body of knowledge in airline operations research. With these two goals in mind this project has set out three separate research objectives. The first two are related to the academic goal of the project and the third is related to the industry goal that this project has.

"Create a model which solves the aircraft recovery problem in a dynamic way and demonstrate the difference between solving in a non-dynamic way."

"Demonstrate the feasibility of using a time-space network for each aircraft for solving the aircraft recovery problem in real-time operations, through developing a search algorithm testing small selections of aircraft."

"Decrease the cost of disruptions by creating a dynamic model that recovers aircraft, to be implemented at Kenya Airways"

The novelty of this project is achieved in a few different ways. First and foremost the dynamic approach used in this research provides an insight into the importance of taking into account the time at which disruption become known. The approach used in this thesis work is the use of a search algorithm that selects aircraft and for each selection finds an optimum solution. Whilst using this search method making use of parallel time space networks for each aircraft such that all aircraft specific constraints can be met. This type of approach has not been used before to solve an aircraft recovery problem.

3.2 Research Framework

The research framework used for this research is an alteration of the framework presented by Verschuren and Doorewaard (2010), in which they define the first column as the 'research background'.

The second is the 'confrontation' this includes the input for the conceptual model as independent variable and how the problem is tackled in the form of the conceptual model. The third column contains the 'operationalisation', which is the use and testing of the model and the fourth and final column contains the conclusions and recommendations. For this research project the research questions as defined in the previous section are spread across the research framework as can be seen in Figure 3.1. Several amendments that have been made in the framework are that the part 'future capacity and demand' is put between the first and second as this falls between background knowledge and part of the constraints/input variables. The other part of the framework which is not put under a specific column is the consultation of experts, this is of course partly background knowledge, but is in fact a information source which will be spread over the entire framework.

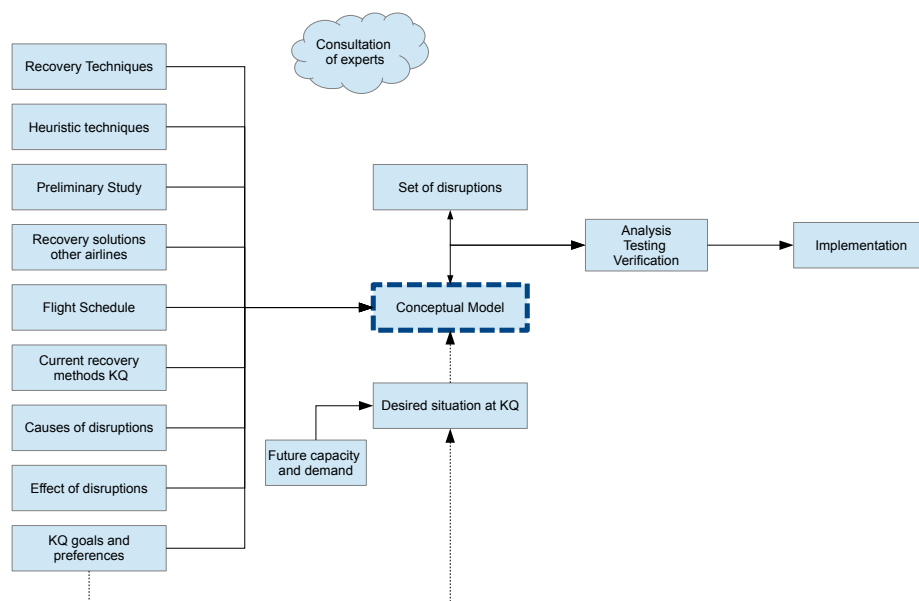


Figure 3.1: Research framework proposed by Verschuren and Doorewaard (2010) adapted to this MSc research

3.3 Methodology and Hypothesis

The methodology of this project is that a simulation will take place of a real situation. In that environment the recovery model will be tested. The test result of the model will be analysed by Duty Managers Operations. Next comparison is made between the performance of the model in (a) the dynamic situation where disruption are solved as they become known and (b) the situation where all disruption are immediately known to the model. The hypotheses of the comparison is as follows:

Solution found to disrupted situations by use of a dynamic model will have higher cost that models of situations where all disruption are know.

The hypotheses is important to be answered but very important as well to determine 'to what extent' the hypothesis is true.

The experimental set-up of the project is quite simple, though completing each of the steps is not. Firstly a model is created that can recover disrupted situations. Data that must be gathered as input for the model is: cost data at Kenya Airways (operating costs, delay and cancellation costs), flight schedule data (and constraints related to the flight schedule), on time performance data as well as several disruption scenarios. Furthermore from literature information must be gathered of how hard and soft passenger cost compare in cases of delays and disruptions. Using all this data the model can be tested and relevant results can be found. The collected data, and KQ case study will be detailed further in Chapter 5.

The physical locations that the work will be done at is; the TU Delft and Kenya Airways Integrated Operations Control Center in Nairobi. The literature study and initial research is be done in Delft and is the first phase of gaining background information. The kick-off of the project is held with all relevant parties present in Nairobi and after that time is split 50-50 between Delft and Nairobi. This way input and information from both industry and university can be gathered.

3.4 Conceptual Model

This chapter describes the conceptual design of the model. This is done through looking at several aspects that are defining of the model's capabilities and limitations.

3.4.1 Scope

Defining the scope of this model is done by first looking at what is feasible within the given time for this research project and secondly where can the most value be added to Kenya Airways and novelty achieved in the field of airline operations research.

Aircraft Recovery

Chapter 2 as well as the professionals at Kenya Airways, confirm that recovery operations have three important resources that are to be looked at, passengers, crew and aircraft. A solution taking all three into account and truly integrating them into a single problem would of course be the most desirable to any airline. However from the literature review (Chapter 2) it is possible to conclude that integrating these parts in this project is not feasible and/or desirable for several reasons:

- **Computation Time** The literature review concludes that to date solutions that look into integrating passenger, crew and aircraft recovery have computation times that are not desirable for operational decision support. From the interviews at Kenya Airways (Mutua et al., 2014) it may be concluded that a goal time of 10 minutes is desirable and should definitely not exceed 20 minutes.
- **Feasibility with project time** from an interview with one of the researches that work on the, to date, most successful attempt at integrating passengers, aircraft and crew it becomes apparent that several years with researchers have been spent making the model presented by Petersen et al. (2012) and creating similar solution for a MSc thesis is not deemed feasible.

The decision is thus made not to integrate the three but look into a single resource. By making this decision there are several aspects of the model that become very important are kept in mind during the entire process:

- **Extendability** The manner in which the model should be written should be written in such a way that the addition of crew and/or passenger should be possible after the end of this project. The manner in which this can be done is discussed in the recommendations Section 8

- **Adaptability** For the model to be properly extendable it should also be easily adaptable, the manner in which the model is written should be highly modular such that modules of the program can be adapted and interchanged.

Due to feasibility, the choice is made to select one of the resources. Deciding which of the three should be based on the resource which has the most impact on the operations at Kenya Airways. From the background research presented in Chapter 5 it clear that of the three resources present in recovery operations aircraft related delays and more importantly aircraft related reactionary delays have by far the most negative impact on the airline's OTP. Thus solving the aircraft recovery problem will have the most positive impact on Kenya Airways' operations.

Dynamic Solution for a Day of Operations

The previous subsection explains the reasons behind choosing for aircraft recovery, this subsection explains the choice for the manner in which disruptions are solved. One of the conclusions from the literature review is that the prevailing technique in literature is to solve a single set of disruptions, sometimes an entire set over an entire day. In actual operations, disruptions are solved as they become known and this is also the manner in which this model solve disruptions. There are several cases in literature where simply a single disruption is solve, one could argue that running this type of solution for several sequential disruptions and saving the new situation would have the same effect. However there is one thing that this does not take into account and should be added; which is the possibility for the model to recover reactionary delays caused by previous disruptions.

3.4.2 Input and Output Definition

This section details the necessary input and output from the model. The output is defined first as the necessary output defines the input.

Input

The input for the model to achieve the given output is the following:

- **Original flight schedule** The operations as originally planned should be input into the model as the goal of the model is to keep as to this planning as closely as possible.
- **Cost data** Cost data can be split into two main categories:
 - The operational cost of flying an aircraft on a certain route, this is important when the if the model replace a planned aircraft with an aircraft of a different type.
 - The cost of delay, this is further detailed in 5.3, but in short can be categorized as hard cost (actually compensation to passengers) and soft cost (the cost of losing a future customer due to dissatisfaction due to the delay).
- **Booking information** The amount of business and economy passengers on each flight is important to determine the cost of delay as well as which aircraft is eligible to fly a certain route.
- **Fleet information** Information about the all the aircraft in the fleet will define which aircraft are eligible to fly which routes from a performance point of view. This may include tail number specific constraints.
- **Disruption information** To be able to solve disruption there must be detailed information about the disruptions to be solved, and when they become known.

Output

- **New schedules and respective cost** The output for the model in a disrupted situation should be a new schedule which can be implemented. The objective of such a new schedule is to be the solution to the disruption with the lowest cost. Because this model is looking to be a decision support tool for Kenya Airways, the model should not only give the lowest cost solution with the accompanying cost, it will also provide the different iterations of finding the solution along with the respective costs. This will provide the operations managers at KQ with several solution options from which they can choose.
- **Schedule evolution** For the dynamic simulation for which the model will be run the evolution of the schedule along the day should be output, so that the effect of running the dynamic situation can be compared to running a single solution.

3.4.3 Objective Function

The objective function of the model as a whole is to reduce the cost of delay through minimizing the delays and cancellations. To be able to determine the total cost of these delays an objective function must be determined giving weights to each of the decision variables. In this model the decision variables are the myriad of choices of schedule that are possible. In short the decision variables are the following:

- Whether to fly a certain flight
- At what time to fly a certain flight
- With which aircraft to fly a certain flight

The decision on these variables will determine the total cost of the objective function. The exact detailing of the objective function can be found in Section 3.1

This concludes the high level conceptual set-up of the model, and this chapter defining the project plan. The following chapter will further detail the Dynamic Recovery Model and Chapter 5 gives the detailed information about the Kenya Airways test case and how the costs and other input data are gathered and/or calculated.

Chapter 4

Model

This chapter explains the manner in which the dynamic aircraft recovery model works in detail. There are several different aspects of the model that are important for understanding the total working of the model. The inner most module is the Selected Aircraft Linear Solver (SALS). The SALS takes a small given selection of aircraft of which some are disrupted and using a linear solver finds the global best solution to the disruptions with the given selection of aircraft. The SALS is explained in detail in Section 4.1. One level higher in the model is the Disruption Set Solver (DSS). The DSS is a solver that solves a set of disruptions that becomes known at a given time using a certain algorithm that looks for the aircraft in a given fleet to find the best selection of aircraft to solve the disruptions. Running the DSS solves all the disruptions known at a given time; also dynamically solving disruption that have become known earlier in time. The DSS is explained in section 4.2. The top level in the model is the simulation of actual situation the main input at this level is disruptions and the time at which they become known, the top level of the model then runs the DSS for each moment in time when new information becomes known. A small schematic of the model setup is given in 4.1.

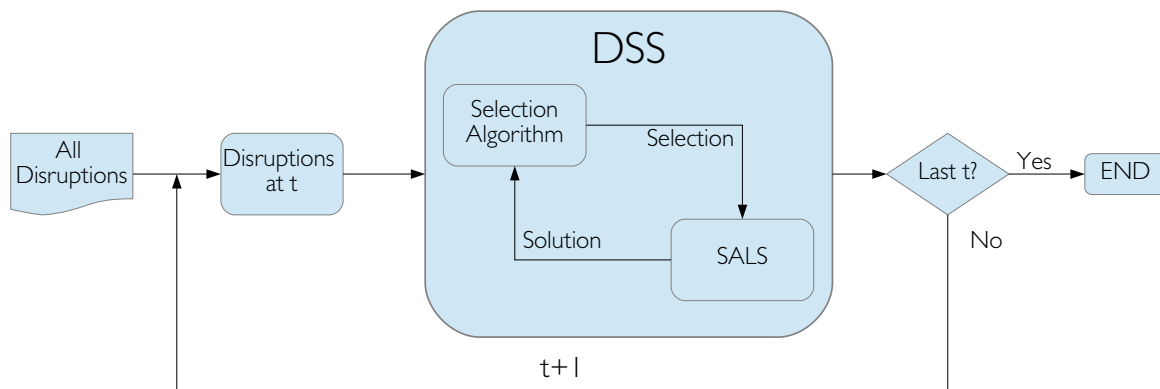


Figure 4.1: A top level schematic of the model showing the relation between the whole model, the Disruption Set Solver and the Selected Aircraft Linear Solver

4.1 Selected Aircraft Linear Solver (SALS)

The selected aircraft linear solver (SALS) is the inner most module of the disruption management modelling framework presented in this work. What this module does is given a selection of aircraft, a flight schedule, flight load factors and a set of disruptions, it finds by means of a linear problem solver the lowest cost solution. As with most linear programs the mathematical formulation consists of sets, indexes, parameters, decision variables, an objective function and constraints. These will be explained

in the sections below.

4.1.1 Sets and Indexes

This section defines the sets that are to be used in the disruption solver linear program module. Firstly the input sets are defined, using these input sets the sets that are actually used by the linear program are defined which is best explained through explaining the time space network. From here an overview of the sets and indexes is presented.

Input Sets

The input sets into the model are taken from the input schedule and KQ fleet information. The sets are flights F (with index i), airports A (with index a), aircraft P (with index p) and a set of discrete times T (with index t) for the length of the time widow which is a predefined. For the set of aircraft P there is a set of equal length create called $Ptype$ (also index p) where each element $Ptype_p$ is the aircraft type for aircraft P_p . For the set F there are several sets of equal length and same index made to save characteristic of the flight: set of scheduled times of departure (STD), set of scheduled times of arrival (STA), set of origins (origin), set of destinations (destination), set of planned aircraft for the flight (tailnr), set of number business and economy passengers booked ($PaxJ$, $PaxY$).

Input sets:

F_i	set of flights
A_a	set of airports
P_p	set of aircraft
$Ptype_p$	set of aircraft types
STD_i	set of scheduled departure times
STA_i	set of scheduled arrival times
$origin_i$	set of origins
$destination_i$	set of destinations
$tailnr_i$	set of scheduled tail numbers
$PaxJ_i$	set of business passenger booked
$PaxY_i$	set of economy passenger booked

Time-space Network

To explain the manner in which the SALS module works it is important to explain the network representation that has been chosen; the discrete time space network. A time space network representation is one consisting of a set nodes (N) and arcs (A_x). Figure 4.2 depicts a discrete time space network. On one axis all the airports are given and on the other axis all the discrete time steps are given. Each node on the network represent a given airport at a given time. The nodes are numbered as depicted in the image, after which a node list is made of all the nodes in which the time and the airport of each node is saved. Arcs are one directional connections between two nodes, and all arc are saved by storing their origin node and destination node in a list. The arcs in the model are split in three different types. The first type are ground arcs (A_{G_n}) depicted in Figure 4.3 where the ground arc index n , is equal to the index of the node from which it departs. Ground arcs connect each node with the next node in time at the same airport. A flight arc A_{F_i} is created for each flight F_i in the set of planned flights F where i is the index of a particular flight. An example of a flight arc is depicted in Figure 4.4, this figure also shows the last type of arcs; delay arcs. Delay arcs, $A_{D_{i,j}}$ are copies of flight arcs A_{F_i} where i is the index of the flight which is being delayed and j is the index of the number of time steps that it is being delayed¹. Where delaying a flight by one delay step, indicates a delay to the

¹Note that $A_{D_{i,0}}$ has the index $j = 0$ means that there is a delay of one time step

following node, in other words a delay equal to the time resolution. The²



Figure 4.2: Nodes in time space network

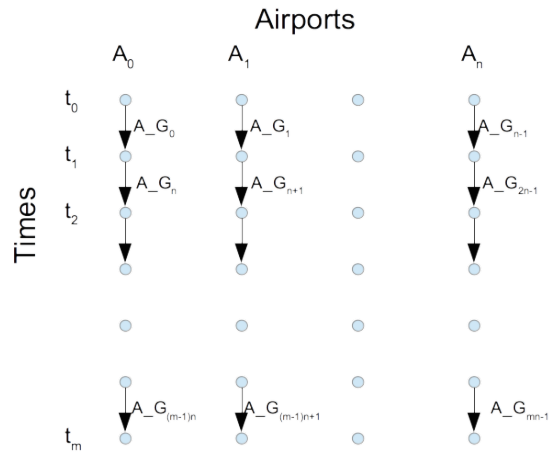


Figure 4.3: Ground arcs in time space network

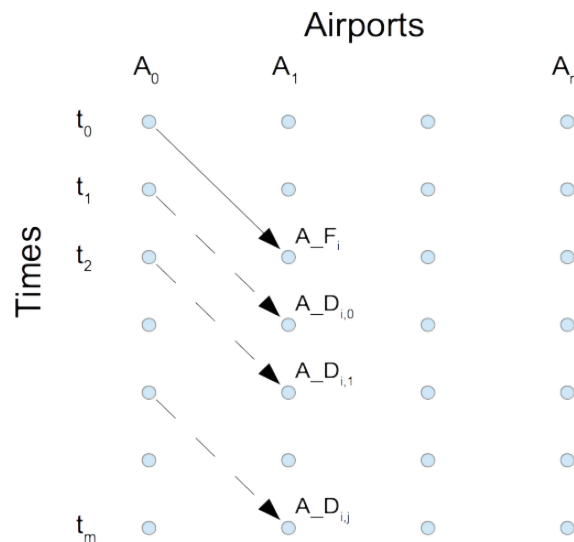


Figure 4.4: Flight and delay arcs in time space network

Extension of Time-space for Each Aircraft

When modelling the situation in real life, it is not possible to represent the network in a single time space network. The reason is because in a single time-space network the linear program cannot distinguish between aircraft but simply constrains whether or not an arcs are selected and how many times they are selected (described in more detail in Section 4.1.2 and 4.1.3). In a single time-space network it is thus not possible to for example constrain a certain aircraft or aircraft type to a certain flight.

If the situation exists where only the aircraft type is of importance but not the specific aircraft it would be possible to solve the problem by creating a time-space network for each aircraft type.

²There is also a fourth type of arc which can be implemented which is a maintenance arc; these maintenance arcs are put in the set of flight arcs and connect two nodes at the same airport, limited delay arcs for the maintenance arcs can be created

This solution is suggested by Thengvall et al. (2003). Within each of the time-space networks aircraft are interchangeable, which in this situation means that aircraft of the same type are interchangeable. In real life situations this is often the case, however there are some limitations. The most important limitation is maintenance, if maintenance is planned for a certain aircraft it cannot be interchanged for another aircraft. Another reason is that there can be aircraft specific constraints that might make it impossible for one aircraft in the fleet not to cover a certain flight.³ Furthermore many of the disruptions that occur happen to a specific aircraft making it vital to the model proposed in this work to be able to constrain a specific aircraft. Figure 4.5 displays the situation where a single time-space network contains two aircraft, in that case at the beginning of the time window it is can be deduced which aircraft occupies which arc. When the two aircraft meet a node the exiting arcs are selected however by the model to meet the continuity constraints (explained in Section 4.1.3) however there is no manner of distinguishing between which arc is flown by which aircraft.

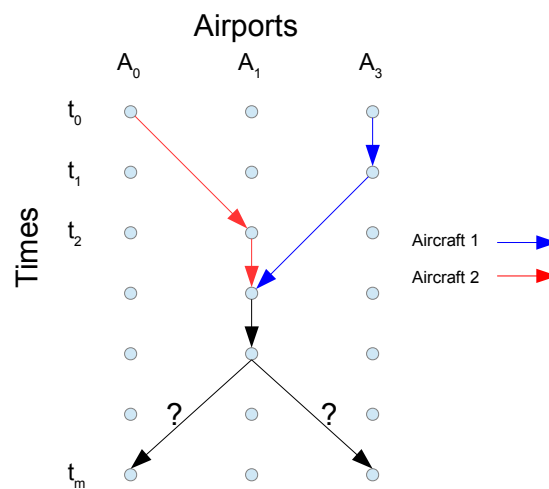


Figure 4.5: Two aircraft in a single time space network who's paths cross on the same nodes; after such a crossing there it is not clear which aircraft occupies which arc as these are integer values.

The manner in which these issues are resolved is by creating a time-space network for each aircraft, in which aircraft specific constraints can be implemented. By applying this extension the model receives an extra dimension, from a time-space network to a time-space-aircraft network. Figure 4.6 show a representation of the parallel time space networks. Each node in the network represents a certain aircraft at a certain airport at a certain time. Extending by the extra dimension of aircraft also extends the used sets by an extra index for the aircraft. All the sets that are used in the linear model are the given below.

³It is found from interviews with experts that there are several cases where a single aircraft might have specific constraints. For example if there is a single engine bleed failure the aircraft can still operate but perhaps not on all routes.

To incorporate minimum turn around time in the model the following technique is applied. The flight and delay arc turn around time is added to the flight time depending on the aircraft type, this is made possible due to the extension to parallel time space networks per aircraft, and ensures that flights in the solution do not depart before turn around is completed. In fact what this technique does is for the linear solver makes it 'look' like the flight is longer by the turn around time depending on aircraft type.

4

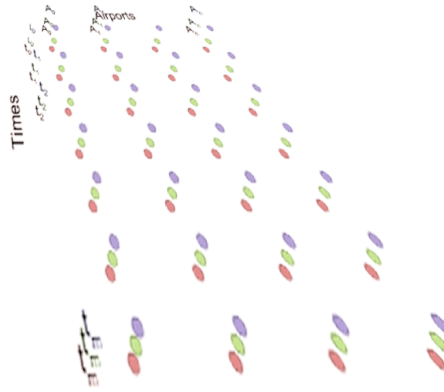


Figure 4.6: The extension of the time space network into the 3rd dimension of aircraft.

Sets:⁵

$A_{G_{p,n}}$	set of ground arcs
$A_{F_{p,i}}$	set of flight arcs
$A_{D_{p,i,j}}$	set of delay arcs
F_i	set of flight
A_a	set of airports
P_p	set of aircraft
N_n	set of nodes in the network
J_j	set of delay steps possible

Indexes:

i	flight index
j	delay time index
a	airport index
p	aircraft index
n	node index

4.1.2 Parameters, Decision Variables and Objective Function

The parameters for this model are the cost of each of the arcs that can possibly be selected, are in fact the cost of selecting each arc. The detailing of the cost is described in Chapter 5, where the direct operating cost are defined as well as the hard and soft cost of delay. The decision variables are the boolean variables which make it possible to select each type of arc and the option of cancelling a flight.

Decision Variables:

⁴ **Alternate solution:** An alternate solution to the aircraft specific constraint is by creating a time-space network for each aircraft type, and then creating a parallel time-space network for each aircraft which has specific constraints, for example those with planned maintenance or those that have disruptions that occur. This solution has been tested for a small case but it is found that path finding algorithms needed (to reconstruct aircraft paths that have crossed each other) are very slow.

⁵ All entries into sets of arcs contain an origin and a destination node, e.g. $A_{F_{p,i}}[0]$ refers to the origin node and $A_{F_{p,i}}[1]$ refers to the destination node.

$\delta_{AF_{p,i}}$	=1 if flight arc i by aircraft p is selected	=0 otherwise
$\delta_{AG_{p,n}}$	=1 if ground arc n is used by aircraft p	=0 otherwise
$\delta_{AD_{p,i,j}}$	=1 if flight i by aircraft p with $(j+1)$ *timestep delay is selected	=0 otherwise
δ_{Canx_i}	=1 if flight i is cancelled	=0 otherwise

Using the above decision variables the objective function becomes the choice of each of the variables multiplied by the cost of selecting each of the variables. The detailing and calculation for the actual costs are presented in Chapter 5. $COP_{p,i}$ is the direct operating cost of aircraft of aircraft p on route flight i . In the operating cost a minimal discount of 1 USD is given to flight if the aircraft p is planned to fly flight i . The reason for this is that there is, if all else equal, a minimal incentive for the model to keep the planned aircraft on the same route. If this 1 USD discount is not included then the model can and will make tail switches for no apparent reason. C_{D_j} is the total cost of delay per economy passenger when delaying a flight by j amount of time steps. The index j is the index to the list J ; which is a list of all the delays possible. The delays possible are delays which are multiples of the time-resolution up to a certain maximum delay. The cost of delay for business passengers is determined through a multiplier (β) of cost of delay for economy passengers.⁶ The calculation of the total cost of delay of a flight for a given delay step is given in Equation 4.1 The cost of cancellation C_{C_i} is the cancellation cost per economy passenger when cancelling a flight. This cost is defined as equal to the cost of the maximum delay plus a ticket refund. Included in the cost of the cancellation should be the ticket price that each passenger has paid, however these are not available to the author of this report so an average value is used for short and long haul flights. The total cost of cancellation for a given flight is presented in Equation 4.2. Finally there is a cost for each ground arc selected; every airport has different ground fees which apply. C_{AG_n} is the cost of ground arc n .

Equation 4.3 combines all of the described decision variables and links each to the associated cost to give the total objective function of the SALS.

$$C_{D_{i,j}} = (C_{D_j}) * (PaxY_i + \beta * PaxJ_i) \quad (4.1)$$

$$C_{C_i} = (ticketprice_i + C_{D_{max}}) * (PaxY_i + \beta * PaxJ_i) \quad (4.2)$$

$$\min \left\{ \sum_{p \in P} \sum_{i \in F} \delta_{AF_{p,i}} * COP_{p,i} + \sum_{p \in P} \sum_{i \in F} \sum_{j \in J} \delta_{AD_{p,i,j}} * (COP_{p,i} + C_{D_{i,j}}) + \sum_{i \in F} \delta_{Canx_i} * C_{C_i} + \sum_{n \in N} \delta_{AG_n} * C_{AG_n} \right\} \quad (4.3)$$

4.1.3 Constraints

This section gives an overview of the constraints that are used in the linear program ensuring that only valid solutions are given. The last set of constraints given are the disruption constraints, these are optional constraints that can be input into the model depending on the causal disruptions present in the given time window.

Flight Coverage

The first constraint is the flight coverage constraint. This constraint ensures that each planned flight is either flown on time, delayed or cancelled. This ensures that flights do not 'disappear' without the respective cost being added to the objective function. The mathematical formulation is given in Equation 4.4.

$$\sum_{p \in P} \left[\delta_{AF_{p,i}} + \sum_{j \in J} \delta_{AD_{p,i,j}} \right] + \delta_{Canx_i} = 1 \quad (4.4)$$

$i \in F$

⁶In the case study done in this report at Kenya Airways the business multiplier is defined at a value of $\beta = 3$.

Node Continuity

The node continuity constraint ensures that at every node in each time space network if an aircraft comes into that node that it is also leaving that node. This constraint ensures that no aircraft are created or destroyed. The mathematical formulation, given in Equation 4.5, the equation consists of the arcs coming into the node minus the arcs moving out of the node being equal to 0. This constraint is valid for all nodes that are not start or end points of aircraft.

$$\left(\delta_{AG_{n-1}} + \sum_{i \in F(A_{F_i}[:,1]=n)} \delta_{AF_{p,i}} + \sum_{i,j \in F,J(A_{D_{i,j}}[:,1]=n)} \delta_{AD_{p,i,j}} \right) - \left(\delta_{AG_n} + \sum_{i \in F(A_{F_i}[:,0]=n)} \delta_{AF_{p,i}} + \sum_{i,j \in F,J(A_{D_{i,j}}[:,0]=n)} \delta_{AD_{p,i,j}} \right) = 0 \quad (4.5)$$

$p \in P$ and $n \in N_{\text{not a start or end node}}$

The above node continuity constraint ensures that no aircraft are created or destroyed throughout the time window. However at the beginning of the time window at certain nodes aircraft enter and must have to be 'generated'. As well as ending points where aircraft need to be 'eliminated'. These nodes are called sources and sinks, respectively. For that reason the starting and ending point constraints are in fact adaptations of the node continuity constraints.

Start point node continuity Each individual aircraft has a starting airport at the beginning of the time window. So for each aircraft the starting node is determined using the flight schedule. The node continuity constraint for that particular aircraft p and that particular node n is set equal to 1 instead of 0. This means that at that node we have generated an aircraft, making that node an aircraft source of one aircraft. The mathematical formulation is given in equation 4.6, it may be noted that arcs coming into this node are left out of the node continuity constraint, the reason is because there are no arcs that enter the nodes at the beginning of the time window.

$$\delta_{AG_n} + \sum_{i \in F(A_{F_i}[0]=n)} \delta_{AF_{p,i}} + \sum_{i,j \in F,J(A_{D_{i,j}}[0]=n)} \delta_{AD_{p,i,j}} = 1 \quad (4.6)$$

$p \in P$ and $n = \text{end node of aircraft } p$

Ending point node continuity For the ending points there are two different options that are possible, which the user of the model can choose between in the model's general input settings:

- **Fixing the end position of an aircraft** This option is similar to the starting point constraints in which the end point of a particular aircraft is fixed by setting the node continuity constraint for one particular aircraft at one particular node equal to -1 instead of 0. In this node there are no outgoing arcs thus the node continuity constraint consists of minus the sum of incoming arcs equal to -1, or as shown in Equation 4.7 the sum of incoming arcs equal to 1.

$$\delta_{AG_{n-1}} + \sum_{i \in F(A_{F_i}[1]=n)} \delta_{AF_{p,i}} + \sum_{i,j \in F,J(A_{D_{i,j}}[1]=n)} \delta_{AD_{p,i,j}} = 1 \quad (4.7)$$

$p \in P$ and $n = \text{starting node of aircraft } p$

- **Fixing the end point to be an aircraft of a particular type** In this option the model is constrained in such a way that an aircraft of a particular type ends at a certain location.⁷ The manner in which this is constrained is that one constraint is written for each airport and each aircraft type. In that constraint the sum of all the arcs with destination node equal to the last node at

⁷This is also the prevailing choice by Kenya Airways, as the individual aircraft is not so important but the type is important for the continued operations past the time window.

the given airport for all the aircraft of the given type is taken. The mathematical formulation is given below in Equation 4.8.

$$\sum_{p \in P_{\text{of type } T}} \left(\sum_{n \in N_{\text{where } t = \text{end and airport} = a} \left(\delta_{AG_{p,n}} + \sum_{i \in F(A_{F_i}[:,0]=n)} \delta_{AF_{p,i}} + \sum_{i,j \in F,J(A_{D_{i,j}}[:,0]=n)} \delta_{AD_{p,i,j}} \right) \right) = \sum_{\text{aircraft of type } T \text{ ending at } a}$$

$a \in \text{Airports and } T \in \text{List of aircraft types}$

(4.8)

Flights inside, entering and exiting time window

Flights entering and exiting the time window are flights that are in the air at the start or the end of the time window. So flights entering are those that depart before the time window and arrive in the time window. Flights exiting are those that depart in the time window but are scheduled to arrive past the end of the time window. Flights coming in and going out of the time window present two challenges, firstly they should be fixed in as flights outside of the time window should not be affected, and secondly a problem arises when creating the flight arcs as no nodes exist outside the time window. Figure 4.7 gives a schematic of a time window in a time space network, showing one flight arc entering, one flight arc inside and one flight arc exiting the time window.

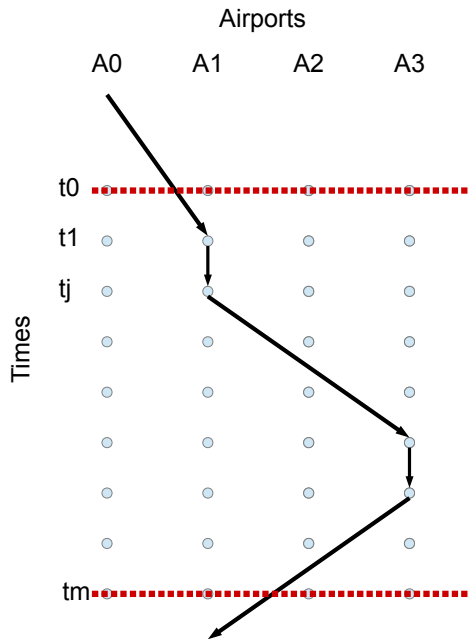


Figure 4.7: Flights inside and crossing the start and end of the time window

- **Challenge 1: Fixing incoming and outgoing flights.** The flights coming into the time window and the aircraft by which they are flown should be constrained to be fixed. Those aircraft on those flights have already departed and cannot be changed. Flights going out the time window should be seen as aircraft ending points and should be fixed for a certain aircraft type rather than one specific aircraft.⁸

⁸For fixing outgoing aircraft type there is also the option of fixing it to a certain tail number, which can, just like the end points constraints, be selected by the user in the model's general settings.

- Challenge 2: No nodes outside the time window** The previous point indicates that the flights crossing the beginning and end of the time window are to be fixed, however these are flights that are missing either origin or destination nodes because no nodes exist outside the time window. The manner in which this is solved is that flights coming in have their origin node set to the first node in the time window at the origin airport. The flights exiting the time window are set to have the ending node as the last node in the time window at the destination airport. Figure 4.8 show how the flight arcs that cross the time window beginning and end are entered into SALS. The flight will appear to be shorter in the time space network. However the actual times of departure and arrival are not changed only the node is changed, and considering that the flights are constrained to be fixed they are also not affected by delays or cancellations, meaning that the flights will still be usable in an unchanged manner for future runs. In addition this constraint has no effect on the start and end constraints described in the previous section as the beginning and ending airports of the aircraft are unchanged.

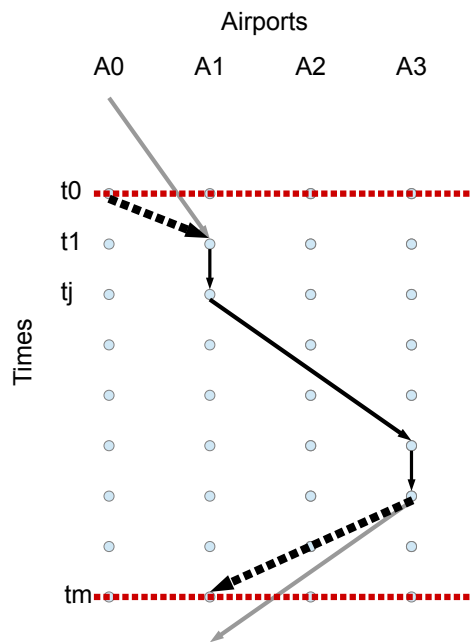


Figure 4.8: The manner in which fixed flights **arcs** are adapted to be inside the time window.

The mathematical manner for determining flights coming in and out of the time window is simple. For flights entering and exiting the time window a search is done for the following conditions given by Equations 4.9 and 4.10 respectively. Equation 4.11 is the equation used to determine which flights are completely inside the time window and are not taken into the model.⁹ Where STD and STA are Scheduled Time of Departure and Arrival respectively. TW_{start} and TW_{end} are the start and end time of the time window.

$$F_{entering} = F_i \text{ for all } i \in ((STD_i < TW_{start}) \cap (STA_i > TW_{start})) \quad (4.9)$$

$$F_{exiting} = F_i \text{ for all } i \in ((STD_i < TW_{end}) \cap (STA_i > TW_{end})) \quad (4.10)$$

⁹Hypothetically it is possible that a flight is both entering and exiting the time window in this case it is still taken into the model though it is completely fixed, thereby not adding to the solution but still taking up computational space because a time-space networks is still created for the aircraft. In practice this will not be the case, because the time window for short-haul is minimum 12 hours and long-haul is 48 hours.

$$F_{inside} F_i \text{ for all } i \in ((STD_i > TW_{start}) \cup (STA_i < TW_{end})) \quad (4.11)$$

Dynamic situation: Flights inside, entering and exiting time window

In the dynamic situation where certain delays and cancellations have already taken place the constraints for flights coming in and going out of the time window change. In the situation where flights are delayed or cancelled it is no longer possible to simply look at the STD and STA of each flight and thereby determine whether or not to fix it or not. So the manner in which this is solved is that for each flight the STA and STD plus the delay time are investigated. This can result in several situations. For the situations mentioned in the previous section this still remains the same for the flights which are to be fixed coming in or going out of the time window except that the delay is now added to the STD and STA. $Delay_i$ is the amount of time which flight i is delayed when loading the flight schedule into the SALS.

$$F_{entering} = F_i \text{ for all } i \in ((STD_i + delay_i < TW_{start}) \cap (STA_i + delay_i > TW_{start})) \quad (4.12)$$

$$F_{exiting} = F_i \text{ for all } i \in ((STD_i + delay_i < TW_{end}) \cap (STA_i + delay_i > TW_{end})) \quad (4.13)$$

$$F_{inside} = F_i \text{ for all } i \in ((STD_i + delay_i > TW_{start}) \cup (STA_i + delay_i < TW_{end})) \quad (4.14)$$

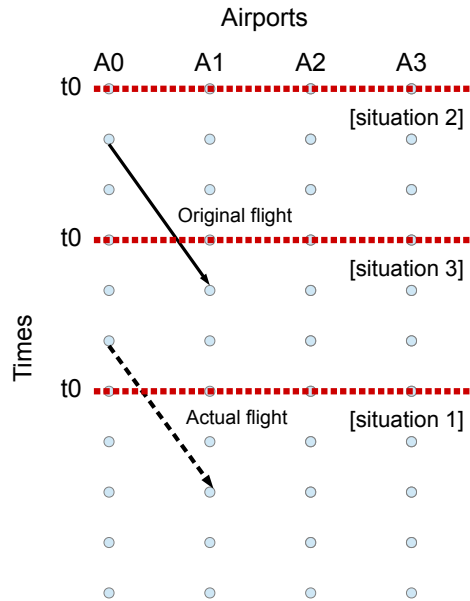


Figure 4.9: An original flight and a delayed flight in a time-space network in which three different situations are possible. Each situation has a different time window start.

In practice all the flights exiting the time window will have a delay equal to zero, the reason for this is that flights cannot be delayed past the time window (see Section 4.1.3), and because the time window never moves backwards, therefore the flights crossing the time window end will never have endured delays. Equation 4.12 fixes all the flights that have already departed and are in the air at the time window start. Figure 4.9 shows three situations of possible time window starts, situation 1 is where a delayed flight is entering the time window. The flights which are inside the time window are given by equation 4.14. For the flights that are inside there are two different situations possible. The

first is where the delayed flight is inside the time window and the planned flight is also in the time window, i.e. meeting conditions given by Equations 4.11 and 4.14. If Figure 4.9 this is where the time window start is set at situation 2. In that case the scheduled times are input into the model such that the flight can be fully recovered, but the delay times are used to determine where the aircraft starts and ends. As the routing of the aircraft has of course been determined in the previous situation with the delay times. The other possibility is that STD_i is before the time window start but when including the delay it is not. In that case the scheduled time will be used as model input, but the flight will be constrained with a minimum delay past the beginning of the time window. The method for this is the same as the constraint use to add delays described in Section 4.1.3. This makes it possible to recover the flight up to the start of the time window. Once again in this case the scheduled time plus delays are used to determine starting and ending positions. There are two reasons that using the scheduled times of departure and arrival (in stead of delayed times) is important, firstly it makes it possible to recovery flight up to the schedule time or the beginning of the time window (the present) which is a desirable situation minimising total delay. The second reason is that the cost of delay is not linear meaning that the incremental cost of delaying a flight by a step of 10 minutes is different for a flight which has already been delayed, and for that reason the actual departure times should always be compared to the scheduled times.

For flights which have been cancelled a fictional maximum delay is given to these flights, this means that these flight will be taken into the recovery possibilities until the start of the time window is past the maximum delay.¹⁰ The flight which has been cancelled are not used when determining the starting or ending positions of the aircraft.

No delay past time window

As described in Section 4.1.1 delay arcs are written in such a manner that that they are copies of flight arcs. The arcs are created up to a maximum of J delay arcs. However more often than not there the maximum amount of delay arcs will cause delay arcs to be created past the end of the time window. Because there are no nodes past the time window delay these arc cannot be created. A constraint is then written which finds all the delay arcs where origin node and destination node are empty values and makes that the sum of all the binary selection variable for these arcs is equal to zero. This ensures that no flights are delayed past the end of the time window. Figure 4.10 shows the delay arcs for which would have destination nodes past the end of the time window in red, these red arcs can not be selected.

¹⁰The maximum delay for the for the Kenya Airways test case is set to 9 hours, this is decided upon in discussion with Thomas Omondi former head of Operations

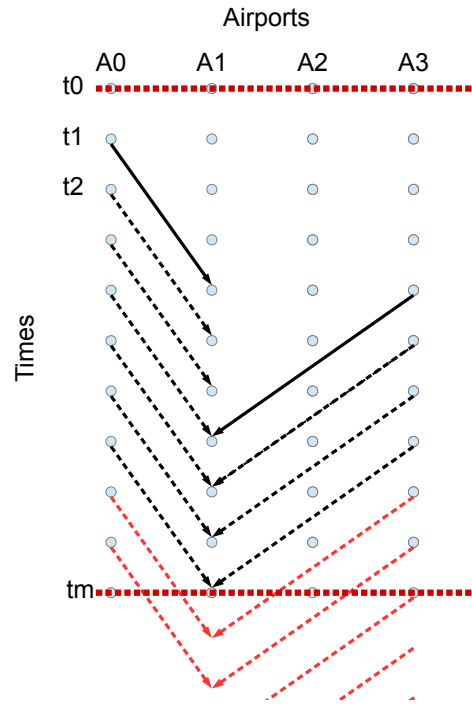


Figure 4.10: An original flight and a delayed flight in a time-space network in which three different situations are possible. Each situation has a different time window start.

Aircraft Specific Constraints

There are several limitation on which aircraft is able to fly which route. For that reason there are several aircraft specific constraints. These are written in a manner where in the initial loading of the schedule the constraints are tested and a boolean array is create with on one axis the all the flight with index i and on the other axis all the aircraft with index p . For each value in this array that is false all the boolean decision variables for all flight arcs and delay arcs for that specific flight i by aircraft p will be added to the constraint of which the sum must equal zero. Such an array and constraint is created for each of the following constraints:

- **Passengers booked constraint** this constraint check for each flight the number of passenger that are booked in economy and business class. The array entry for flight i , and aircraft p receives a boolean value TRUE if aircraft p can accommodate the passengers booked on flight i . 4.15 give the mathematical formulation of the constraint, it should be noted that the equation is applied to both economy and business class.

$$\sum_{p, i \in (\text{capacity}_p < \text{passengers}_i)} \left(\delta_{AF_{p,i}} + \sum_{j \in J} \delta_{AD_{p,i,j}} \right) = 0 \quad (4.15)$$

- **Range constraint** this constraint check that aircraft p can fly the required distance of flight i . If so, the boolean entry into array entry i, p is TRUE. The mathematical formulation is given in 4.16

$$\sum_{p, i \in (\text{Range}_p < \text{distance}_i)} \left(\delta_{AF_{p,i}} + \sum_{j \in J} \delta_{AD_{p,i,j}} \right) = 0 \quad (4.16)$$

- **Fire category constraint** this constraint is similar to the previous two constraints except that the check that takes place is a check to determine whether the destination airport fire category of flight i meets the requirement of aircraft p .
- **Miscellaneous constraints** due to the set up of the parallel time space networks it is possible to add in any other constraint specific to any route or aircraft.

Disruptions

The input of disruption is done through writing constraints. An automatic disruption constraint writer function is created in the model so that a user friendly input interface for is created to input the disruptions. The possible disruption constraints are described below.

- **Delay flight** The input for the delay flight constraint consists of the flight number to be delayed and the amount of time to delay it by. The delay time can be given in two ways, either an amount of time by which to delay the flight or a time until which the flight should be delayed. The constraint then makes all the flight and delay arcs departing before the given minimal delay equal to zero, forcing the flight to be at least delayed the given time. Equation 4.17 is the mathematical formulation of the constraint

$$\sum_{p \in P} \delta_{AF_{p,i}} + \delta_{AD_{p,i,j}} = 0 \text{ for all } j \in J \leq \text{delay} \quad (4.17)$$

- **Flight at certain time** This disruption is similar to the previous disruption but rather than leaving the possibility to also further delay the flight this constraint forces a flight at a certain time. It does so by fixing a certain delay arc for flight i and delay step j across the set of aircraft, the constraint is given in Equation 4.18.

$$\sum_{p \in P} \delta_{AD_{p,i,j}} = 1 \quad (4.18)$$

- **Cancel flight** In the decision variables δ_{AC_i} is 1 if a flight i is cancelled. If there is thus an disruption in which an operator for what ever reason imposed that a flight is to be cancelled this is done by constraining the δ_{AC_i} to be 1.

$$\delta_{AC_i} = 1 \quad (4.19)$$

- **Aircraft unavailable** This constraint makes a certain aircraft unavailable from a certain time until a certain time. This constraint looks at all the flight and delay arcs of a certain aircraft departing or landing in a certain time window and makes the sum of them equal to zero. The manner in which the time window is selected is done by selecting a range of nodes from the first airport to the last airport at start and end times respectively as they are numbered in chronological order, see Figure 4.2. This method is a way of selecting all the nodes in a certain time window.

$$\begin{aligned} \sum_{i \in F_{\text{selection}}} \delta_{AF_{p,i}} + \sum_{i \in F} \sum_{j \in J_{\text{selection}}} \delta_{AD_{p,i,j}} &= 0 \\ F_{\text{selection}} &= F_i \text{ for all } i \in (t_{\text{start}} \leq STD_i \cup STA_i \leq t_{\text{end}}) \\ J_{\text{selection}} &= J_j \text{ for all } j \in (t_{\text{start}} \leq (STD_i + j * \text{timestep}) \cup (STA_i + j * \text{timestep}) \leq t_{\text{end}}) \end{aligned} \quad (4.20)$$

- **Airport unavailable** similar to the aircraft unavailable this constraint it finds all the arcs that start or end at a certain airport in a certain time window over all the aircraft. Equation 4.21 gives a simplified mathematical representation of the constraint, where the selection of F is

defined as all the flight arcs that depart from or arrive at the selected airport between the given start and end times.

$$\begin{aligned}
 & \sum_{p \in P} \left[\sum_{i \in F_{selection}} \delta_{AF_{p,i}} + \sum_{i \in F} \sum_{j \in J_{selection}} \delta_{AD_{p,i,j}} \right] = 0 \\
 & F_{selection} = F_i \text{ for all } i \in \left[\begin{aligned} & ((t_{start} \leq STD_i \leq t_{end}) \cap (origin_i = airport)) \cup \\ & ((t_{start} \leq STA_i \leq t_{end}) \cap (destination_i = airport)) \end{aligned} \right] \\
 & J_{selection} = J_j \text{ for all } j \in \left[\begin{aligned} & ((t_{start} \leq STD_i + j * timestep \leq t_{end}) \cap (origin_i = airport)) \cup \\ & ((t_{start} \leq STA_i + j * timestep \leq t_{end}) \cap (destination_i = airport)) \end{aligned} \right] \quad (4.21)
 \end{aligned}$$

Disruptions in the dynamic situation

When using the SALS in the dynamic situation disruptions are taken into account that meet the following two conditions: (1) the time that the disruption becomes known is before or equal to the present time (beginning of the current time window) and (2) the disruption has a primary effect on the current time window. The latter is tested in the model by looking at the disruption type and then checking that the disruption has an effect reaching the current time window. In disruption constraints for delays, airports unavailable and aircraft unavailable this simply means checking the attribute 'until time' is inside the time window. For cancelled flights these are taken into account until the time window has moved past the maximum delay past the scheduled time of departure. Secondary or reactionary delays do not need to be input into the model as these may still be recovered.¹¹

4.1.4 Conclusions Regarding the Selected Aircraft Linear Solver

A few conclusions which can be drawn with respect to the Selected Aircraft Linear Solver is that it is an extensive linear program which is based on the use of parallel time space networks for each aircraft. The use of the parallel networks has the downside that the number of decision variables and constraints increases rapidly, especially node continuity constraints. The upside is that the use of this network means that a myriad of constraints can be easily implemented as well as that the model could easily be extend to crew and/or passengers. The performance of this module is assessed in chapter 7. One of the important conclusions of the performance is that this module is not suited for solving an entire network of a decent size airline in one run. For that reason the manner in which this module is implemented in the model as a whole is by running it for given selections of aircraft to solve disruptions. The manner in which this is done is explained in the following Section 4.2

4.2 Disruption Set Solver

In the previous section the inner most module has been explained. This is the linear program which finds the best solution to a given input of selected aircraft and flight schedule. The module described in the previous section is not capable of solving the entire schedule of an airline, thus the scope of the linear program must be limited. The reason it cannot solve the entire schedule is due to limited memory. The manner in which the solution space can be limited is inspired by a solution used by Medard and Sawhney (2007). The manner in which the solution space is limited is by limiting the problem in two dimensions. Figure 4.11 shows these two dimensions, firstly a recovery time window is defined in which recovery operations take place, and secondly the selected crews are limited to several candidates for the solution. This technique is adopted for this aircraft solver. And this section explains how the best selection of candidate aircraft for the solution is found to yield the lowest disruption cost.

¹¹It must be noted that even if all the primary delays have disappeared before the beginning of the time window the secondary delay will still have an effect on the time window as certain flight may already have been flown, and the aircraft positions due to these delays may be different.

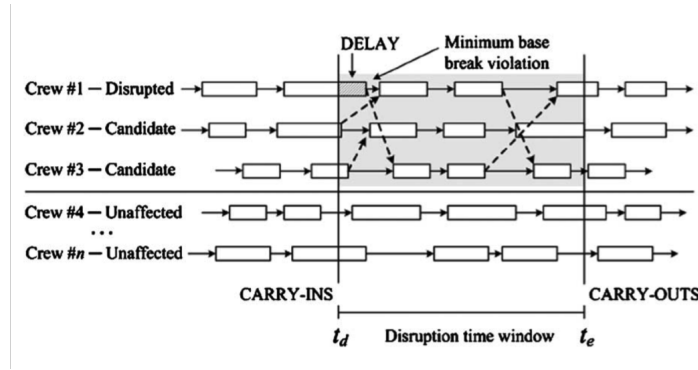


Figure 4.11: Figure from Clausen et al. (2010) displaying technique used to limit the crew recovery problem size

The disruption set solver is in fact an algorithm, which for a given total fleet and a set of disruptions finds a best selection of aircraft to use for the solution. The manner in which this solution is found is by testing different selections of aircraft in the SALS module. The manner in which the search for the selections takes place is as follows:

- Step 1 Fix the disrupted aircraft into the selection. This step looks at the disruptions that are to be solved and fixes the aircraft that are directly affected by the disruption into the selection.
- Step 2 From all the aircraft that are not disrupted filter the aircraft by aircraft type. This step does not necessarily mean that only aircraft of the same type are selected but could for example divide the fleet by long and short haul flights. This selection of aircraft defines the aircraft solution space.
- Step 3 Place all the aircraft in the aircraft solution space in order by time on ground at the airports where the disrupted aircraft are flying to/from. This step is inspired from actual operations at Kenya Airways. Interviewing duty operations managers and seeing how they go about their work, it becomes clear that one of the criteria when looking for aircraft to solve a disruption is seeing how much 'free' time the aircraft have.
- Step 4 Run through the selection in the order in which the aircraft are given for α aircraft at a time. The value of α is determined through trial and error to find a selection of α aircraft for which running the solution does not run out of memory. The selection size of candidate aircraft is always α . For iteration value i starting at 1 the following steps are done:
 - Step 4a Run the disruptions solver linear program for a selection of candidate aircraft from the aircraft solution space $\alpha * (i - 1)$ until $\alpha * i$ ¹²
 - Step 4b Save the solution, selection, and solution cost
 - Step 4c Check if all aircraft in the solution space have been run. If not, increase i by 1 and return to step 4a. If so, move to Step 5
- Step 5 From the solutions found in step 4 select the solution with the lowest cost. From this solution determine which aircraft are actually used for the solution i.e. which aircraft have a changed schedule. Fix these aircraft together with the disrupted aircraft.
- Step 6 Place all aircraft that are not fixed in random order.
- Step 7 Repeat steps 4,5 and 6 until the selection of aircraft used in the solution does not change for X iterations. Where X is a pre-defined value.

¹²If $\alpha * i$ is large than the last index of the aircraft solution space then the last α aircraft are selected, ensuring that the selection of candidate is as large as possible.

Step 8 Save the schedule, the delays and determine where the aircraft are ending. If aircraft end at different locations than planned, then make the tail numbers are changed in the remaining schedule.

The above steps are included in a flow chart given in Figure 4.12 as well as an illustrative example on a small selection given in Figure 4.13.

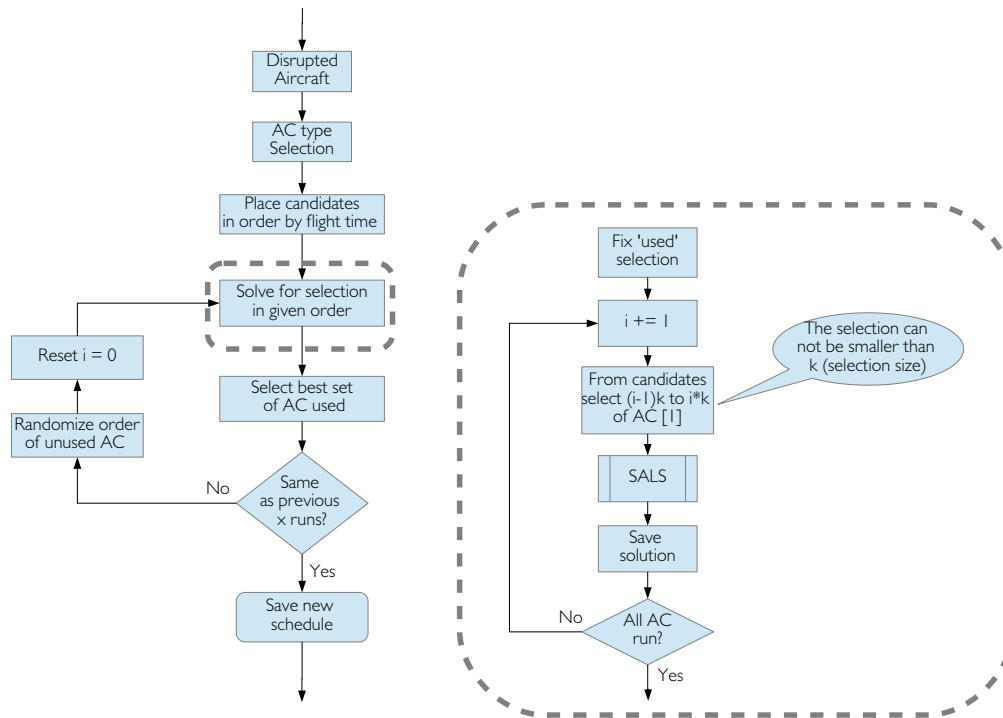


Figure 4.12: Flow diagram of the Disruption Set Solver (DSS)

Disrupted	All the aircraft of the same type (or interchangeable type)								
									
STEP 3	Place all aircraft in order by amount of time on the ground								
									
STEP 4	Run the solver for first (selection=3) aircraft <i>Aircraft that have a box are the ones that are actually used in the solution, those without box have unchanged schedule. Those highlighted in green are the solutions with lowest cost.</i>								
									
									
									
STEP 5,6	Select the lowest cost solution (select only the aircraft that are used, when equal chose solution affecting least AC)								
									
STEP 7 (4)	Step 7 is actually repeating 4-6								
									
									
									
STEP 7 (5,6)	Select the lowest cost solution (select only the aircraft that are used) Place all other aircraft in random order and run for (selection = 3) aircraft								
									
									
STEP 7	Select the lowest cost solution (select only the aircraft that are used) Place all other aircraft in random order and run for (selection = 3) aircraft								
									
									
Finish	Save the best solution selection of aircraft if it does not change for 'X' iterations								

Figure 4.13: Example of how the selection algorithm works on a sample selection of aircraft.

4.3 Fleet Splitting

Fleet splitting refers to dividing the fleet into smaller parts to accelerate the speed at which the DSS is able to find the best solution. The DSS is then run separately for different selections of aircraft. There are two different ways in which the fleet can be split. The first is the split by non-overlapping parts of a network, this may be for example wide and narrow body aircraft, as these rarely replace one and other in disrupted situation. The second is the split by aircraft type, which may be overlapping in networks/routes. Both of these splits are features of the model that can be selected by the user. Depending on the fleet composition and airline's network the user can select if and how to split the fleet.

4.3.1 Non-overlapping Fleet Split

If the total fleet of aircraft can be split into two non-overlapping parts of the network then this type of split can and should be applied to increase the computational performance. The two different parts of the solution are solved separately for the disruptions that affect that part of the aircraft selection. This is done by running the DSS for each part of the split fleet. The solutions of the two runs of DSS are then combined to form one new schedule. The reason this is possible is that there are no routes that are overlapping between the fleet types, i.e. no routes which are flown by both sides of the fleet split.

4.3.2 Overlapping Aircraft Type Split

After splitting the total fleet into non overlapping networks, within these networks the size might still be at such a size that an even smaller selection is desirable. The manner in which this is done is different to the split describe in the previous section because there is no longer the possibility of splitting the fleet into non-overlapping parts. In this case any split can take place that the user desires, but it is best to split by aircraft which are likely to replace one and other. For example in the Kenya Airways case the short-haul fleet is split by similar aircraft type, being the Embraer 170 and 190 on one side and the Boeing 737-300, -700 and -800 on the other side. This case is used to explain the manner in which this split works: If a disruption occurs in the Embraer fleet, then first the DSS is run for the Embraers, the selection used in the best solution is stored. This (smaller) selection of Embraers is combined with Boeing 737's and the DSS is run again for the new larger selection. Because of the elimination of part of the Embraer fleet the total computation time becomes less. In the case where both are affected; the DSS is run for the two separately and then run again combining the two solutions. In both cases the final run of the DSS takes both fleet into account and is saved and combined with the solution to the long-haul for a total solution for that point in time.¹³

4.4 The Dynamic Solution

The previous three sections describe the fleet split module, the disruption set solver (DSS) and the selected aircraft linear solver (SALS). The combination of these parts makes it possible to solve a set of disruptions that becomes known at a given time. However, looking at airline operation, disruptions become known during the course of the day. This section describes the simulation of such a situation. This situation is called the dynamic situation, as the goal of this type of situation is that the solution found in the first instance is not a fixed solution; it is still possible to recover some of the delays that have been assigned making the decisions made changeable or dynamic. The overall model used

¹³Before investigating a split by aircraft family a slightly different approach is investigated where the fleet is split into sets of identical aircraft. For the KQ case this meant 5 types (Embraer 170, 190, Boeing 737-300, 700 and 800). For each the disrupted fleet the DSS is run and the solution aircraft sets are then combined with the un-disrupted fleets and then run again into the DSS. The total solution is then saved. This split was for the KQ case was not fit because it means certain fleet types would only have a couple of aircraft, furthermore the split of the short-haul in two part made the model perform quick enough

to solve the dynamic situation is called Dynamic Recovery Model (DReM) and this section explains how it works. This section is divided into two parts; Subsection 4.4.1 gives a general outline of the simulation that takes place, Subsection 4.4.2 describes several aspects in the model which make it possible to recover delays in a dynamic manner.

4.4.1 General Outline of the Simulation

At the basis of DReM is a simulation of the reality. As described in Chapter 3 part of the novelty of this research comes from not solving a single disruption but solving a set of disruption as they would arrive in real operations.

To simulate the reality there are two types of simulation which can be used: time-step simulation or event-based simulation. Time-step simulation runs the model at a given time-interval and takes into account all the disruptions that are known in that interval. Event based simulation runs the model for each time a new event happens, in this model that means running the model each time that a new disruption or set of disruptions becomes known. In this model the choice is made for the latter, running the model for each time disruptions become known.

Figure 4.14 depicts the flow diagram of the DReM. The figure show the set of inputs coming in to the model, which is nearly identical to the input into aircraft selector module, with the difference that now the total set of disruption is input into the model. One of the aspects of each disruption in the disruption set is the time at which it becomes known (t). From all the times, t , at which disruptions become known the model is run.

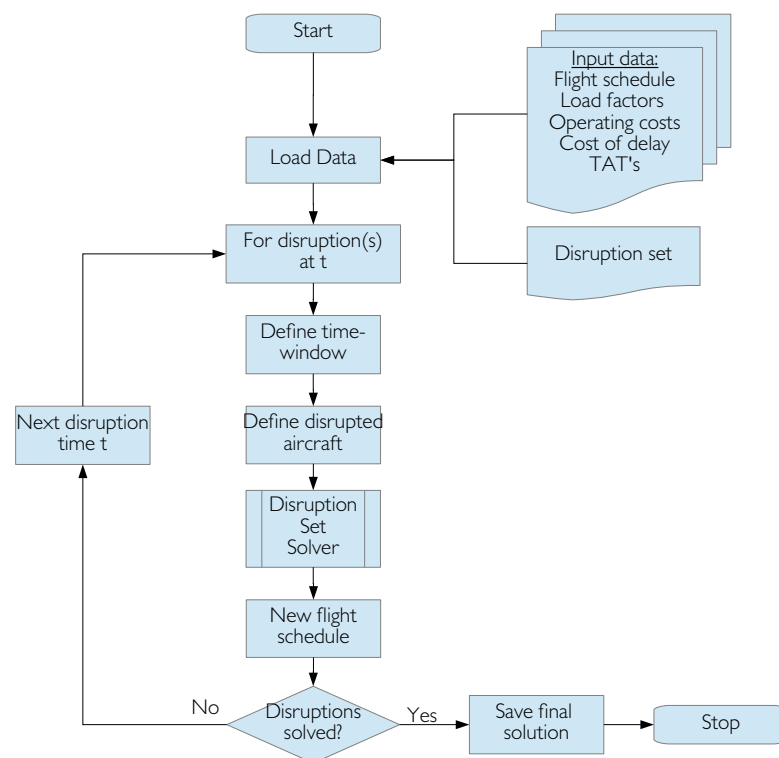


Figure 4.14: Flow diagram of the DReM (Dynamic Recovery Model)

4.4.2 Saving the Schedule in a Dynamic Environment

When looking at the dynamic aspect of the simulation model, dynamic refers to the fact that the problem that is being solved is changing as time progresses. The set of disruptions that is solved at the first instance will have an effect on the operations of the rest of the day. By the time a subsequent disruption becomes known, decisions will have been made with respect to the first disruption that may not be able to be reversed. This section describes how schedules at each iteration are stored and which decisions are then fixed in the next iteration.

At the end of each run of the Disruption Set Solver the new version of the schedule is saved in a .csv file. There are several additional aspect related to each flight which are also saved, these are a column columns containing the delay in minutes and a boolean column for whether a flight is cancelled. So that the file can easily be read and interpreted for each flight the different costs are also included. Columns are thus added to indicate the soft and hard cost of delay or cancellation and a column is added to indicate the DOC. Furthermore there are two columns containing the new departure and arrival times.

As explained in Section 4.1.3 the flights which are included in the next time step in the model use the adapted situation including the delay times to determine which flights are inside and crossing the time window. As well as to determine the starting and ending position. However when writing the flight and delay arcs into the time-space network the scheduled times are used. Even if this means that some flight are placed outside of the time window. The reason this is done is that delays can then be recovered as well as that the cost of delay function is relative to the original schedule. The next step is that all arcs that are outside of the time window are made illegal and the model can then be solved. In this manner the model is always attempting to return as much as possible to the original scheduled operations.

4.5 Conclusions Regarding the Model Set-up

The Dynamic Recovery Model is set up in layers; the top level is the dynamic simulation that runs the Disruption Set Solver (DSS) for the different fleet type for each time that new information becomes known. This DSS is the next level down, which in turn call upon the following level the SALS. The SALS has several different modules in it's set up to create and write, time-space network, constraints, and selecting the correct parts of the data loaded into the DSS. The DSS module is the one which will be applied if the tool is to be implemented as this is the solver for the set of all the disruptions known at a certain point in time. The model is set up in such a way that each of the separate modules can be accessed easily, this means that the model can easily be adapted and extended. All in all a model is created that will provide a complete solution for a period of operation in a realistic manner. This is the case because any aircraft related constraint can be implemented and the dynamic simulation takes into account when disruptions become known. The chapter following this one provides information about the Kenya Airways case study and Chapter 7 provides the results achieved by this model on the KQ case.

Chapter 5

Kenya Airways Case Study

Part of the strength of this MSc thesis project has been the opportunity to do it in cooperation with Kenya Airways (KQ). This cooperation between TU Delft and Kenya Airways has been invaluable on two different levels. Firstly in the problem definition phase, discovering the issues that KQ is currently facing and having interaction with those actually solving disrupted operations has made it possible to true define a project scope that will not only extend the body of knowledge in academia but will also be applicable in practice. The second and most important aspect of the cooperation is access to real life data. Being able to test the model on actual disrupted situation with actual input data regarding schedules, disruptions, passenger info and costs, means ensures the validity of the model.

The first section of this chapter gives some background information about Kenya Airways, it's current operations and the collaboration between Kenya Airways and Delft University of technology. The following section each look into a different set of input data into the model. Where each of the sections explains how the data is gathered and/or manipulated such that it can be properly put into the model.

5.1 Situation at Kenya Airways

This chapter investigates the current and future situation at Kenya Airways and whilst doing so providing the context of this research project. Section 5.1.1 provides some background information about Kenya Airways, it's current operations and the ambitions that the airline has for the near future. Section 5.1.2 provides information about the current recovery procedures at Kenya Airways and the performance there-of. Finally Section 5.1.3 places this project within the broader scope of the airline and ongoing research.

5.1.1 Background Information

This section provides some brief background information about Kenya Airways (KQ), it's current operations and it's ambitions for the future. Kenya airways was founded in 1977 following the break-up of the East African Community and subsequently resulting in the demise of the jointly owned East African Airways. Kenya Airways was founded by the Kenyan government. In 1996 Kenya Airways became the first African flag carrier to become privatized and is currently a public-private partnership. The Kenyan government is the largest shareholder of the company, holding a 29.8% stake, fellow SkyTeam partner KLM hold a 26.7% stake and the remainder of the shares is publicly traded.

Kenya Airways has defined it's ambitions for the future in a plan called *Project Mawingu* (Swahili for clouds) expanding the KQ network with the addition of several destinations and aircraft each year. The growth aspirations that KQ has for the future are to operate 115 destination by 2021 which means more than doubling the number currently operated (Kenya Airways, 2011). The strong growth aspiration that Kenya Airways has will result in a more complex network and thus the size

General info		Fleet	Operational (on order/option)
HQ and HUB	Nairobi	Boeing 737-300	2(1/0)
Destinations	56	Boeing 737-700	4(3/4)
Employees	4001	Boeing 737-800	6
Alliance	Skyteam	Boeing 777-200ER	4
		Boeing 777-300ER	3
		Boeing 787-8	6
		Embraer 190	15
		Embraer 170	3
Financials [B KSh/ B USD]			
Revenue	98.8/1.14		
Net income	-9.01/-0.104		

Table 5.1: Some general information about Kenya Airways (Kenya Airways, 2014)

and complexity of recovery operations will increase. For this reason there is a need to change along with the ever changing situation for the airline.

5.1.2 Kenya Airways Current Operations

This section describes the current operations at Kenya Airways. Subsection 5.1.2 analyses the types of delay that Kenya airways is currently experiencing and gives insight into the current On Time Performance (OTP). Subsection 5.1.2 looks at them manner in which Kenya Airways deals with disruptions.

Delays and On-Time Performance

This section investigates the causes of delay at Kenya Airways as well as taking a look at the Kenya Airways' On-Time Performance (OTP). The types of delay an airline experiences are different for each airline. For example weather delays have a much greater impact in Europe and North America than they do in Africa. Another example is that a low cost carrier will not have less passenger related delays as passenger connectivity is not a service they provide. The breakdown of the delays at KQ is given in the Figure 5.1, which shows that the majority of the delays are reactionary delays. The root causes for these reactionary delays are given in the breakdown presented in Figure 5.2, which in turn is dominated by technical and aircraft rotation delays, both aircraft related delays. All in all it is fair to say that the majority of the delays at Kenya Airways are aircraft (47%) and flight operations (19%) related. These are in fact also the delays that are on average the longest, Figure 5.3 shows the average delay time per delay type.

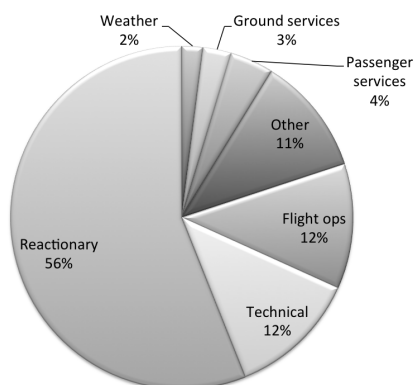


Figure 5.1: Delay breakdown by type

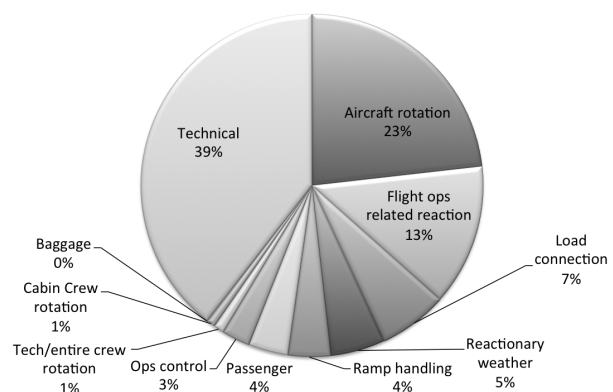


Figure 5.2: Reactionary delay breakdown by type

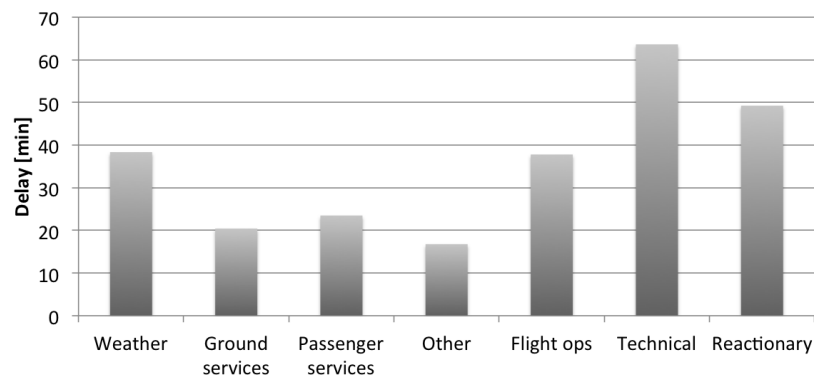


Figure 5.3: Average delay time per type of delay

Recovery Procedure Kenya Airways

The currently recovery operations at Kenya Airways happens manually with in the central role the Duty Operations Manager (DMO). The Integrated Operations Control Center (IOCC) is where all global operation of Kenya airways are monitored and decisions for changed operations are made. The physical set up of the IOCC is in such a way that the DMO is in the center of the room surrounded by those from whom he receives input for decision making. Figure 5.4 shows the manner in which the decision making process is oriented around the DMO. The figure clearly shows the in- and output the DMO receives and gives from and to several different parties. The focus of this research project is on the process circled in red, the actual re-planning of the aircraft and finding a way to make sure that the knock-on effect of the disruption is minimal. Interviews with KQ Duty Operations Managers (Mutua et al., 2014) has given extra insight that the processes depicted in Figure 5.4 which portrays the in- and output and communication necessary, however the most challenging task for the DMO is generating a new plan.

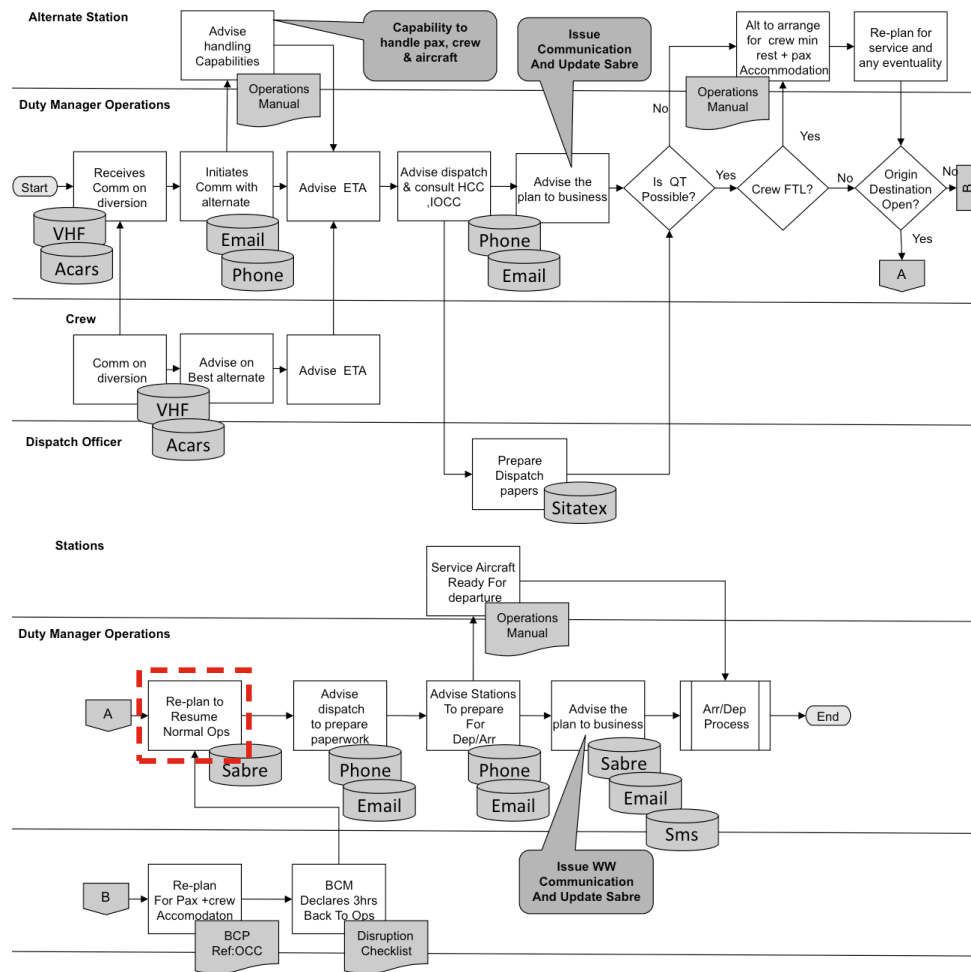


Figure 5.4: The decision map for disrupted situations at Kenya Airways

5.1.3 Kenya Airways and this Project

This MSc Thesis project is one in several projects that have taken place between Kenya Airways and Delft University of Technology. Figure 5.5 gives an overview of the projects that have been done between Delft University of Technology and Kenya Airways. The majority of the projects have been OTP related, this project also clearly fits into those that are OTP related.

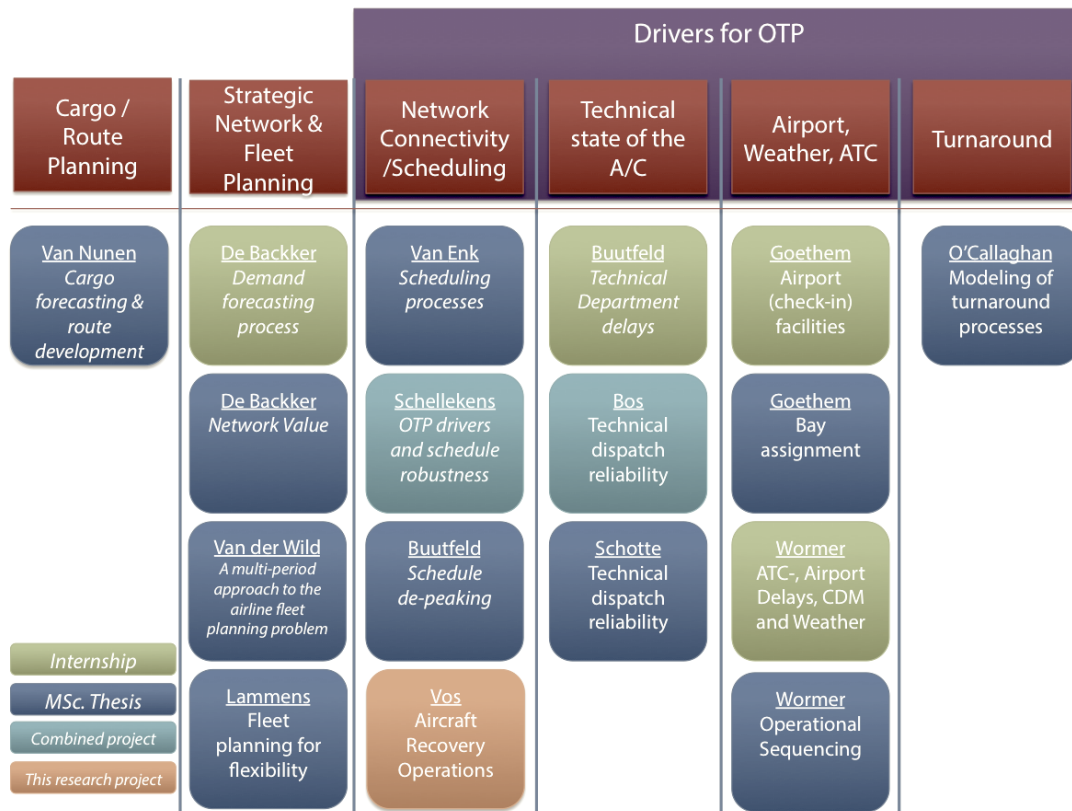


Figure 5.5: Projects done in collaboration between KQ and TU Delft

When looking at the addition that this project can be to the operations of Kenya Airways, the ultimate goal of the project is that the model be implemented and thereby help to reduce the number of delays and/or the total cost of delay. Inherent to this is that the model will best work if the most comprehensive approach is taken and all possible delays should be solved by the model. Such an approach would mean taking into account aircraft, passengers and crews. The most successful approach to such a model in literature is Petersen et al. (2012), however this has been a project of several years with several researcher thus it is not deemed feasible to achieve such a solution within the scope of this project. Furthermore the solution times that Petersen et al. (2012) present are 20-30 min which is quite long for a decision support tool. Thus the focus of this project is on the most import delays, as described in Section 5.1.2, these is aircraft related delays. Once again the ultimate goal is that the model be implemented, but even if this will not be the case this research can provide Kenya Airways, and those working in recovery operations with insights into cost based delay management that may result in improved recovery operations.

5.2 Operating Cost

On of the inputs into the model is the direct operating cost (DOC) of each aircraft type. When looking at recovery operation this becomes a relevant input when tail switches occur between different types of aircraft. For example a Boeing 737 replacing an Embraer 190. When switching tails of the same aircraft type there is no cost difference but changing between types there will be a difference. When looking at the operating cost in this model only the direct operating costs are taken into account, as recovery operation will have no influence on the indirect operating cost. The direct operating cost's that are taken into account are the following: fuel cost, maintenance cost per block hour, landing fees, navigation, handling and ground handling costs. The direct cost, which has been ignored is the passenger meal cost, the reason for this is because if one aircraft type replaces another this cost will remain the same as the number of passengers will not change. The data received from the Kenya

Airways financial department has been analysed for the period October 2013 to October 2014. The data is extracted to yield the cost per aircraft type per route it has flown. The limiting factor in this case is that over the year analysed not each aircraft has flown each route that it could possibly fly. In some cases an aircraft type may only have flown a certain route handful of times meaning the data is not very accurate. For this reason a simplification is made in which the DOC per block hour per aircraft type is computed and used to determine the DOC per aircraft type per route. After this average DOC per block hour is calculated the validity is analysed of using this average. Looking at within each fleet type it becomes clear that there is a significant difference in the DOC for each route compared to the average per hour. When looking at the differences for each aircraft type over all the routes there is a standard deviation of $\sigma = 0.1116$. However when comparing different aircraft types on the same route the standard deviation drops rapidly, with an average standard deviation over the all the routes of $\sigma = 0.0615$. What this means is that although using average DOC per block hour might not be a good method to compare DOC on different routes, to compare different aircraft on the same route the error becomes less. It must still be noted that this using this technique is still a simplification, which impacts the calculation of DOC.

5.3 Cost of Delay

To determine the cost of delaying a flight there are several factors that must be taken into account. The two main areas in which delay cost can be split are hard costs and soft costs. Hard cost refers to actual costs that can be directly attributed to delays. This could for example be the fuel cost due to an en-route delay or the compensation an airline pays to a passenger for a delay. The soft cost of delays refers to missed future revenue due to the fact that a passenger experiencing a delay will be dissatisfied with the airline and will in the future be more likely to choose to fly with another airline. This section will investigate the hard and soft costs of delay in the Kenya Airways case in Subsection 5.3.1 and 5.3.2 respectively and the total cost of delay function and how it will be implemented is given in Subsection 5.3.3. At the basis of this section is the ongoing research into cost of delay by Cook et al.¹

5.3.1 Hard Cost

The hard cost of delay can be attributed to several different costs. Some of which for the purposes of this research can be omitted as they will not affect the outcome of the solutions. This is a list of the hard cost that may be attributed to delay:

Passenger Compensation

When there are significant delays that take place airlines can have a compensation plan in place for the satisfaction of their passengers.² These compensation may be in the form of (food) vouchers, lounge access or for very long delays accommodation in hotels. The compensation structure for Kenya airways is depicted in Figure 5.6

Elongated flight time

If delays occur en-route due to for example congestion at the destination airport or due to re-routing around foul weather this will result in a longer flight time. Which will have an effect on the fuel consumption and on the maintenance cost. Maintenance cost, which is related to the amount of cycles but also to the flight hours will increase just as fuel consumption will. The cost incurred due to elongated flight time will not be taken into account in the model. The reason for this is because the model looks at how to react to delays. The cost related to en-route delays is

¹Cook et al. (2004), Cook and Tanner (2009), Cook et al. (2009) , Cook and Tanner (2011a), Cook and Tanner (2011b) and Cook et al. (2012)

²In some places this is in fact required by law.

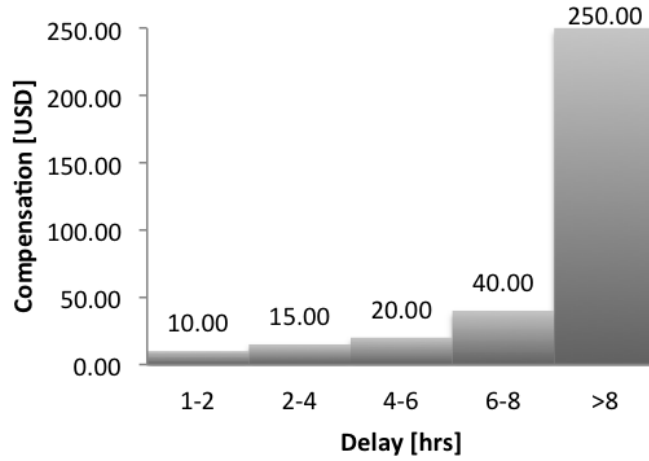


Figure 5.6: The compensation per Kenya Airways passenger depending on the delay time

a primary delay and not a reactionary delay, thus cannot be avoided through recovery operation upon which this model focuses.

Marginal crew cost

Nissen and Haase Nissen and Haase (2006) describe the difference in payment structures between the US and Europe, where US airline generally pay crew according to flight hours where European airline are generally based of fixed salaries. At Kenya Airways crew costs follow the European structure of fixed salaries. However crew that work more than a certain threshold receive compensation in the form of performance compensation. The effect of a delay might be that a crew overworks the threshold and will therefore receive performance compensation. The Collective Bargaining Agreement Kenya Airways and Aviation and Allied Workers Union (2012) between the crew unions and Kenya Airways define productivity payment for flight time exceeding maximum duty time up to a maximum legal duty period of 12 or 15 hours for domestic and international respectively. As well as productivity payment for hours worked above a monthly threshold.³ Considering scope of this research is limited to aircraft recovery and does not track individual crews or crew members a simplification is made with respect to crew cost, which is that the average crew cost will be used per route per aircraft type. This results in the fact that performance compensation is not taken into account. The difference in crew cost between aircraft types is. The effect of this simplification is discussed in Subsection 5.3.3.

5.3.2 Soft Cost

The soft cost of delay is defined as the cost of passenger dissatisfaction. Which is the cost of losing a customer due to his/her dissatisfaction with the service he/she has received. Cook and Tanner (2009) hypothesize on the S-curve of the probability that a passenger will switch airline for their next trip due to the delay. In later research Cook et al. (2012) investigate in more detail the exact shape and parameters of the function. The Equation 5.1 is presented by Cook et al. (2012) to model the propensity that a passenger will switch due to a delay.

$$\delta = \frac{1}{k(1 + e^{a-bt^c})} - k' \quad (5.1)$$

In Equation 5.1 delta is the propensity that a passenger will next time choose another airline depending on the delay time t . Where $k = e^a/(1 + e^a)$ and $k' = e^{-a}$. The constants a , b and c

³These thresholds are different per fleet type: for B777 and B767 it is 60 hours, for B737 series it is 50 hours and for Embraers it is 40 hours.

are found by Cook et al. (2012) through manual iteration across a significant data set from European airlines. The values that best fit the equation are $a = 3.0$, $b = 0.1$ and $c = 0.9$. Using these values it is possible to recreate the S-curve presented by Cook et al. (2012) which can be seen in Figure 5.7 showing the relation between switching propensity and delay in minutes. The switching propensity at 90 minutes is 94% and beyond 90 minutes does not change much. This is relevant for the simplification of the time-bands, explained below.

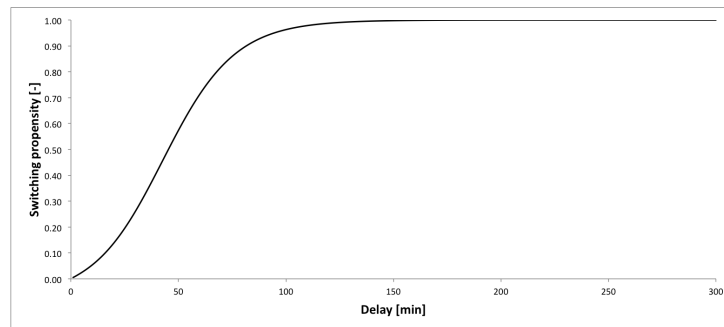


Figure 5.7: The propensity that a passenger will switch airline due the delay experienced

In earlier research by Cook et al. (2004), survey data yield the average soft cost of delay per average passenger per average delay minute is determined to be € 0,18 in 2003.⁴ Cook et al. (2012) use this average value along with actual distribution of delayed flight versus delay time to determine the cost of delay per minute for different delay time-bands. Not that the 15 minutes time-bands are up to 90 minutes, which is a fair assumption as the amount of delays in each time-band after that is less than one percent, and the switching propensity does not change much. For this research the average of € 0,18 in 2003 is adjusted for European inflation and presented in USD.⁵ The results of these calculation are presented in Table 5.2.

Table 5.2: Soft cost per minute of delay as presented by Cook et al. (2012) and corrected values to USD in 2014

Delay	0-15	16-30	31-45	46-60	61-75	76-90	90+
Fraction of delays	61%	19%	8%	4%	2%	1%	5%
Delay Cost[EUR/min]	0.05	0.17	0.37	0.58	0.75	0.86	0.92
Corrected 2014 [USD/min]	0.08	0.27	0.58	0.91	1.17	1.35	1.44

The method used by Cook et al. (2012) is applied to a distribution of smaller time-band of ten minutes, which is also the resolution used for the recovery model in this research. The results are presented in Table 5.3

Table 5.3: Result of Cook's method applied to smaller time-bands

Delay	0-10	11-20	21-30	31-40	41-50
Fraction of delays	49.8%	19.2%	11.0%	6.0%	3.7%
Delay Cost[USD/min]	0.05	0.15	0.31	0.53	0.77
Delay	51-60	61-70	71-80	81-90	90+
Fraction of delays	2.4%	1.5%	0.9%	0.6%	5.0%
Delay Cost[USD/min]	1.00	1.18	1.32	1.40	1.48

⁴Cook et al. (2012) argue that the average value of soft cost of delay is still valid 8 years after date as there are no indications that passenger dissatisfaction w.r.t. delay has changed. Differences due to inflation are not mentioned.

⁵European inflation used are taken from European Central Bank website (www.ecb.europa.eu) and the Euro to USD exchange rate average over Jan. - Sep. 2014 is used

The soft cost of delay presented in Table 5.3 is the soft cost that will be use in this model. Though extensive research has been done into these values there are several limitation with these values. Firstly these values have been derived from European airlines and in this research are applied to an African airline. Secondly, as indicated by Cook et al. (2012), the curve differs per route and flight time. The examples they give is a passenger missing business meeting, a passenger will be less likely to plan a meeting within 60 minutes of long-haul than a short-haul flight. Or a passenger with a long connection will be less dissatisfied that one with a short connection. Concluding this section on soft cost, much research is necessary to find the exact values of the curve that fits each flight leg, which is not directly desirable or necessary for the scope of this research. Thus the average values found by Cook et al. (2012) provide a strong basis and best representation, to date, of the soft cost of delay.

5.3.3 Total Cost of Delay

For the total cost of delay as input for the model three sources of information are used. The hard and soft cost of delay per passenger as described in the previous sections. As well as the amount of passengers booked on each flight. The combination of these two gives a total cost of delay per flight in the Kenya airways network. Figure 5.8 depict the cost of delay per passenger as it is implemented in this research.

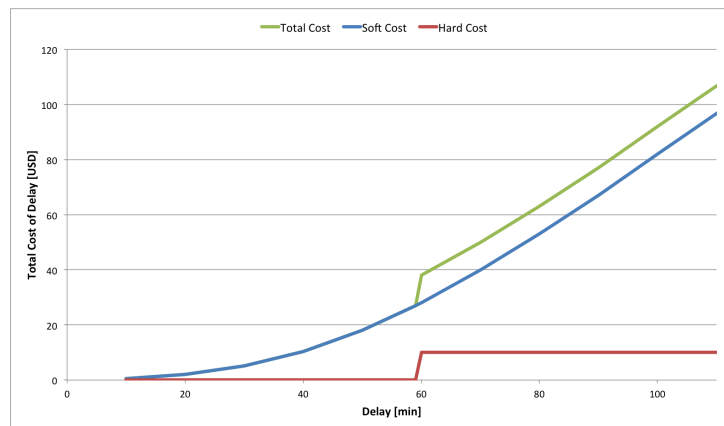


Figure 5.8: The soft, hard and total cost of delay versus the delay time

5.3.4 Passenger data

One of the inputs into the model is passenger load data, this is retrieved from MayFly one of the software packages used at Kenya Airways to analyse performance. The data gathered from MayFly as web-based software is converted in to text files, which can then be imported into the model. The data provided by MayFly to the model is the passenger numbers for each flight for both business and economy passengers. This input data is used to calculate the cost of delays and cancellations. At Kenya Airways a multiplication factor β is applied to the value of business passengers versus economy passengers. The value of this multiplier, $\beta = 3$.

5.4 Schedule and Disruption Scenarios

The main input into the model is the scheduled operations and the disruptions. This section explains where the data comes from and the processing that is necessary for it to be used in the model.

The flight schedule is retrieved from SABRE Movement Control, the software package used by Kenya Airways at OCC to track all the flights. The schedule provides the flights, times of departure and arrival, as well as the tail numbers of the aircraft that fly each flight. The schedules retrieved

from SABRE are in excel format and can thus be directly loaded into the model. In total 10 different scenarios are tested and these are taken from two different sources:

- **SABRE Movement Control** The first is the SABRE Movement Control Reports, which reports all of the delays for a given day as well as the delay codes. Using this information about the delays some processing will be done to input the delays into the model. Each type of delay will result in one of the types of delay that can be input into the model. For example all technical delays will be input as aircraft unavailable constraints, and all weather related delays at a certain airport as airport unavailable delay. All the delays will be input into model except for the delays of less than 10 minutes and reactionary delays caused by aircraft rotation. The reason delays less than 10min may be ignored is because these are smaller than the resolution of the time space network. The reason reactionary aircraft delays are omitted is because these are exactly the delays which this model is solving.
- **Duty Manager Operations' training exercises** The second source for disrupted situations are several descriptions of test scenarios for training purposes of DMO's. The scenarios are descriptions of situations and along with the proposed solutions. These scenarios do not have schedules that can be loaded into the model. The manner in which these are tested is that the disruptions described by the scenarios are applied to the schedule of a different day of operations.

Information concerning the time when disruptions become known is not recorded at Kenya Airways. To gather information about when disruptions become known at the operations control center, two days are spent in the control room recording when information about disruptions comes in. Furthermore interviews are held with DMO's to determine what typical times are relative to disruption when the information becomes known. In these interview the, to be tested scenarios are discussed, and together with the DMO's suitable times are determined for when information comes in. (Mutua et al., 2014) The final ten scenarios, which are retrieved in the following manner:

- Seven of the scenarios are selected from training exercises used for DMO's and which are adapted for the schedule that is available. The reason this adaptation is necessary is because the scenarios are given as descriptions of disruptions and there is no digital schedule available for those scenarios.
- Three of the scenarios are full days of disruptions from the Kenya Airways network in October 2014 each selected for the high number of reactionary delays. All of these scenarios have been applied to the schedule of 21-23 November 2014. The reason that this is done is because the operations as scheduled (including tail numbers) at a certain point in time cannot be retrieved from SABRE (KQ software package). Only the final tail numbers can be retrieved for past situations. For that reason the disruptions of a specific day are applied to the scheduled operations of another day.⁶
- The final scenario is an actual disrupted day where the flight schedule before and after the disruption are known. In this disrupted case the model was tested whilst at the Kenya Airways Operations Control Center and the final solution could be compared with the one implemented.

⁶According to the DMO's it is very difficult to truly compare model findings with what actually happens over the course of an entire day. The reason is that many different tail switches happen often for convenience purposes such as gate positioning or a crew request. Many of the reasons for these switches are not recorded, making it difficult to trace back.

Chapter 6

Verification and Validation

This chapter aims at verifying and validating the model and the achieved results. It is important to have a clear understanding of what is meant by verification and validation, for that reason these are first defined:

- **Verification** is testing the model if it is working correctly. In other words checking to see if each module is doing what one would expect it to do.
- **Validation** is checking to see if the model that has been built is in fact the right model. Is the model applicable to the situation? And are the solutions found the right solutions for the real life situation.

Firstly the conceptual model is validated to show that the use of this model is applicable and correct in this situation, this is done in Section 6.1. To verify the model, the model is tested on a series of small situations and the solutions found are checked against what would be expected; this is presented in Section 6.2. Finally a validation of the model is done with several duty operations managers (DMOs) at KQ to validate the final results; the findings are presented in Section 6.3

6.1 Validation of Conceptual Model

The validation of the conceptual model is done by analysing several statements that are key in defining the conceptual model and the manner in which it is built. The statements are validating using face validity. This is technique used in behavioral science (Gravetter and Forzano, 2011) in which argumentation and expert opinion determine whether a statement is valid. In this research face validity is used to determine the validity of the following statements that are of key importance to the conceptual model.

"A model that reduces cost is desirable for a commercial airline" This statement is trivial but it strongly contributes to the validity of this model. Rather than only looking at on-time performance the concept of this research rests on the fact that the total of hard, soft, and operating cost for airlines is reduced.

"Modelling for cost reduction also improves on-time performance" When investigating the numerous researches conducted by Cook et al. about the increasing soft cost as delays propagate and considering the hard costs airlines incur when delays occur; this statement can be confirmed as a valid statement.

"On-time performance, for airlines is of the utmost importance for an airlines service"

This statement is confirmed by former KQ Head of Operations Control, Thomas Omondi and is what the DMO's strive for every day. Providing the best service to passengers through ensuring the

highest OTP.

"If a choice is made between aircraft, crew or passenger recovery; the recovery of Aircraft has the greatest potential impact"

This final statement refers to a choice specific to this thesis project, given the limited scope of 30 weeks. The choice is to create a model for aircraft recovery rather than crew or passenger recovery, and within that field demonstrate the research objectives. The manner in which this is validated is through checking delays and their causes for the given case study at Kenya Airways. Figure 5.1 in Chapter 5 gives the breakdown of the delays by cause, and the breakdown of the reactionary delays. The figure shows that slightly more than two thirds of all delays and three quarters of reactionary delays are aircraft related; validating the statement that the aircraft recovery problem has the largest potential impact.

6.2 Verification

In this section a series of verification tests are performed on a small network to demonstrate the correct working of the model. The tests that are performed are split into several subsections; in each subsection a different type of small network is given, as most suited to that particular set of tests.

6.2.1 Simple Delay Tests

The first set of tests is done on a network that contains only one aircraft (FFA) and a series of flight legs flying on one route (Flights numbered 1 through 8 on NBO-MBA). All the flights in this network are fully booked unless stated otherwise. The tests performed on this small network, involve testing propagating delay, return flight cancellation, cancellation of the least full flight, and testing the threshold between propagating delay and a cancellation.

The first test done is a test where flight nr 1 is delayed by 30 minutes because the aircraft is unavailable. Because this schedule is set up in such a way that the turn around time (TAT) is equal to minimum TAT the delay is expected to propagate through all eight flights. As can be observed in figure 6.1 this is in fact the case. This will be the case up to a certain point, at some point the delays will cause the last flight to cross the time window, which is not allowed. In this case that threshold lies between delaying flight 1, scheduled at 6:00, to 9:30 and to 9:40¹ as can be seen in Figures 6.3 and 6.5 respectively. As can be observed the first two fights are cancelled. The reason the first two are cancelled is because, these would be delayed the most, so by cancelling those the total cost is minimal.

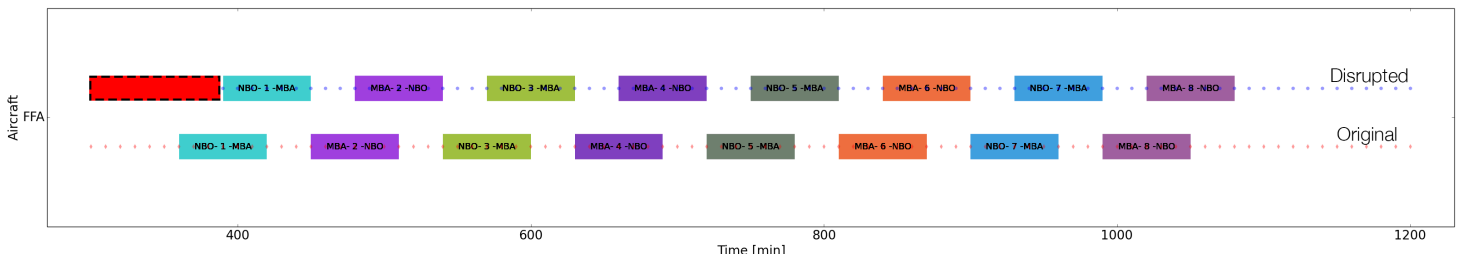


Figure 6.1: A short delay of 30 minutes on flight nr 1 is propagated through the network

¹Times in figures are in minutes thus 6:00 is 360 min and 9:30 is 570 min

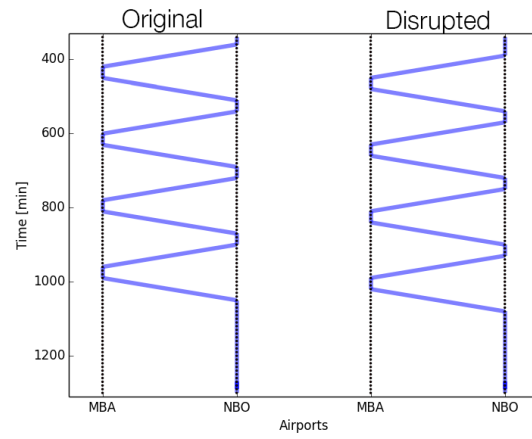


Figure 6.2: Time-space representation of Figure 6.1

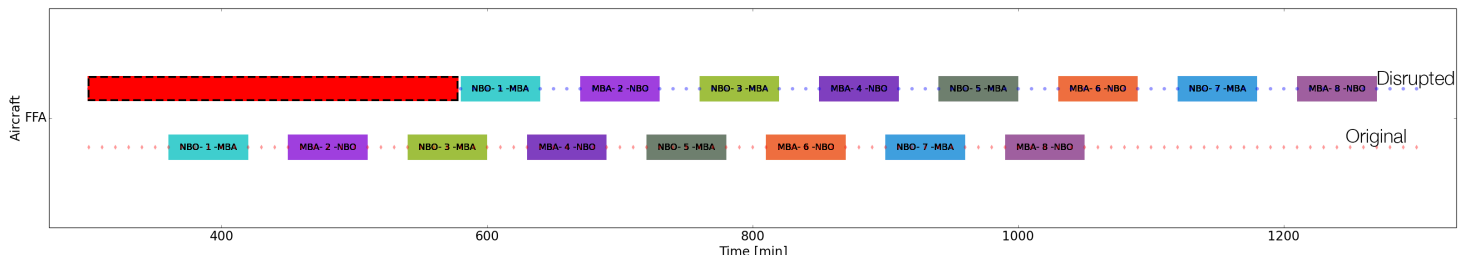


Figure 6.3: The maximum delay that is still allowed to propagate through the network

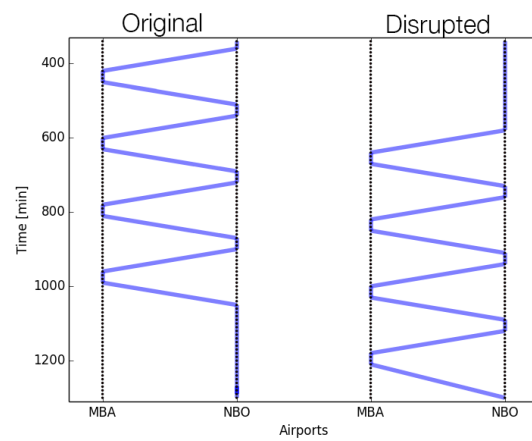


Figure 6.4: Time-space representation of Figure 6.3

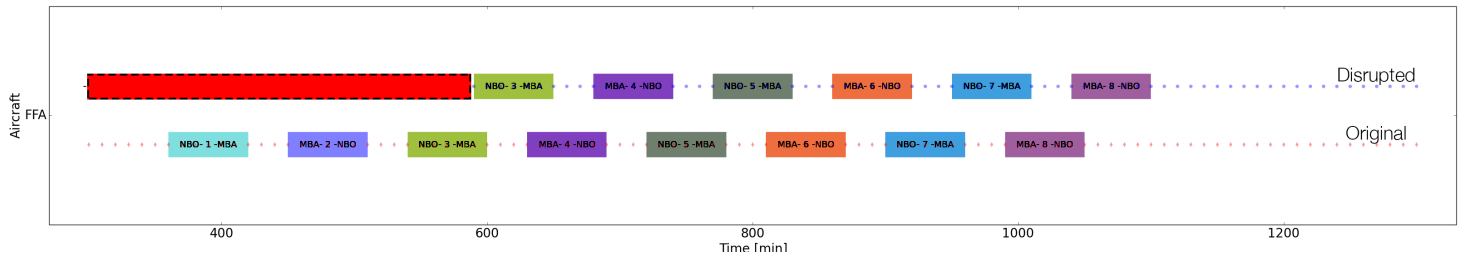


Figure 6.5: A delay that cannot be propagated in within the time window, thus the solution is to cancel two flights in the most cost effective manner

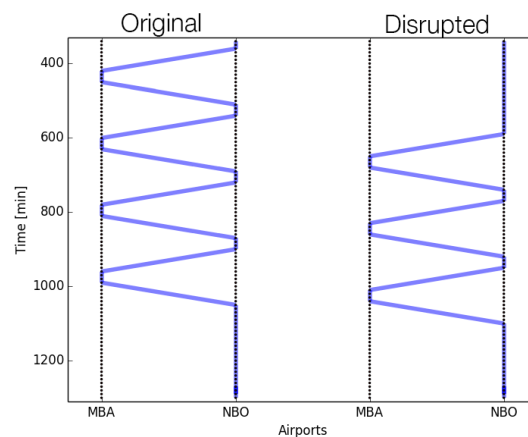


Figure 6.6: Time-space representation of Figure 6.5

6.2.2 Cancellation

In this subsection cancellations are tested. The verifications done test to see if the correct flights are cancelled, depending on the time that the cancellation becomes known. In the two tested scenarios flight 3 is cancelled, and flight 2 has less passengers booked than flight 4. The difference between the scenarios is that in the scenario depicted in Figure 6.7 the time that the cancellation becomes known is after flight 2 has departed and in the scenario depicted in Figure 6.9 the cancellation is known at the beginning of the day of operations. The results are as expected, where if known beforehand flight 2 with fewer passengers is cancelled rather than flight 4, however when this is not a possibility due to the time found out then flight 4 must be cancelled.

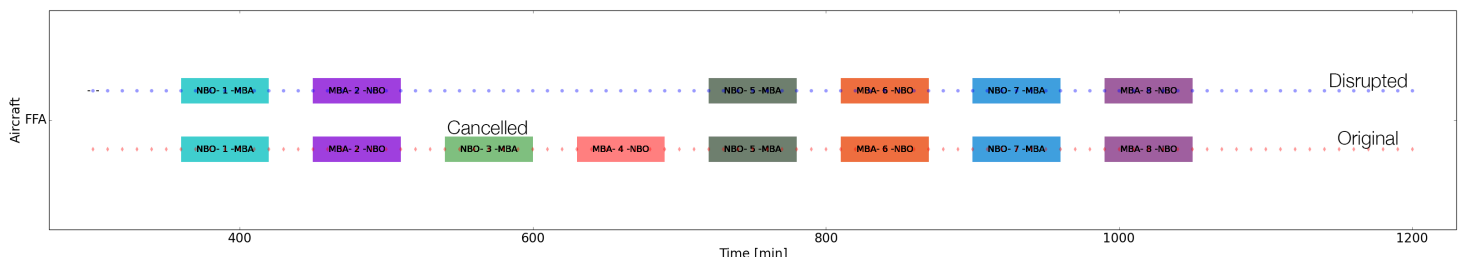


Figure 6.7: Flight 3 cancelled and the time that this becomes known is after the departure of flight two.

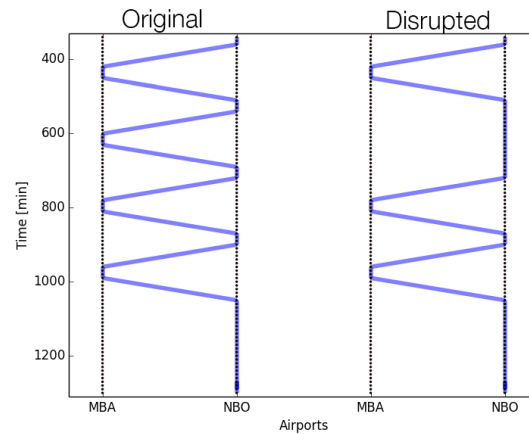


Figure 6.8: Time-space representation of Figure 6.7

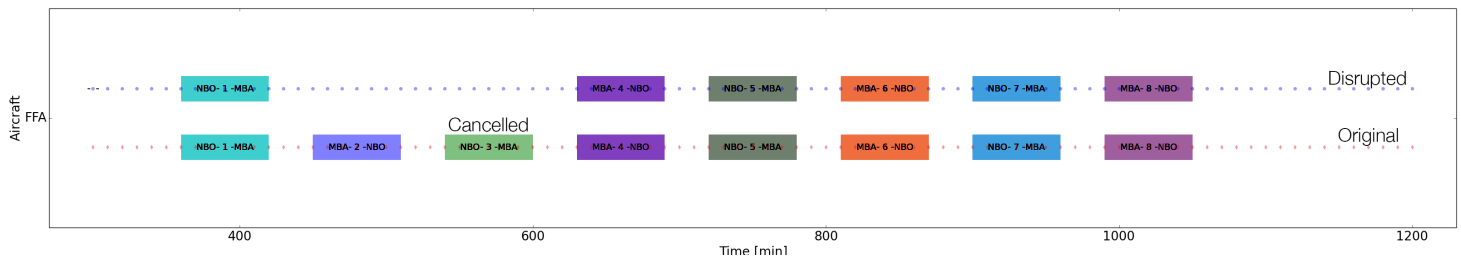


Figure 6.9: Flight 3 cancelled and the time that this becomes known is at the beginning of the day. Flight two model selects flight two to cancel instead of 4 because this there are less passengers booked on this flight.

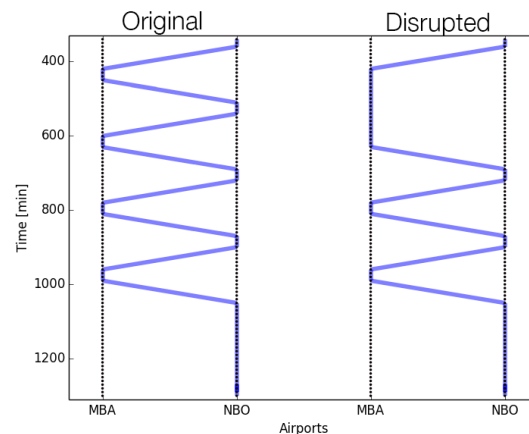


Figure 6.10: Time-space representation of Figure 6.9

6.2.3 Tail switches

Every aircraft has a unique registration number that is always written on the aircraft's tail, the term tail number or in short tail is used to refer to a specific aircraft. Tail switching, refers to the action of switching the aircraft that is planned to fly a route. This section verifies that the tail switches made by the model presented in this research are valid and happen where expected. Below are scenarios that display that the correct switches are occurring.

The first scenario is a simple scenario displayed in Figure 6.11. In this figure aircraft FFA has a technical problem due to which it is obstructed from flying flight 1 on time. Aircraft FFB is of the same type and is only planned to fly later, for that reason the aircraft are switched so that both flights can be flown on time and the total cost is minimised.

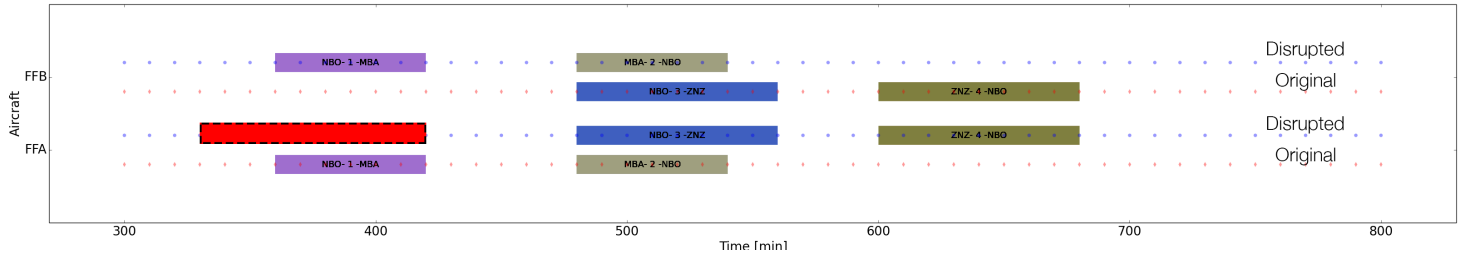


Figure 6.11: A tail switch between FFA and FFB occurs as FFA is disrupted but has an earlier flight than FFB, thus the switch results in less total delay (Schedule A).

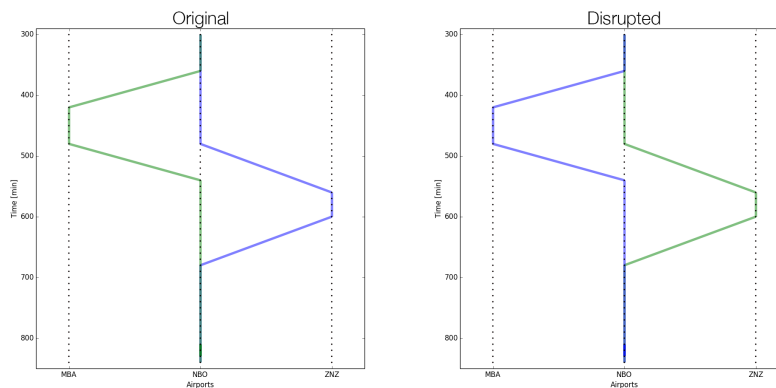


Figure 6.12: Time-space representation of Figure 6.11

If the situation occurs as shown in Figure 6.13, FFA is disrupted for the period marked in red. Here there is no aircraft available directly to replace FFA directly but aircraft FFB is available after it arrives from Zanzibar (ZNZ) and the minimum turn around time is met.

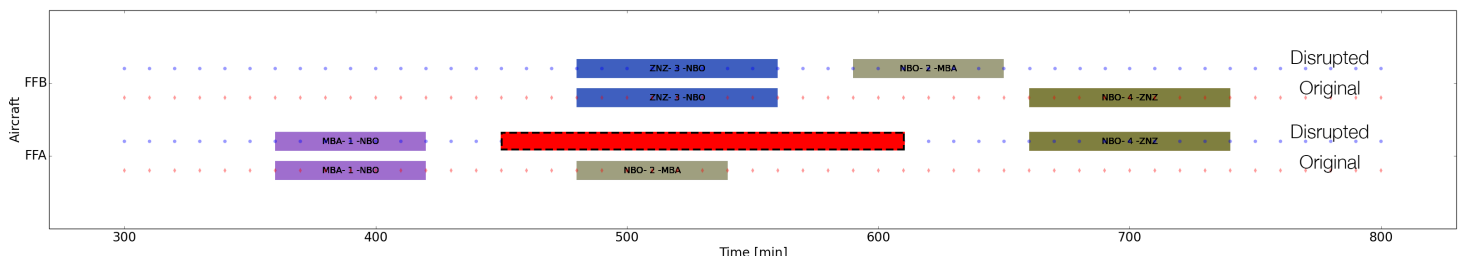


Figure 6.13: Situation where a tail switch is only possible once FFB arrives at NBO (Schedule B)

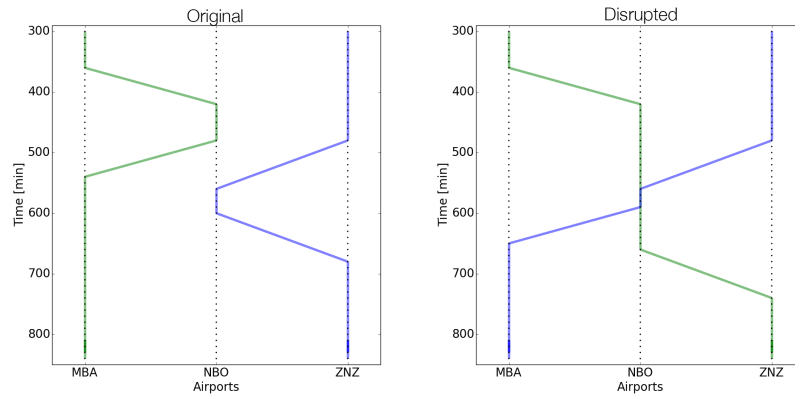


Figure 6.14: Time-space representation of Figure 6.13

Figure 6.15 depicts a similar situation to that in Figure 6.13 however where the FFB is now replaced by KYH. KYH is of a different fleet type than FFA and FFB. In this situation no tail switches can take place because the aircraft must the ending positions must be the same for each fleet type, otherwise there might be problems that occur past the end of the time window.

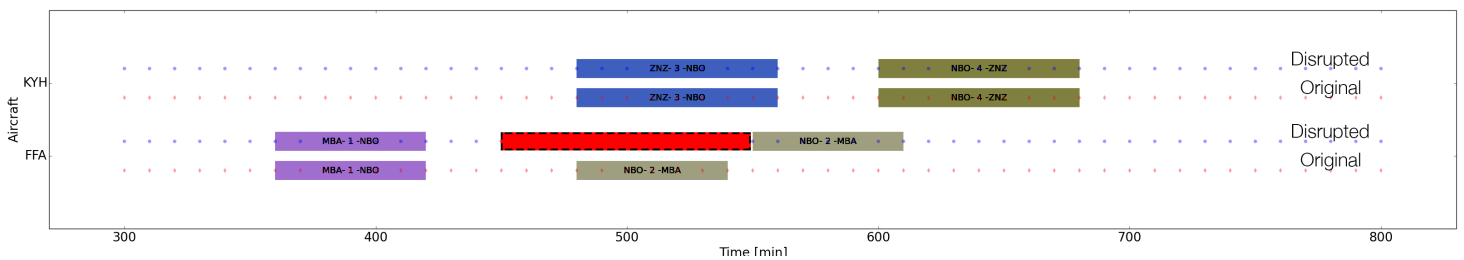


Figure 6.15: Situation where there are two different aircraft type and no switch can take place due to the required number of each aircraft type at each airport at the end of the time-window. (Schedule B)

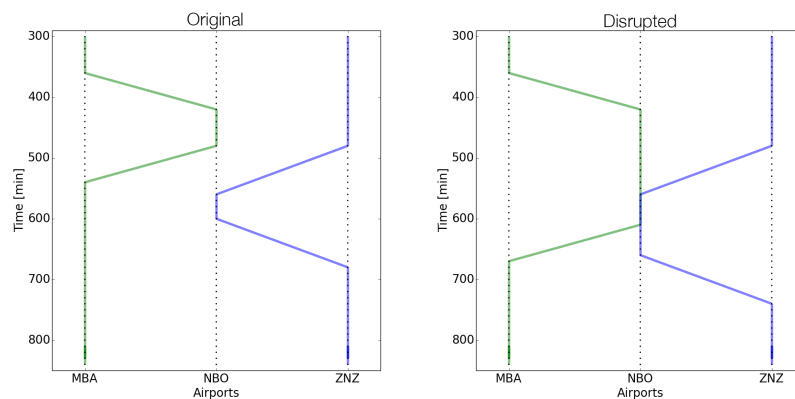


Figure 6.16: Time-space representation of Figure 6.15

Figures 6.17 and 6.19 depict a situation similar to that given in Figure 6.11 except that the aircraft are different. In this case aircraft FFA is disrupted and KYH is undisrupted. FFA is an Embraer 190 able to carry 84 economy and 12 business class passengers and KYH is an Embraer 170 with a capacity of 64 economy and 8 business class passengers. Figure 6.17 show the situation where flight 1 is full and a switch can thus not occur and where Figure 6.19 shows a situation where both flight 1 and 2 are half full and can thus be replaced by the smaller Embraer 170.

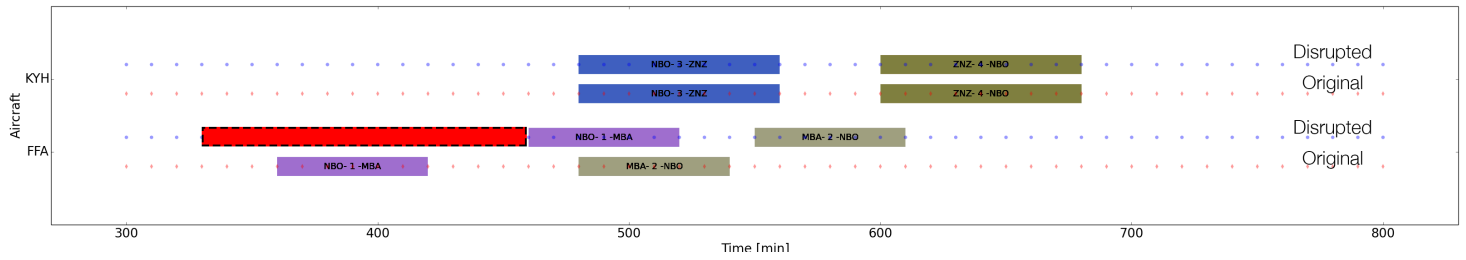


Figure 6.17: Situation where there are two different aircraft types and switch cannot take place because KYH cannot accommodate the passengers booked on flights 1 and 2 (Schedule A)

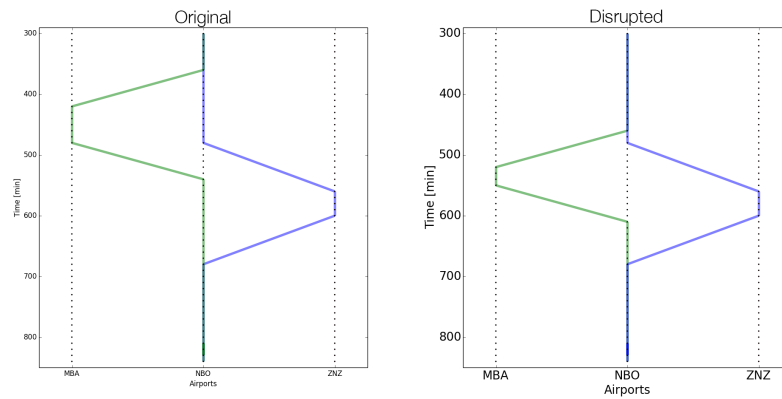


Figure 6.18: Time-space representation of Figure 6.17

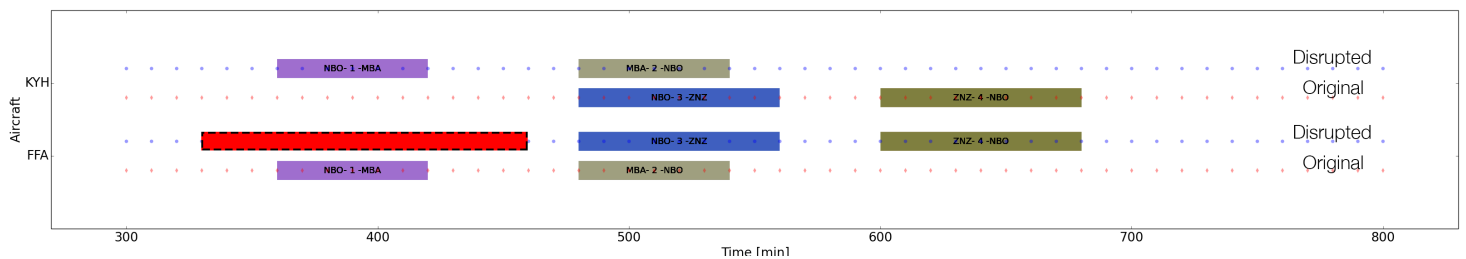


Figure 6.19: Situation where there are two different aircraft types and the smaller aircraft KYH is able to switch with the larger FFA because flights 1 and 2 are only half full (Schedule A)

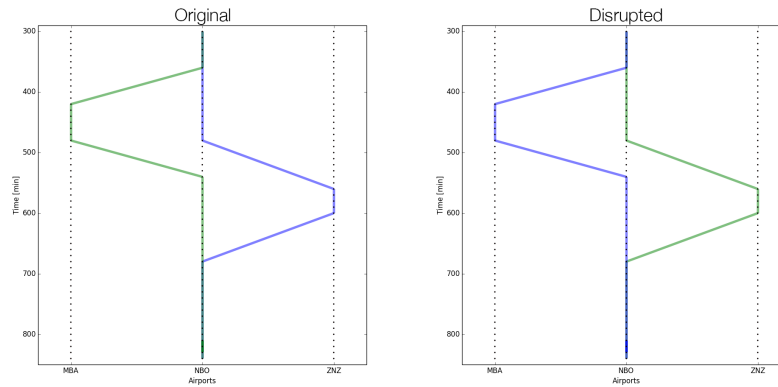


Figure 6.20: Time-space representation of Figure 6.19

6.2.4 Dynamic Situation Tail Switches

This case shows the working of the dynamic case. This is a case with two aircraft KYH (Embraer 170) and FFA (Embraer 190). Figure 6.21 and 6.23 show the steps the case and the solution. KYH has technical difficulties, this is the first information that becomes known, a tail switch is not possible considering all flights are fully booked, so the flights to be flown by KYH (flight 1 and 2) are delayed, as seen in Figure 6.21. At some point later in time it becomes known that the flights to be flown by FFA are delayed by 3 hours due to connecting passengers from a long haul flight. Due to this extra time the initial delay on the flight 1 and 2 can be partially recovered by letting FFA fly flight 1 and 2 as well. Important is to note that this second option is also a solution to the first disruption but would have been more expensive, as the operating cost is higher and the total passenger delay is more.

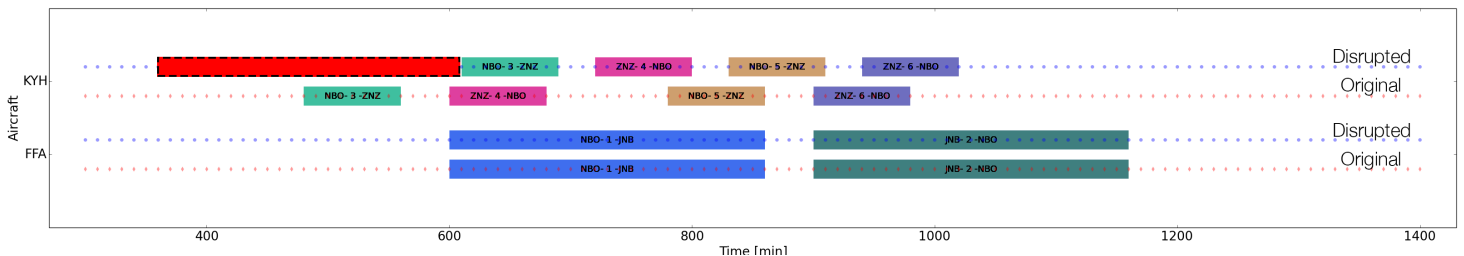


Figure 6.21: Dynamic situation solution after the first disruption becomes known; KYH unavailable until 610min. (schedule C)

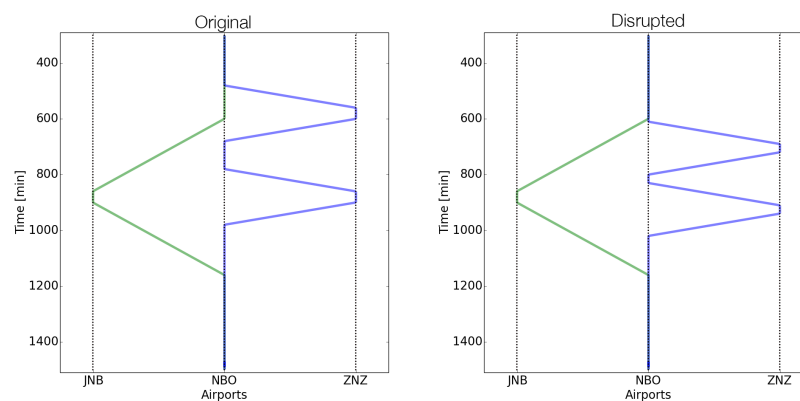


Figure 6.22: Time-space representation of Figure 6.21

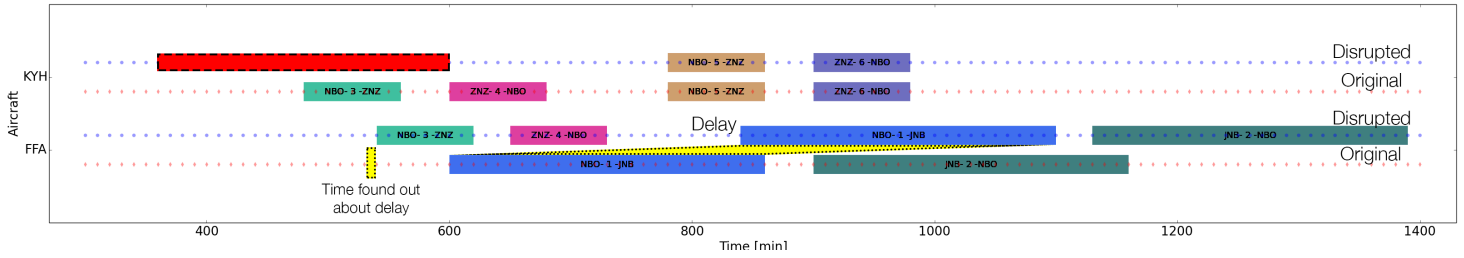


Figure 6.23: Dynamic situation after after second disruption becomes known; flight 1 delayed by 3 hours. This situation shows how the dynamic situation recovers some of the anticipated delay after the situation in Figure 6.21. (Schedule C)

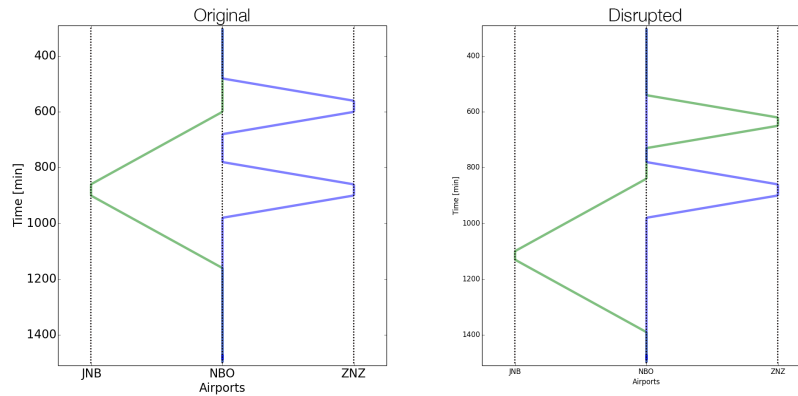


Figure 6.24: Time-space representation of Figure 6.23

6.3 Results Validation

6.3.1 Run With Minimal Delay

To check the initial working of the model the schedule is loaded into the model and is tested for an input disruption of a flight with minimal delay of ten minutes. Tests with minimal delay are done for flights of each aircraft type checking to see if there are any discrepancies in the schedule. There is one problem that arises: when importing data from SABRE (KQ software package) through-flights and triangular-flights that are spread over multiple days are saved as shown in Table 6.1.² The model works with times only rather than dates. After loading the schedule the model will then add 24 hours to the time for each day after the first date. (See flight 602 on the 22nd and the time corrected) The model can also easily correct for flights that arrive on a different day than the departure by checking if the departure time is later than the arrival (See flight 408b STA corrected from 0h10 to 24h10) The model does not however detect that problem a occurs when a flight leg of a through flight is completely in the next day but still saves the date of the previous day (As the case for 408c where STA and STD in the model should be corrected to 25h10 and 27h10, otherwise the continuity constraint will not work correctly). These dates for the through flights are changed manually in the data. For final implementation into the model the data will be directly linked into SABRE and thus the time-stamp used in SABRE can be used, but can currently not be exported.

²Though imported in this manner, once the model starts running the times are rounded to nearest 10 minutes.

Date	Flight number	Tail number	Origin	Destination	STD original	STA original	STD adapted	STA adapted
11/21/14	408a	FFC	NBO	JIB	1930	2205	1930	2205
11/21/14	408b	FFC	JIB	ADD	2255	10	2255	2410
11/21/14	408c	FFC	ADD	NBO	110	315	110	315
11/22/14	602	FFC	NBO	MBA	630	730	3030	3130

Table 6.1: Example of how SABRE exports flights. The STD adapted and STA adapted columns show what the exported data is adapted to when loading it into the model.

Another issue that arises in this test run is that the model makes several tail switch where a larger aircraft with few passengers booked can be replaced by a smaller aircraft. Through these switches the model reduces the total cost. The reason this is an issue is because the model is making several changes to the schedule in an undisrupted situation, which might be seen as undesirable as this tool is built for disruption management and not aircraft allocation. Though some of such changes are desirable (Mutua et al., 2014) it is not desirable that the entire schedule be changed. In the smaller scenarios tested this is not an issue as there are few changes and according to the Duty Operations Managers at Kenya Airways is even desirable to a certain extent. However for larger disruption this may result in large changes in the schedule that do not contribute to solving the disruption. The manner in which this is solved for the full day test cases is that at the beginning of the day of operations the model is run to optimise the tail allocation, and this new allocation is then used as the schedule. When then testing the minimum disrupted case on the newly allocated schedule only the minimal delay occurs and no switch occurs, validating the model works correctly on the new schedule.

6.3.2 Validation with Duty Operations Managers

The validation of the model is done by checking the results found by the model with industry experts Benedict Mutua, Bernard Oguna and Edward Muamburi. All of who are Duty Operations Managers (DMO) at Kenya Airways and have many years of experience in solving disruptions. The scenarios that are tested with them are a combination of scenarios that have been created for DMO training purposes and real scenarios adapted for testing the dynamic aircraft recovery model. The tested scenarios are described in Section 5.4 and are detailed in Appendix B.

The validation with the DMO's was not a one-off interview but has been an iterative process in which many of the bugs in the model have been resolved. Often going back to the drawing board and re-writing code and fixing issues that were not spotted the verification phase. The conclusions from the sessions with the DMO's are the following.

- **Given the scope the solution are valid** Using the final version of the model in each of the tested scenarios the solution is found to be a valid solution to the problem given the input and the scope of the model. In these cases the DMO's have given the conclusion that the solutions found are solutions that can be used in real life to resolve the disruption.³ Considering that the DSS is set up to serve as decision support for aircraft recovery and that the solution found could be used, the model is found to be valid.
- **Factors limiting validity** Though the model within the scope of the project is found to be valid, there are still a few factors that limit the model's validity outside the defined scope.
 - **Engine Bleed** One issue that still occurred was a case that was not put into the model: there was an engine bleed failure on an aircraft meaning it was able to fly but not on every

³In the solutions found by the model there are some things that would still need to be checked before actually implementing the solution, such as crew issues or passenger connectivity.

route. This case can be fixed in easily by adding an aircraft specific constraint for each aircraft with such a failure. The engine bleed constraint is not in the final model because there is no direct information available to the author which routes can be flown with an engine bleed failure.

- **Crew issues with tail switching** Though the DMO's agree with that the operational cost should be kept low often the amount of tail switches that are done between fleet types are quite numerous. In these scenarios the number of flights flown by Embraers increases and the number of flights by Boeing 737's, decreases. This will mean that the scheduled crews for Embraers are required to fly more flights, which could cause problem from a crew perspective. This issue is one that can be solved by selecting different model setting, for example it is possible to block tail switches between aircraft type, or it is possible to ignore direct operating cost making all tail switches possible but not making it an incentive to switch. The effect of this is analysed in Section 7.3

6.3.3 Performance Validation

One of the objectives of this project is the creation of a model that will result in cost reduction and implementation at Kenya Airways. For that reason validation of the computational performance is of importance. When answering the question "is the right model built?", the question thus needs to be answered with the answer to the following question, "does the model find solutions quick enough to be of use to DMO's?". The answer to that question is yes. Through interviews with DMO's and an extensive period spent at Kenya Airways it is determined that ideally solutions should be found within 15 minutes, and this is the case for this model. Section 7.2 provides a more detailed analysis of the model's performance.

6.4 Conclusions Regarding Verification and Validation

The verification and validation describe in this chapter has confirmed that the model in the current state is working correctly for the scope that has been defined for this research project. From a conceptual point of view the model is valid as there are many gains that can be achieved from the implementation of a dynamic aircraft recovery model, especially when implemented as a decision support tool in which an operator can use the results from the model as a basis or as inspiration to solve a disruption. The verification done through tests on small single disruptions have confirmed that the sub-modules of the model are working as they would be expected. The model is validated with the KQ duty operations managers showing that the model works correctly for the given scope.

It should be noted that at the beginning of this chapter, when defining validation the question is posed, 'is the right model built?'. Although the model works correctly and can be used for solving disruption for aircraft as a decision support tool, the lack of passengers and crew in the model limits the validity of the model for automatised implementation.

Chapter 7

Results

This chapter investigates the model outcomes, and does so by looking at several different aspects regarding the model. To give an understanding of what the output and solution found by the model, Section 7.1 details one of the solutions to a full day disrupted scenario. Section 7.2 looks at the model performance in terms of computation times. The reason this section is detailed first is because trimming the model towards optimal performance is a highly iterative process which done in such a way that the model can achieve the best results in the shortest time. Section 7.3 looks at the sensitivity of the model to several different input parameters which can be selected by the user of the model.

7.1 One Solution Explained

In this section one of the four full day solutions is given. This has the purpose of illustrating the how the DReM achieves the results, and thereby also explaining how the results can be read. The case that is described in this section is the full day scenario 1. The remainder of the solutions to the full day scenarios can be found in Appendix C. First a description of the scenario is given. This is followed by a graphical representation as the DReM prints the results.

The scenario used in this case a true KQ scenario from 25/11/2014. On that day there were several issues that occurred. Firstly it is important to note that there are two aircraft, FFA and FFD, that are in long term maintenance and are therefore not available nor do they have planned flights. The reason this is needs to be mentioned is because the long term maintenance does not appear in the maintenance list that is retrieved. Thus these aircraft are input as aircraft unavailable. During the night-time maintenance there are two aircraft that encounter problems. The first becomes known to the DMO at 3:51 and that is that KYQ will be grounded the entire day and is expected to be operational again as of 16:30. Shortly after, at 3:58 it becomes known that there is a technical issue with aircraft FFH and that it will be out of the running until 7:45.¹ In the course of the morning it as KYR is flying from Nairobi (NBO) to Mombasa (MBA) it encounters a technical problem. The aircraft is still able to fly the return flight but after that must receive maintenance. It is expected that KYR is grounded the rest of the day.

- Aircraft 5Y-FFA unavailable all day (long term maintenance)
- Aircraft 5Y-FFD unavailable all day (long term maintenance)
- Aircraft 5Y-KYQ unavailable from 4:10 until 16:30 found out at 4:00
- Aircraft 5Y-FFH unavailable from 4:10 until 7:30 found out at 4:00
- Aircraft 5Y-KYR unavailable from 11:40 until 24:00 found out at 9:30

¹The times that the disruptions become known are normally not recorded. But in this test scenario they and for other scenarios typical values are used, which come from interviews with DMO's.

Before displaying the solution in Figures 7.2 and 7.3. It is important to be able to read the figures. Figure 7.1 provides an insight into how the solution figures can be read. This type of graphical representation is the same as the one used in aircraft schedule tools such as SABRE. Displaying the data in this way makes it easy to comprehend for DMO's.

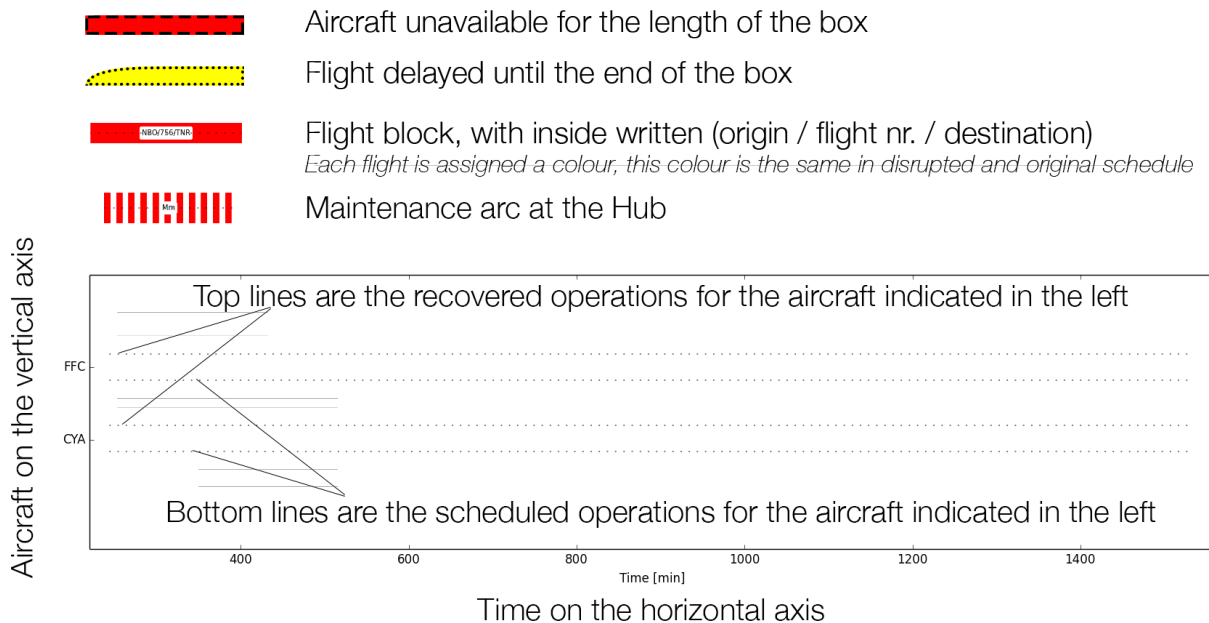


Figure 7.1: Explanation of how to read the figures that display the recovery solutions.

To solve this disrupted day of operations DReM runs two iterations; one at 4:00 for the two disruptions that become known and one at 9:30 for the third disruption. The solution after the first is given in Figure 7.2 depicts the solution found after running the first iterations, solving for two disruptions. Figure 7.3 displays the solution found for the iteration at 9:30 and thereby also shows the final schedule flown. In both the figures only the aircraft who's flight schedule is different from the scheduled operations is graphed.

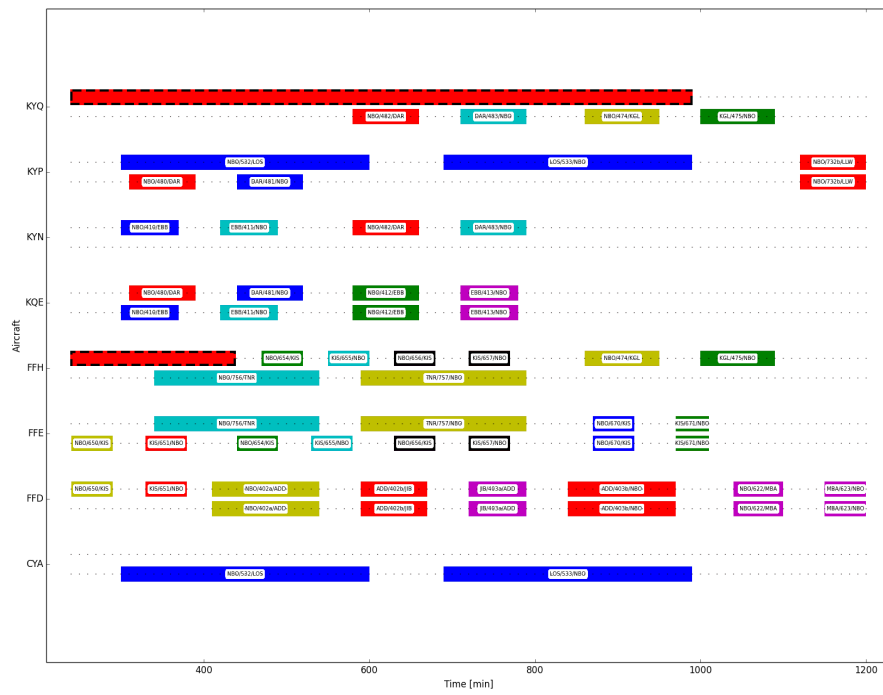


Figure 7.2: Solutions found after running Full Day scenario 1 at 4:00

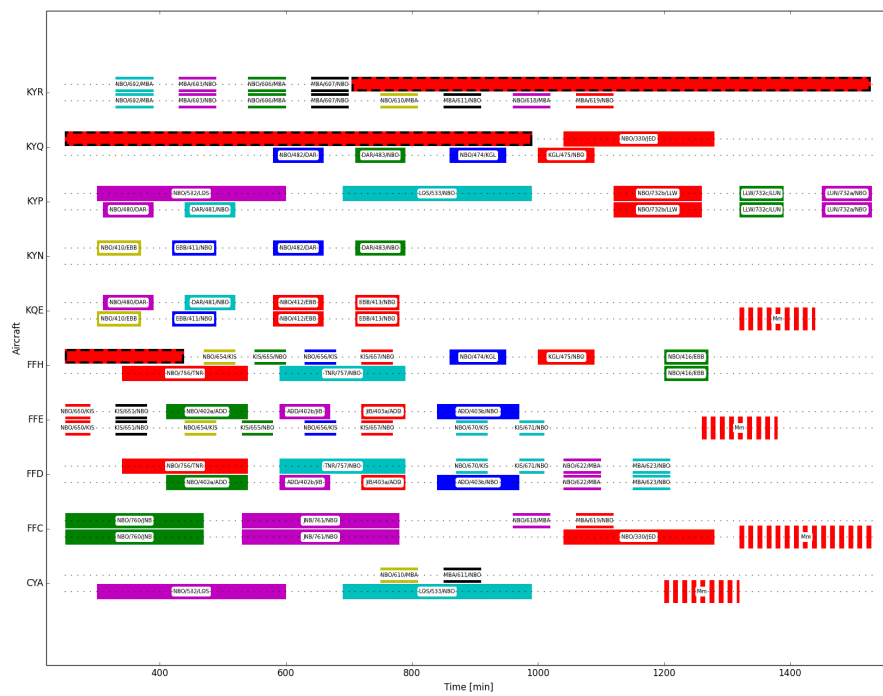


Figure 7.3: Final solution found after running Full Day scenario at 9:30

7.2 Computational performance

In airline recovery operation handling speed of the Operations Control Center (OCC) can make the difference between having to delay or cancel flights or not. Decision at OCC must happen quickly but must not be made hastily. The DMO must make sure that he has all the important input to make a proper decision. The model developed in this thesis project is set up with the goal of providing some of that information. The goal is that the model be implemented as a decision support tool for real time operations. Interviews with Kenya Airways DMO's determine that, depending on the disruption, the final decisions should be made in a time-span of 30 to 60 minutes (Mutua et al., 2014). In these interviews it is also determined that a decision support tool should thus provide a feasible solution to a disruption within a time-span of 10-15 minutes. In the created model the module which will work as a decision support tool support tool is the Disruption Set Solver (DSS), this is the module which solves for all the disruptions known at a given moment in time. The DSS meets the 15 minute requirement in all of the 38 runs of DSS in the tested full day scenarios and in 93.3 percent of the DSS runs, the 10 minute limit is met.

As described in Chapter 4 the DSS runs two different parts. The first part runs through the selected fleet(s) in which aircraft have been ordered and saves the selection of aircraft providing the lowest cost solution. The second part, with the best solution in the previous step, runs through the same selected fleet same in random order in search of a better better selection of aircraft providing a solution with lower cost. When the solution no longer improves the stopping condition is met and the best solution is printed.

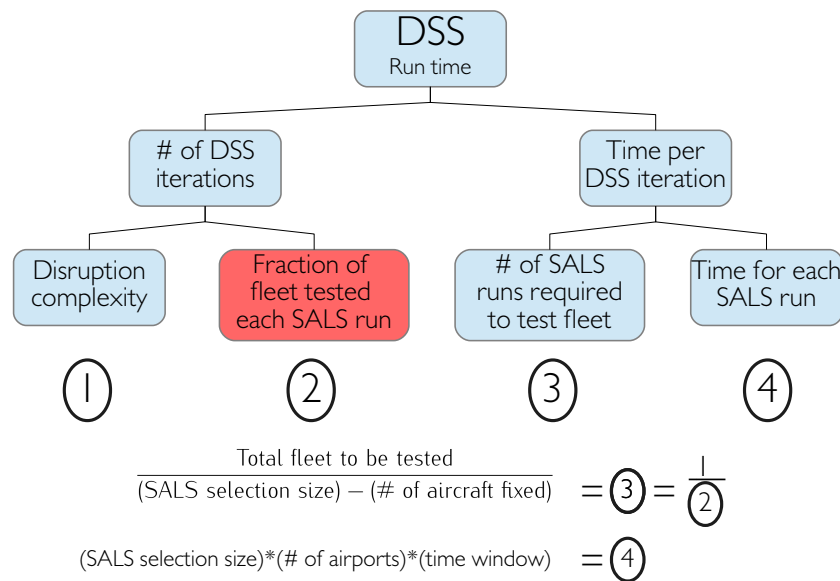


Figure 7.4: Diagram displaying the breakdown of the main factors affecting DSS run time. Number two is red, because it is related inversely to the factor above it.

Figure 7.4 shows the full breakdown on the most important factors which affect the computation time of the DSS. The performance of the DSS is determined by two factors. Firstly the amount of iterations necessary until the solution no longer improves, given as the left branch in Figure 7.4. Secondly, the time necessary for one iteration of DSS given as the right branch. The number of iteration needed (left branch in Figure 7.4) is determined by two factors. Firstly the disruption complexity which is a factor that is difficult to define numerically, but is related to the number of aircraft required by the solution. For example when there are more aircraft used in the optimum solution, more aircraft need to be selected when iterating through the fleet. The second factor is the ease at which these aircraft are found, this is directly related to the fraction of the fleet which is tested each run. For example, if all aircraft of the fleet are being tested in one run then the number of iterations will be one. It is

important to note that the number of iterations in DSS is affected by the two mentioned factors, but is not determined in a numerical relationship.

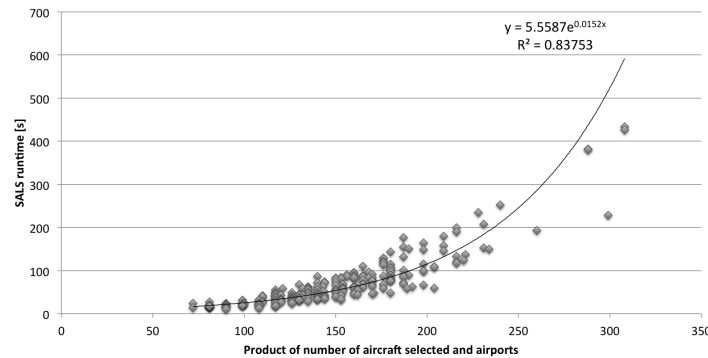


Figure 7.5: SALS run time against the product of aircraft and airports for a given time window of 16 hours and a resolution of 10 minutes

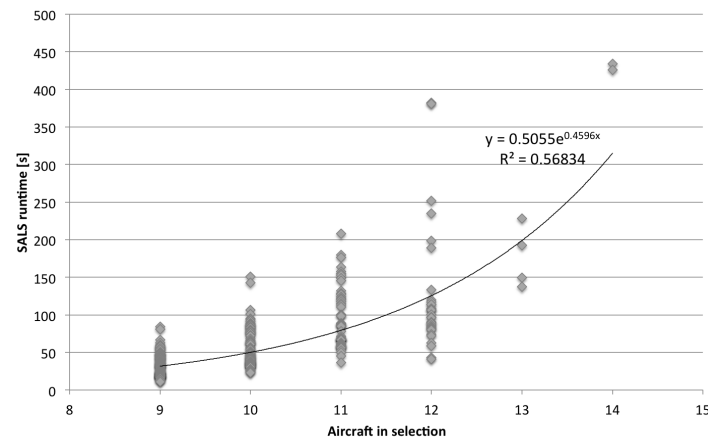


Figure 7.6: SALS runtime vs number aircraft in selection for a given time window of 16 hours and a resolution of 10 minutes

Synthesising the above findings at the bottom of the line there are three main factors which affect the DSS runtime:

- **Disruption complexity** is an important factor which determines the amount of aircraft which will be in the final solution. This factor is a given input, is not measurable and can not be changed.
- **Total tested fleet size / number of newly tested aircraft** The number of newly tested aircraft is the number of aircraft in the test size (independent variable) minus the number of aircraft fixed in the incumbent solution (dependent variable). This factor affects two sides of the equation. In a direct manner it determines the number of runs of SALS are required to test an entire fleet. In a less direct manner it affects the amount of iterations of DSS which are required. As a larger fraction of the fleet is that is tested each time will result in the ideal combination of aircraft being found sooner. To improve the total run time, the total fleet size that is to be tested should be kept small and the number of aircraft selected for each run of SALS should be kept big (This is an input). The total fleet to be tested can also be input by the user if desired, but it can also be decreased in size by running the DSS for sections of an airline's entire fleet. The manner in which DReM splits the fleet is described in Section 4.3.
- **SALS Run time** This has an exponential relationship between time window size (independent variable) times the number of aircraft in each run of SALS (independent variable) times the

number of airports (dependent variable) ². This exponential relationship increases rapidly, and can be limited in two different ways, firstly limiting the time window, and secondly limiting the size of the selection.

- **Time window length** The length of the time window is determined through iterative tests and discussing solutions found with the DMO's at Kenya Airways. For the short haul it is determined that a 12 hour time window is the minimum time window length and that with a 16 hour time window nearly all disruption can be solved. The reason for this is that the 16 hour time window covers nearly an entire day of short haul operations. For the long haul network, the computation time are quick because the number of airports and flights operated are limited and setting the time-window length to 48 hours still provides adequate computation times. Furthermore a long haul network needs more time to recover operations as flights are much longer.
- **Time window resolution** The resolution in all instances has been set to 10 min as this is the best suitable resolution in an airlines operations. A smaller resolution is not necessary as these will not affect the solution quality and a larger resolution would require rounding of the minimum turn around times, which are 30,40 or 60 minutes depending on the aircraft type.
- **SALS selection size** The SALS selection size is determined dynamically and is thus not fixed for all of the iterations within the DSS. The SALS selection in each iteration of DSS has two different parts, a selection of fixed aircraft and a number of aircraft which changes for each run of SALS. This is explained in section 4.2. The changing part is the number of undisrupted aircraft that are tested in each run of SALS. Firstly a minimum number of undisrupted aircraft to be tested is determined. This is done through trial and error, while looking at the number of iterations necessary to solve the DSS. It is experienced that the minimum size of undisrupted aircraft to be tested should be at least 4 each run. The total selection size is set to a minimum of 9 aircraft, as this result in an acceptable SALS run time with 96 percent of runs quicker than 1 minute and 76 percent less than 45 seconds. What this two setting mean is that depending on the number of fixed aircraft, the number of changing aircraft is determined. If the fixed selection is smaller or equal to 5, the total SALS size is 9, if larger than 5 the SALS size is the number of fixed aircraft plus 4 (the minimum number of aircraft to be tested). These are the values determined for the KQ case and might differ if applied to a different case study.

7.3 Sensitivity Analysis

7.3.1 Pre-selection ordering

In the development of this model there are two different methods of pre-ordering selections of aircraft which are used, to stimulate finding the best solution in the quickest way. The first is placing aircraft in order by total time they spend on the ground (from most to least). The other method is placing them in order by the amount of time they have on the ground at the airports at which disruptions occur. When testing both methods with the data sets there is no direct correlation found between the type of ordering and the final solution found, in all the cases tested the two orderings came to the same final solution in the same amount of DSS iterations of the model and comparable computation times. Of course this can be partly attributed to the fact that ordering only has effect on the primary iteration in the DSS as after that random search is used to further optimize. Though the effect was not noticeable on the testsize of 69 runs there might be an effect on larger problems.

²The number of airports can of course be selected by excluding certain aircraft from the solution or by sorting aircraft in a certain way, however this contradicts the method of randomly searching the entire solution space and would limit the possible solutions found

Full Day Scenario	Soft in-cluded	Simulation runtime	Max pri-mary	DOC change	Soft Cost	Hard Cost	DOC + Hard Cost	Total Cost
1	YES	41:19.4	10:11.2	818	374	0	818	1192
	NO	49:06.4	13:23.9	-2054	39004	2710	656	39660
2	YES	29:44.1	04:22.7	-5709	24955	3125	-2584	22371
	NO	Out memory, selection size too large for single iteration						
3	YES	27:02.6	05:11.7	-1741	3587	0	-1741	1846
	NO	28:21.4	04:38.2	-3019	11931	0	-3019	8912
4	YES	32:54.2	06:33.9	-9819	38415	3950	-5869	32547
	NO	39:40.9	09:25.5	-18693	84290	6560	-12133	72560

Table 7.2: Comparison of running DReM for full day situation with and without soft costs in objective function. Where Max Primary is the maximum time to find a first solution, i.e. the longest time to find a solution the the disruptions at a certain point in time. In run 2 there was a memory problem as at the third iteration within the second DSS time step, the number of disrupted aircraft became larger than 24

An analysis is done on the final solution found and where those aircraft are in the initial ordering. Table 7.1 shows the average position of the non-disrupted aircraft used in the solution in the total list of aircraft tested in that run of DSS. The average position is given as a fraction of the size of the selection of aircraft, the reason for this is because the total selection size changes and absolute positions should not be compared. When observing the results it can be seen that, as expected, the best solutions found for the disrupted scenarios contain aircraft with more ground-time than the average aircraft in the fleet (Average is 0.5). An interesting finding is that in general the total amount of ground time is more relevant to the aircraft in the solution than ground time is at specific airports where disrupted aircraft are planned to fly.

Ordering	Average position
by total groundtime	0.357970091
by grountime at disruption locations	0.412871946

Table 7.1: The average aircraft positions of the non-disrupted aircraft used in the solution, within the list of all the aircraft of the run in order

7.3.2 Objective Function

This section looks at the effect of the objective function on the results achieved. The objective function consists of the direct operating cost, the cost of delays and cancellations, both of which are split in to hard and soft cost. This section investigates the effect of each part on the total solution.

Hard and Soft Costs

This subsection investigate the effect of the hard and soft cost on the on the final solutions. The manner in which this is tested is that the solution is found for two different situations one situation which includes soft costs and one situation which excludes soft cost. In the situation where the soft cost is not taken into the objective function the hard cost has been slightly adapted. The adaptation that has taken place is that the hard cost of delay for delays from 10 until 50 minutes are given the minimal value of 0.01 USD. The reason this is done is so that the model does not select delay arcs when a flight should in fact be on time, as nil cost of delay could result in that. It should be noted that looking at only hard only, due to the stepwise function there is no difference in cost between delays on the same step.

The results displayed in Table 7.2 show that when the objective function only contains hard cost the cost of delay in fact increases in both soft and hard cost of delay. In first instance this might seem unexpected however the objective function also contains the DOC, and as the results show the situation where soft cost is not in the objective function the sum of DOC and hard cost of delay decreases drastically. What in fact is happening in this situation is that flights are being delayed to make tail switches possible, as this reduces the direct operating costs more than it increases the hard cost of delay. This problem is enhanced by the fact that the function for hard cost is a stepwise function, which means that once a flight is delayed to a certain step there is no incentive not to delay it further within that delay step. In scenario 2 with only hard costs the number of switches that take place becomes larger than 24 aircraft which results in a memory problem. In reality there would also be a serious issue if were 24 aircraft switching tails as a single point in time. A conclusion which can be drawn from these tests is that the hard costs of delay are of such a small size that in comparison to the direct operating cost they do not form an adequate incentive for on-time performance. An other conclusion which may be drawn is that the soft cost of delay is a significant enough incentive for on time performance. This conclusion is validated by KQ DMO's who indicate that the hard cost of delay is rarely a reason for them to pursue OTP, passenger satisfaction is.

Direct Operating Cost

The reason that the direct operating cost (DOC) of each aircraft type for each route needs to be taken into account is because if tail switches take place between aircraft of different types this will have an effect on the direct operating cost. If for example the solution is found for aircraft that are all of the same type the the DOC will not change if two aircraft are switch. Below three different cases illustrate the possible situation when several fleet types are used to solve a disruption:

- Case 1: An Embraer 190 (96 seats) has a technical issue. A Boeing 737-800 (145 seats) is available. In this case the model will make a trade-off between delaying the flight until the Embraer is expected to be working or to switch the aircraft and use the more expensive Boeing to operate the flight. This depends on the amount of expected delay and number of passengers on board.
- Case 2: A Boeing 737-800 (planned flight full) has a technical issue. An Embraer 190 is available. In this case the model does not allow the Embraer to replace the Boeing. In real life the Duty Manager Operations could choose to leave passengers behind.
- Case 3a: A Boeing 737-800 (planned flight half full) has a technical issue. An Embraer 190 becomes available once returned the hub. In this case the Embraer will replace the Boeing taking over the flight regardless of the delay.
- Case 3b: A Boeing 737-800 (planned flight half full) has no issue. An Embraer 190 is available. In this case there is no disruption but because the Embraer is less expensive to operate and is available and capable of taking over the flight the model will make the tail switch.

Case 3b illustrates that if possible the model does not only solve disruption but also finds the best aircraft to use on a route given the amount of passengers booked. This situation is discussed with DMO's (Mutua et al., 2014) who indicate that this is a desirable situation and that this also happens in actual operations. The manner in which this has been solved as described in Section 6.3.1 is that at the beginning of the simulated day the schedule is optimised for the ideal tail allocation so that a minimum cost and optimal tail allocation is achieved. As described in Section 6.3.1 this has the limitation that certain factor outside the scope might be affected, such as crew which might be assigned more or less flights. The downside of these type of desirable switches in cases 3a and 3b is that they affect the problem computational performance. When such a switch takes place the switched aircraft are taken up in the selection of aircraft used in the solution. This means for the subsequent iteration of the Disruption Set Solver (DSS) these aircraft become part of the fixed selection, which either reduces

the number of aircraft which can be tested in each iteration ³ or the total selection size is increased ⁴. In both cases the computation time increases, where the former has a linear effect on computation time as it affects the amount of runs needed to test all the aircraft. The latter has an exponential effect on the computation time as the SALS selection size increase, this relation is describe in section 7.2.

To test the effect of the direct operating cost on the total solution the model is run in two different manners, once with the actual direct operating cost and once with a direct operating cost equal for all aircraft, an unrealistic situation which might however result in less delay. The following table give an overview of the total operating cost, the total cost of delay for both situations in each tested case.

Full Day Sce- nario	DOC in- cluded	Simulation runtime	DSS runs	Max pri- mary	DOC differ- ence	Soft cost	Hard cost	Total cost
1	yes	41:19.4	2	10:11.2	818	374	0	1192
	no	25:32.6	2	11:29.1	5990	0	0	5990
2	yes	55:13.1	6	08:15.2	-5709	24955	3125	22371
	no	1:05:31.0	6	10:24.1	0	25048	3125	28173
3	yes	26:19.8	4	02:29.1	-1741	3587	0	1846
	no	38:47.5	4	04:52.6	9990	3574	0	13564
4	yes	26:09.4	3	03:36.1	-9819	38415	3950	32547
	no	23:41.4	3	03:16.3	0	38581	3950	42531

Table 7.3: Comparison between runs including and excluding direct operating cost in the objective function. Where Max Primary is the maximum time to find a first solution, i.e. the longest time to find a solution the the disruptions at a certain point in time.

To conclude it may be said that the removal of DOC from the objective function results in a less cost effective solution to the problem. This is the expected outcome considering an important cost is not taken into account when finding the solutions. When comparing the hard and soft costs of delay the situation it may be observed that the hard cost of delay is the same in all the situation but the soft cost is in fact not the same in any instance. Upon closer investigation of the results it becomes clear what the reason for this difference is. In fact, it becomes clear that there is no difference in the flights which have larger disruptions. There is however a difference the flights chosen for the shorter delays, these often have slightly different passenger numbers resulting in slightly different solutions. The difference is minimal as it is in both cases less than one percent.

Stopping Condition

The stopping condition of the DSS (Disruption Set Solver) is set up in such a way that the DSS stops when the solution does not change for a certain number of runs. When investigating what the best number of unchanged runs should be, the conclusion may be drawn that a single unchanged run suffices. The manner in which this conclusion is drawn is that a runs are done on all the test scenarios with the stopping condition set to a value of 6 iterations unchanged before stopping. When observing the results in total the DSS was run 38 times, only once did the result improve after two equal runs, and never after more than two. The conclusion can that be drawn from this, is a stopping condition where the solution does not change for one run is a valid one. The reason is that searching the rest of the aircraft with a random selection of four, does not improve the solution when testing for the entire fleet six times. Thus indicating that the stopper condition equal to six times the same solution yields the same results as one time the same solution.

³the case if the fixed selection is smaller than the minimum selection size, in this model set to 9

⁴the case if the amount of to be newly tested aircraft is less than the minimum to be tested, in this model set to four

7.4 Dynamic Modelling

One of the objectives of this research is to investigate the effect of dynamic modelling on the results achieved by the aircraft recovery problem. Table 7.4 gives an overview of the results for the runs that have been done for the dynamic and the non-dynamic situation. The hypothesis given in Chapter 3 that the cost in the dynamic situation would be higher is found to be correct. This is the expected outcome given that in the non-dynamic situation all the disruption are known at first instance and thus proactive measures can be taken to solve the disruptions.

Full Day Scenario	Situation	Difference DOC	Soft cost	Hard cost	Total cost
1	Dynamic	818	374	0	1192
	Non-dynamic	202	0	0	202
2	Dynamic	-5709	24955	3125	22371
	Non-dynamic	-7827	20438	2396	15007
3	Dynamic	-1741	3587	0	1846
	Non-dynamic	-3369	3647	0	211
4	Dynamic	-9819	38415	3950	32547
	Non-dynamic	-9897	30890	3674	24667

Table 7.4: Dynamic vs non-dynamic results on actual disruptions in KQ case

One of the key findings from the tested scenarios is the extent in which there is a difference in cost of delay. In the tested situations the total cost of the disruptions in the non-dynamic situation was on average 22.9 percent of the cost in the dynamic situation. However this is not a correct representation of the results because very large proportional differences are achieved when the absolute difference is small. If the total difference in cost of the four scenarios is compared between dynamic and non-dynamic; the non-dynamic situation is 69.2 percent of the cost of the dynamic situation. This clearly shows how large the effect is of being able to proactively solve a disruption. From this result it is possible to conclude the following: The solution that is found in the non-dynamic situation differs greatly from a realistically achievable solution, in the tested scenarios the cost reduction if all disruptions are known at the beginning of the day is 30.8 percent. When modelling a period of disrupted operations it is not possible to get a realistically achievable solution if all the disruptions are assumed known at the beginning of the day.

Chapter 8

Conclusions and Recommendations

This section provides conclusions and recommendations with respect to the research. The research conclusions are divided into, the results achieved by the model (Section 8.1), the addition to the body of knowledge (Section 8.2) and the applicability of the model (Section 8.3). The recommendations and limitations are given in Section 8.4.

8.1 Results

The results from running the model in this research are analysed in two different perspectives. The actual results the model achieves in terms of cost depending on the disruption input and the input parameters, and secondly the performance of the model.

Dynamic vs Non-dynamic

The Dynamic Recovery Model is run for two different situations, on in which the actual time at which disruptions become known are used, this is the dynamic (changing) situation and secondly a situation where all the disruption are known at the beginning of the day, this is the non-dynamic situation. When comparing the result over four days of real scenarios provided by Kenya Airways, the total cost of in the non-dynamic situation was 69.2% of the cost in the realistic dynamic situation.

Model Performance

An important aspect in recovery operations is that the problem is not only solved, but is solved within real-time such that the disruption is can be solved as quickly as possible. The measurement of performance in this research is done by the run-time of the DSS, which is the module that solves disruptions at each point in time. The DSS for the tested scenarios is run on different 38 instances and always achieves a solution within 15 min and in 93.3 percent of the runs converges to a solution within 10 minutes.

8.2 Extension of the Body of Knowledge

This research, being part of a Master of Science thesis work, set out to extend the body of knowledge in the field of airline operations research. More specifically looking at recovery operations, this research adds three different elements to the current body of knowledge:

- **Dynamic model** The DSS model created takes as input a (previously) disrupted schedule as well as a set of disruption and solves towards returning to an original schedule. This is an approach to the recovery problem that has not been used before. The use of this approach in a simulated environment has provided insight in the limitations of using approaches where all

the disruptions are known at one point in time. This clearly displays the difference between dynamic and non-dynamic modelling.

- **Aircraft based search** The technique used in this model where an optimum solution is found for a selection of aircraft and a search algorithm is developed that searches through selections of aircraft rather than flights is a unique approach. The use of such an approach means that when implemented as decision support tool, an operator can input or give preference for certain aircraft.
- **Parallel time-space** The use of time-space networks is an idea first introduced by Thengvall et al. (2003) but was implemented per fleet type rather than for individual aircraft. This research implements the use of parallel time space networks per aircraft making the addition of aircraft specific constraints easily implementable. Furthermore this research shows the feasibility of such an approach if combined with an aircraft search heuristic.

8.3 Application of the Model

The model is created with the purpose of two different applications:

- **Simulation of reality** The dynamic model makes it possible to simulate and test an actual disrupted day of operations where not all disruptions are known at the beginning of operations.
- **Decision support tool for airlines** Within each time step the model created is able to dynamically recover the disrupted operations for aircraft. The input schedule at that point in time might be already disrupted or different from the scheduled operations. Other input information is about disruptions that are becoming known to the Duty Operations Manager (DMO). The application of the model in real time is possible with the achieved computation times. Furthermore, the solutions have been validated with the DMO's at Kenya airways. It should be noted that the problem size for which the model is tested is for the case of a 42 aircraft in the Kenya Airways Case. However, the fleet is split by long- and short-haul aircraft and the model is actually run for a fleet size of 27 short-haul aircraft as the largest size. The application of this model to larger airlines is possible though it should be investigated what for that airline specific is the best search method and best splitting technique of the total network.

One application of the model that was not in first instance anticipated but might prove useful for airlines is running the model to achieve reduction in direct operating cost on the day of operations. The model is created in such a way that it optimises for minimum cost, taking into account the direct operating cost, and constraints, which determine which aircraft can fly which leg. The result is that the model does not only solve disruptions but also finds possible tail switches in scheduled operations, which results in total cost reduction. The model could thus be applied to an airline's schedule at the beginning of the day of operations to see if the total operating cost for that day can be decreased. The limitation in such a situation is that the model in the current state does not take into account crew or passenger constraints.

8.4 Limitations and Recommendations

8.4.1 Disrupt Later Flights Rather than Earlier Ones

One recommendation is that it is investigated what the effect is on the operation of which flight should be selected to be delayed or cancelled. Currently the model solves a disrupted situation for lowest cost within a given time window. This is done without taking into account that if there is a choice between delaying two flights; delaying an earlier flight means the delay will surely not be recovered at a later stage. It is imaginable that there exists a tactical advantage to delay a later flight rather

than an earlier flight. Furthermore due to the moving time window delaying/ cancelling the later flight means that new opportunities arise when solving the problem again at a later stage. This results in the following recommendation:

Test to see the effect on the total solution if a bonus or discount is added to delaying/ cancelling later flights.

To add to this previous recommendation, the current situation is that the model re-calculates the best solution for each time that a new disruption becomes known however if no new disruptions become known during the course of the day it might still be possible to find a better solution to the disruptions given the fact that the time window will have moved. For the tested scenarios the disruptions were evenly spread out over the day but a recommendation for completeness is:

In the simulation environment add an element that makes sure that the model is runs at least at minimum interval, and test to see whether the runs done at the intervals improve the solution found.

Though in the current situation the solution might not directly improve it is imaginable that the combination of the two aforementioned recommendations could improve the total solution. If the model is to be implemented in actual operations, it is imaginable that the model is constantly running in the background, or running at intervals of 30 minutes.

In the interviews with the DMO's, the issue of delaying earlier or later flights has been discussed and has also been experience in the several days that the author has spent at the KQ OCC (Mutua et al., 2014). There is a dual goal when disruptions occur, firstly to limit the total amount of disruption and secondly to return to scheduled operation as quickly as possible. What happens in practice is that a DMO first attempts to solve the disruption at hand for the flights in the near future, often having impact on flights further in the future. In this way the DMO 'buys some time' to later get back to solving the newly creating disruption in the future. The technique is in fact a form of a greedy solution to first solve the problem in the near future and later solve the problem in the further future. Whether or not this type of solution is applied depends on the DMO's own experience and insight in a given situation. These recommendations are thus given as investigations that could possibly improve the solutions found, and help the implementation in actual operations.

8.4.2 Cost Function

In the cost function there are several limitations in the model that can improved, this subsection lays out the limitation is the cost function. The limitations are divided into three parts. The direct operating cost, the hard cost of disruption and the soft cost of disruptions.

Direct Operating Cost

Due to the fact that the direct operating cost for each aircraft type for each route was not available in the data received from Kenya Airways a decision is made to make a simplification by finding the average direct operating cost per block hour to compare the different aircraft types on the different routes. In Chapter 5 it is calculated that the error occurring due to this simplification is not large, and the deviation from the actual values, especially when comparing aircraft types rather than routes is minimal. However for completeness it is recommended that more extensive calculations are done for each route to better determine the direct operating cost. It is not expected that the small improvement in accuracy will have a significant (perhaps not even noticeable) effect on the solutions found. However, it does provide a more accurate display of the reality to the users of the model.

Hard Cost of Disruptions

The improvement in the hard cost of disruptions lies in two areas. The first recommendation is to use actual ticket prices in determining the hard cost of a cancellation. Currently the hard cost of a

cancellation assumes a hotel stay and average ticket price to be reimbursed when cancelling long or short haul flights. The use of an actual price will provide better insights. A limitation of course is that passengers are often accommodated on flights the next day, in which case the ticket fare is not reimbursed.

The second recommendation with respect to the hard cost of disruption is to investigate the cost of tail switches of disrupted aircraft shortly before the departure time. In some case an aircraft may receive a technical problem once the aircraft is fully loaded with baggage and passengers, currently there is no cost if the aircraft is switched with another aircraft. So the recommendation is the following:

Investigate the cost of switching aircraft for each fleet type for different times of decision before the scheduled time of departure. This additional cost should be implemented in the model by adding this additional cost for flights that are schedule to depart within certain time from the present.

If the above recommendation is implemented it can be implemented for any part of the model and not only for scheduled time of departure. For example if the decision is made to delay a flight by several hours, and then a new disruption occurs just before the new departure time, this addition switch cost can still be easily applied. Making this type of cost a valuable addition to the dynamic model.

Soft Cost of Disruptions

The calculation of the soft cost of delay according to the several works by Cook et al. ¹ has a number of limitations:

- Using an average soft cost of delay assumes that delaying a passenger on every flight has the same cost. In reality this will not be the case, it might for example be more expensive to delay passengers that are connecting or that are on long haul flights, or on routes with a lower frequency.
- The data used is information from the European market, the African market is different and might react differently to delays.
- The soft cost of delay is based on research from 2003. Though the prices have been corrected for inflation, the world at large and the world of airlines has since changed enormously. In 2003 Facebook and other social media as well as smart phones did not exist. The introduction of these media has probably greatly changes the soft cost of delay. Nowadays, disrupted situations at airlines sometimes appears equally quickly on Twitter or Facebook as it does on the Duty Operations Manager's screen. This greatly changes the reach disruptions have and potentially also changes customers' purchasing patterns.

The above limitations in fact all would benefit from one recommendation, which is further research into the cost of delay for current situation, the African Market and the routes for the Kenya Airways case. In the further research the effect of social media should be investigated on the total futures sales as well as looking at the individual routes and which flights those passenger are likely to take. The switching propensity described in 5.3 could be applied per route for the potential future flights which those specific passenger might take. All in all these proposed researches are very extensive and are thus not easy additions or improvements.

8.4.3 Scope Extension

The scope of this research has been defined in such a way that the research looks into the recovery of aircraft. Part of the reason for defining the scope in this way is because looking at aircraft is the

¹Cook et al. (2004), Cook and Tanner (2009), Cook et al. (2009) , Cook and Tanner (2011a), Cook and Tanner (2011b) and Cook et al. (2012)

most significant to investigate when looking at the delays and reactionary delay at Kenya Airways, this is explained in Section 5.1.2. However two other significant factors that are of critical importance to solving disruptions are crew rotations and passenger connectivity. It is not said that without these two this tool cannot be useful as a decision support tool, but it is strongly recommended that the scope of the recovery model be extended past only aircraft. The extension for crew can be done in such a way that further parallel time space networks are created for crew. This will however, result in a slower dynamic recovery model, thus it should be investigated what the best search method through this new solution space should be. The extension into the passenger side of the problem could be done in such a way that the time-space networks is not increased in size but that additional arcs are added between flights that have large number of connecting passenger (for example flight pairs that have more than a certain number of connecting passengers). These additional variables can be linked directly to whether the two flight arcs are selected and what the minimum connecting time between them is. If this connection arc can be chosen then there is no lost connection cost and if un-selected will result in lost connection cost, which will have a related cost in the objective function. Once again this addition will have an effect on the computation speed of the model though it is expected that the effect will not be as great as the extension for crew.

The effect that these constraints may have on the computation time is best explained in an illustrative example. For the Kenya Airways case if we look at the tests done by the iterations of SALS a typical problem will contain about 30 flights of the total 150 flights in the Kenya Airways network. If we assume that each flight contains 3 sets of significant connections, say more than 10 passengers connecting to one flight. It is then fair to assume that one of these three will be inside the selection of flights in that SALS (active) and two connections will be outside the selection (passive). For the passive connection (outside the selection of flight that can be changed) only one constraint needs to be written to determine whether the connection will be reached. This is a constraint connecting the flight arcs and delay arcs of the flight inside the window to the unchangeable arc outside the window that ensure that the connection is met. When the connection is active, both flights changeable inside the time window, then the previously describe constraint needs to be written for each delay step possible in either in or outbound flight. The total delay steps used is 54 (9 hour max delay, and 10 minute steps). For the typical SALS run this will thus result in an increase in 540 active constraints and 20 passive constraint in a typical run of SALS 90% of computation time goes to constraint writing round about 37,000 constraints. This extension will probably lead to an increase in computation time of less than a few percent. In comparison the extension to crew as a resource results in the addition of time-space networks for **each** crew in the selection of SALS. With the addition of a single time-space network there is the addition of at least $(14 \text{ hrs} * 6 \text{ steps/hr}) * (\text{typically } 12 \text{ airports}) = 1008 \text{ nodes}$, which means the addition of at least that many node continuity constraints, and that is not even including flight and delay constraints.

8.4.4 Identical Nodes

The use of a time-space network results in a very easy to understand and robust network representation that is easily extended and constrained. The use of parallel time space networks uses the conceptually simple technique and extends it in such way that aircraft specific constraints can be easily added. The downside of the network representation is that there are many nodes in the network that can impossibly be reached by the aircraft in that time-space network. And computation power is still used to write continuity constraints for these nodes. This section explains to manners in which this computation time could be decreased.

The first method is by first doing a quick analysis of what the earliest and aircraft can reach a certain airport is, and then deleting all the nodes at that airport, for that aircraft earlier in time. It is difficult to say whether this technique will result in less computation time as it is heavily dependent on the network at hand.

The second method is to build a database of CPLEX problems in which time space network of a certain shape are saved. The number of files that should be saved should have a range of 8 to 16

aircraft, 10 to 24 airports and 12, 14, 16 and 48 hour time windows. This will result in a database containing 672 parallel time space networks, with all the node continuity constraints already written. These can then be loaded into and then all the flight and delay arcs should be added and the respective constraints should be written. This also means all the nodes at which flight and delay arcs the node continuity constraint needs to be re-written. To give an indication of how this might work on a long haul network, a real example is used with a 36hr time window, 10 min time step, 13 airports and 9 aircraft, there are then 25,272 node continuity constraints. Upon investigation of these constraints it is observed that only 9,882 have flight/delay arcs entering or exiting. This means that by using this method it could save the time of writing 15,390 constraints, where this problem had in total 33,472 constraints. Then considering that constraint writing takes up 90 percent of the computation time of SALS this can potentially result in a drastic decrease in computation time.

8.4.5 Times Disruption Become Known Sensitivity

A recommendation for further research is to investigate the sensitivity of the solution quality to the time which the disruptions become known. This research has investigated the difference between finding out about disruption at actual times versus the situation where all disruption are known at the beginning of the day. There exists an opportunity to investigate the sensitivity of the solutions found by DReM depending on what time the disruptions become known. Such a study could outline to what immediate communication of disruption is important.

8.5 Concluding Remarks on the Research Objectives

This research has defined three main research objective, which in this section are concluded upon.

"Create a model that solves the aircraft recovery problem in a dynamic way and demonstrate the difference between solving in a non-dynamic way."

The Dynamic Recovery Model (DReM) created for this thesis work simulates the aircraft recovery on a day of operations. In the DReM the time at which disruptions are found out is part of the input and thus the model run both dynamic and non-dynamic simulations. Thereby meeting the objective that has been set out. This research has come to the conclusion that on the given test cases, on average the cost of disruptions when the model is run in the non-dynamic way is 69.2% of cost of disruptions in the dynamic situation. This is a significant difference and strongly confirms the hypothesis, that knowing the disruptions at the beginning of the day results in lower cost of disruptions.

"Demonstrate the feasibility of using a time-space network for each aircraft for solving the aircraft recovery problem in real-time operations, through developing a search algorithm testing small selections of aircraft."

When investigating the second objective it is important to look at two parts of the objective. One part is to create the model using the novel approach of combining two ideas; the use of the time-space network for each aircraft in combination with a search algorithm for selecting aircraft. The other part is that the real-time use of the model is demonstrated to be feasible. This research has shown that for the given test cases the DSS is capable of finding a first solution within a time-frame of 15 minutes, and in 93 percent of the cases finds the solution in less than 10 minutes. The solutions found have been validated with industry experts. It is fair to say that the feasibility of finding a result using this proposed technique is demonstrated in this research.

The industry objective is to *"Decrease the cost of disruptions by creating a dynamic model that recovers aircraft, to be implemented at Kenya Airways"*

The objective of making a model that is implementable has partially been reached. The model has several limitations that restrict it from being implemented directly for finding a total solution to disrupted situation. However the model is fit for use as decision support for Operations Managers. The modular setup and use of parallel time space networks makes it easily adaptable. Furthermore, the way in which the model quickly finds an initial solution and then sets out to improve it means that the Operations Manager can be presented with several solutions. The DSS module solves disruptions at a given point in time and does so within 15 minutes. The results the model achieved have been validated with the duty managers operations at Kenya Airways, and the manner in which results are presented is in a way they can understand. The model if linked directly to the data sources from KQ this model will be fit for use as a decision support tool.

Appendix A

Formulation of the Selected Aircraft Linear Solver (SALS)

This section give an overview of the mathematical formulation of the Selected Aircraft Linear Solver (SALS).

Sets

$A_{G_{p,n}}$	set of ground arcs
$A_{F_{p,i}}$	set of flight arcs
$A_{D_{p,i,j}}$	set of delay arcs
F_i	set of flight
A_a	set of airports
P_p	set of aircraft
N_n	set of nodes in the network
J_j	set of delay steps possible

Indexes

i	flight index
j	delay time index
a	airport index
p	aircraft index
n	node index

Decision Variables:

$\delta_{AF_{p,i}}$	=1 if flight arc i by aircraft p is selected	=0 otherwise
$\delta_{AG_{p,n}}$	=1 if ground arc n is used by aircraft p	=0 otherwise
$\delta_{AD_{p,i,j}}$	=1 if flight i by aircraft p with $(j+1)$ *timestep delay is selected	=0 otherwise
δ_{Canx_i}	=1 if flight i is cancelled	=0 otherwise

Objective Function

$$\min \left\{ \sum_{p \in P} \sum_{i \in F} \delta_{AF_{p,i}} * C_{OP_{p,i}} + \sum_{p \in P} \sum_{i \in F} \sum_{j \in J} \delta_{AD_{p,i,j}} * (C_{OP_{p,i}} + C_{D_{i,j}}) + \sum_{i \in F} \delta_{Canx_i} * C_{C_i} + \sum_{n \in N} \delta_{AG_n} * C_{AG_n} \right\} \quad (A.1)$$

Constraints

Flight Coverage:

$$\sum_{p \in P} \left[\delta_{AF_{p,i}} + \sum_{j \in J} \delta_{AD_{p,i,j}} \right] + \delta_{Canx_i} = 1 \quad (A.2)$$

$$i \in F$$

Node Continuity:

$$\left(\delta_{AG_{n-1}} + \sum_{i \in F(A_{F_i}[:,1]=n)} \delta_{AF_{p,i}} + \sum_{i,j \in F,J(A_{D_{i,j}}[:,1]=n)} \delta_{AD_{p,i,j}} \right) - \left(\delta_{AG_n} + \sum_{i \in F(A_{F_i}[:,0]=n)} \delta_{AF_{p,i}} + \sum_{i,j \in F,J(A_{D_{i,j}}[:,0]=n)} \delta_{AD_{p,i,j}} \right) = 0 \quad (A.3)$$

$$p \in P \text{ and } n \in N_{\text{not a start or end node}}$$

Start point node continuity:

$$\delta_{AG_n} + \sum_{i \in F(A_{F_i}[0]=n)} \delta_{AF_{p,i}} + \sum_{i,j \in F,J(A_{D_{i,j}}[0]=n)} \delta_{AD_{p,i,j}} = 1 \quad (A.4)$$

$$p \in P \text{ and } n = \text{end node of aircraft } p$$

End point node continuity (specific tail nr):

$$\delta_{AG_{n-1}} + \sum_{i \in F(A_{F_i}[1]=n)} \delta_{AF_{p,i}} + \sum_{i,j \in F,J(A_{D_{i,j}}[1]=n)} \delta_{AD_{p,i,j}} = 1 \quad (A.5)$$

$$p \in P \text{ and } n = \text{starting node of aircraft } p$$

End point node continuity (specific aircraft type):

$$\sum_{p \in P_{\text{of type } T}} \left(\sum_{n \in N_{\text{where } t = \text{end and airport} = a}} \left(\delta_{AG_{p,n}} + \sum_{i \in F(A_{F_i}[:,0]=n)} \delta_{AF_{p,i}} + \sum_{i,j \in F,J(A_{D_{i,j}}[:,0]=n)} \delta_{AD_{p,i,j}} \right) \right) = \sum_{\text{aircraft of type } T \text{ ending at } a} \quad (A.6)$$

$$a \in \text{Airports and } T \in \text{List of aircraft types}$$

Fix entering and exiting flights

Entering:

$$\delta_{AF_{p,i}} = 1 \quad (A.7)$$

Where:

$$i \in ((STD_i + delay_i < TW_{start}) \cap (STA_i + delay_i > TW_{start})) \quad (A.8)$$

$$p = \text{Scheduled aircraft for flight } i \quad (A.9)$$

Exiting:

$$\delta_{AF_{p,i}} = 1 \quad (A.10)$$

Where:

$$i \in ((STD_i + delay_i < TW_{end}) \cap (STA_i + delay_i > TW_{end})) \quad (A.11)$$

$$p \in P = P_{\text{of same type as aircraft for flight } i} \quad (A.12)$$

Passengers booked constraint

$$\sum_{p,i \in (\text{capacity}_p < \text{passengers}_i)} \left(\delta_{AF_{p,i}} + \sum_{j \in J} \delta_{AD_{p,i,j}} \right) = 0 \quad (\text{A.13})$$

Range constraint

$$\sum_{p,i \in (\text{Range}_p < \text{distance}_i)} \left(\delta_{AF_{p,i}} + \sum_{j \in J} \delta_{AD_{p,i,j}} \right) = 0 \quad (\text{A.14})$$

Disruption Constraints

Delay Flight

$$\sum_{p \in P} \delta_{AF_{p,i}} + \delta_{AD_{p,i,j}} = 0 \text{ for all } j \in J \leq \text{delay} \quad (\text{A.15})$$

Cancel Flight

$$\delta_{AC_i} = 1 \quad (\text{A.16})$$

Aircraft Unavailable:

$$\begin{aligned} \sum_{i \in F_{\text{selection}}} \delta_{AF_{p,i}} + \sum_{i \in F} \sum_{j \in J_{\text{selection}}} \delta_{AD_{p,i,j}} &= 0 \\ F_{\text{selection}} &= F_i \text{ for all } i \in (t_{\text{start}} \leq STD_i \cup STA_i \leq t_{\text{end}}) \\ J_{\text{selection}} &= J_j \text{ for all } j \in (t_{\text{start}} \leq (STD_i + j * \text{timestep}) \cup (STA_i + j * \text{timestep}) \leq t_{\text{end}}) \end{aligned} \quad (\text{A.17})$$

Airport Unavailable

$$\begin{aligned} \sum_{p \in P} \left[\sum_{i \in F_{\text{selection}}} \delta_{AF_{p,i}} + \sum_{i \in F} \sum_{j \in J_{\text{selection}}} \delta_{AD_{p,i,j}} \right] &= 0 \\ F_{\text{selection}} &= F_i \text{ for all } i \in \left[\begin{aligned} &((t_{\text{start}} \leq STD_i \leq t_{\text{end}}) \cap (\text{origin}_i = \text{airport})) \cup \\ &((t_{\text{start}} \leq STA_i \leq t_{\text{end}}) \cap (\text{destination}_i = \text{airport})) \end{aligned} \right] \\ J_{\text{selection}} &= J_j \text{ for all } j \in \left[\begin{aligned} &((t_{\text{start}} \leq STD_i + j * \text{timestep} \leq t_{\text{end}}) \cap (\text{origin}_i = \text{airport})) \cup \\ &((t_{\text{start}} \leq STA_i + j * \text{timestep} \leq t_{\text{end}}) \cap (\text{destination}_i = \text{airport})) \end{aligned} \right] \end{aligned} \quad (\text{A.18})$$

Appendix B

Scenario Descriptions

Below is presented a list which includes the disruptions that are input into the model:

- Scenario 1: Two aircraft un-expectedly unavailable
 - Aircraft 5Y-FFA unavailable from 8:00 until 16:00 found out at 7:00
 - Aircraft 5Y-FFD unavailable from 8:00 until 16:00 found out at 7:00
- Scenario 2: Late crew from other flight
 - Flight KQ760 delayed until 6h35 found out at 3:00
- Scenario 3: No crew available resulting in cancellation
 - Flight KQ860 cancelled (20:20) found out at 19:00
- Scenario 4: Tech issue taking longer to be resolved
 - Aircraft 5Y-FFA unavailable from 8:00 until 10:00 found out at 7:00
 - Aircraft 5Y-FFA unavailable from 8:00 until 11:00 found out at 8:00
 - Aircraft 5Y-FFA unavailable from 9:00 until 14:00 found out at 9:00
- Scenario 5: Delay KQ112 for 3 hours due to connecting passengers
 - Flight KQ112 delayed until 23:40 found out at 20:00
- Scenario 6: Mombasa closure for 4 hours
 - Airport MBA unavailable from 10:00 until 14:00 found out 9:00

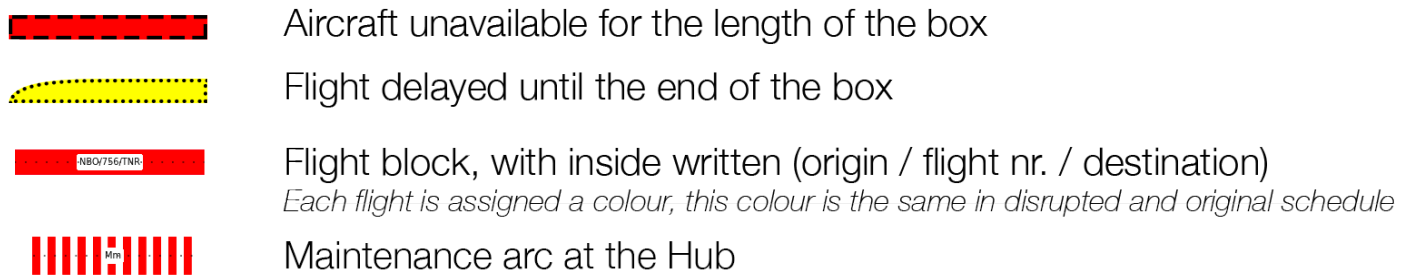
The real-life scenarios:

- Full day 1:
 - Aircraft 5Y-FFA unavailable all day
 - Aircraft 5Y-FFD unavailable all day
 - Aircraft 5Y-KYQ unavailable from 4:10 until 16:30 found out at 4:00
 - Aircraft 5Y-FFH unavailable from 4:10 until 7:30 found out at 4:00
 - Aircraft 5Y-KYR unavailable from 11:40 until 24:00 found out at 9:30
- Full day 2:
 - Aircraft 5Y-KYD unavailable from 4:10 until 16:30 found out at 4:00

- Aircraft 5Y-FFH unavailable from 4:10 until 7:30 found out at 4:00
- Flight KQ550a until 7:00 found out at 4:30
- Flight KQ512b until 15:00 found out at 13:50
- Flight KQ502 until 14:40 found out at 13:40
- Flight KQ670 until 14:40 found out at 13:40
- Flight KQ416 until 20:40 found out at 19:20
- Flight KQ503 until 21:40 found out at 20:50
- Full day 3:
 - Aircraft 5Y-KYQ unavailable from 4:30 until 6:00 found out at 4:00
 - Aircraft 5Y-FFD unavailable from 5:10 until 7:00 found out at 5:00
 - Flight KQ550b until 10:10 found out at 9:00
 - Flight KQ860a until 21:20 found out at 20:40
 - Flight KQ764 until 18:00 found out at 17:20
- Full day 4:
 - Aircraft 5Y-KYS unavailable from 4:50 until 6:20 found out at 4:00
 - Flight KQ502 until 16:20 found out at 13:50
 - Flight KQ764 until 18:20 found out at 17:10
 - Flight KQ204 until 21:20 found out at 19:00
 - Flight KQ512b until 14:30 found out at 13:50
 - Flight KQ408a until 20:30 found out at 19:00

Appendix C

Simulation Solutions



Aircraft on the vertical axis

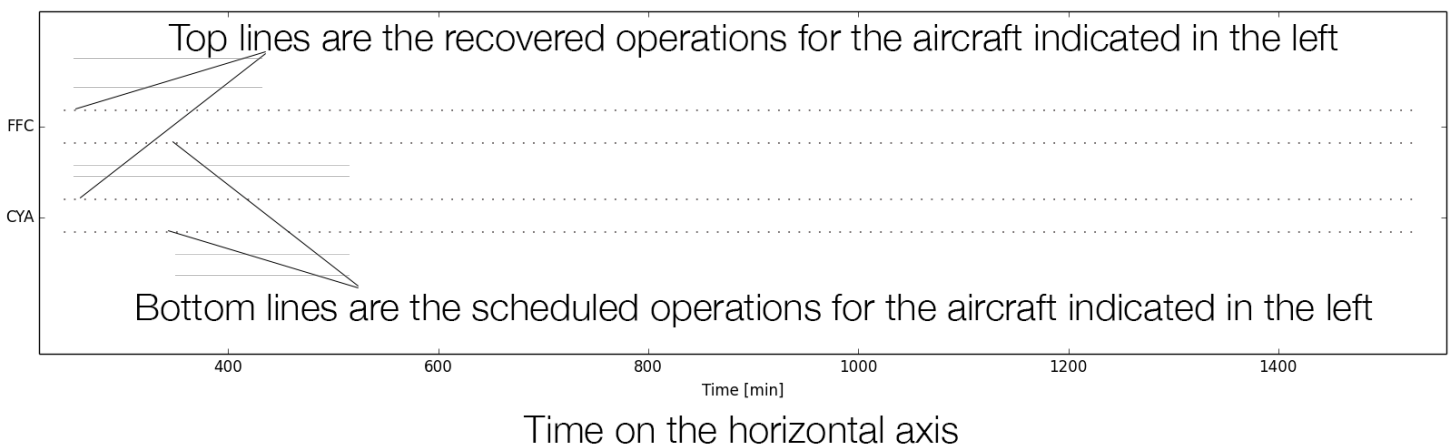


Figure C.1: Explanation of how to read the figures that display the recovery solutions.

C.1 Full Day Scenario 1

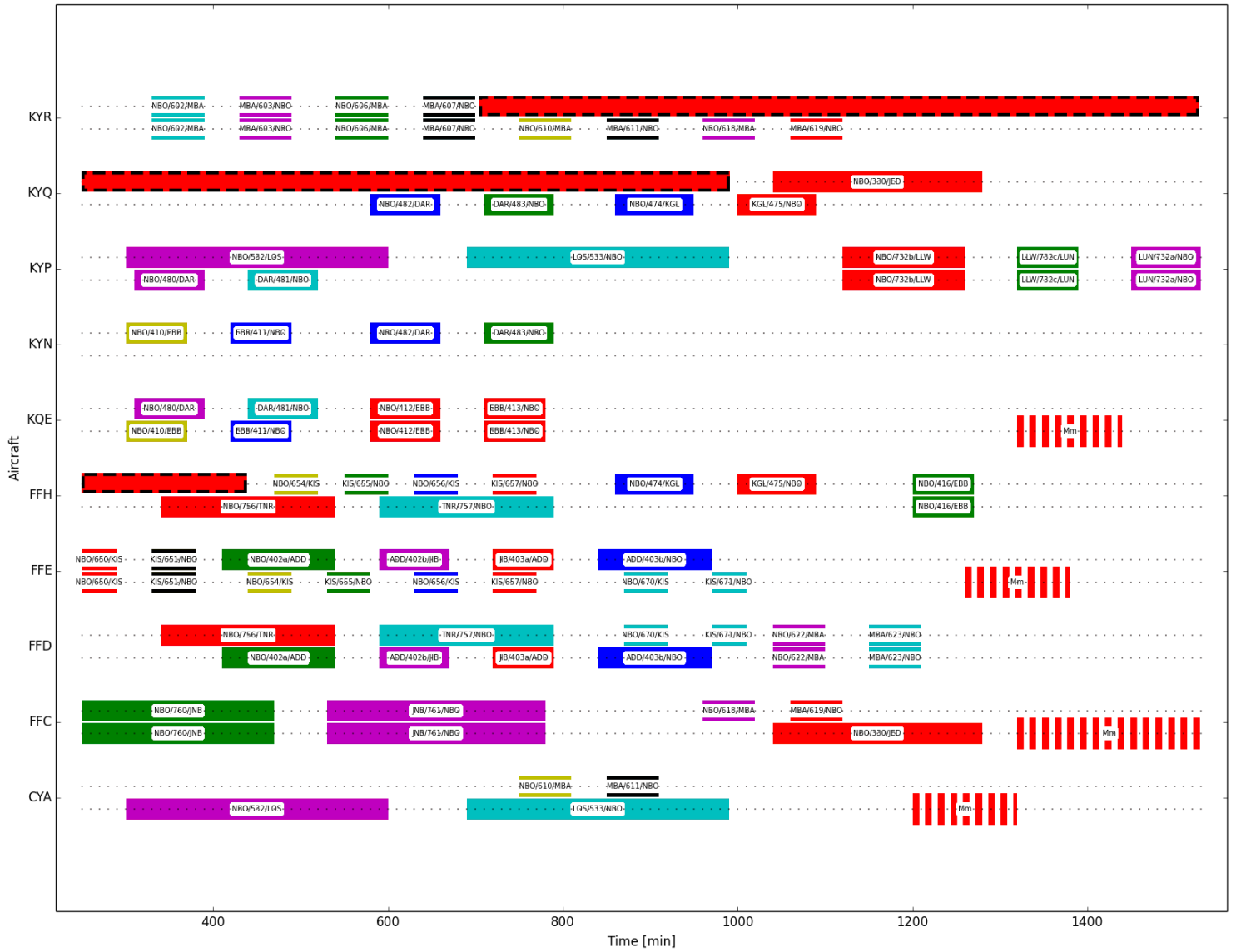


Figure C.2: Full Day scenario 1 final schedule

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
101	KQT	KQT	LHR	NBO	1900	2730	0	89	24
102	KQU	KQU	NBO	LHR	2050	2940	0	100	20
112	KZB	KZB	NBO	CDG	2040	2920	0	150	20
202	KQS	KQS	NBO	BOM	1410	2010	0	176	18
310	KZE	KZE	NBO	DXB	1610	2120	0	110	19
330	KYQ	FFC	NBO	JED	1720	2120	0	33	4
348	KYH	KYH	NBO	KRT	2050	2340	0	38	2
350	KYS	KYS	NBO	JUB	450	630	0	64	6
351	KYS	KYS	JUB	NBO	720	900	0	28	1
352	KYS	KYS	NBO	JUB	950	1130	0	61	6
353	KYS	KYS	JUB	NBO	1220	1400	0	21	1
354	KYH	KYH	NBO	JUB	1200	1350	0	22	6
355	KYH	KYH	JUB	NBO	1440	1620	0	28	2
402a	FFE	FFD	NBO	ADD	650	900	0	60	7
402b	FFE	FFD	ADD	JIB	950	1110	0	60	7
403a	FFE	FFD	JIB	ADD	1200	1310	0	23	2
403b	FFE	FFD	ADD	NBO	1400	1610	0	23	2
410	KYN	KQE	NBO	EBB	500	610	0	95	16
411	KYN	KQE	EBB	NBO	700	810	0	73	8
412	KQE	KQE	NBO	EBB	940	1100	0	92	6
413	KQE	KQE	EBB	NBO	1150	1300	0	73	11
414	FFK	FFK	NBO	EBB	1420	1540	0	64	12
415	FFK	FFK	EBB	NBO	1630	1740	0	74	4
416	FFH	FFH	NBO	EBB	2000	2110	0	62	4
418	FFF	FFF	NBO	EBB	1600	1710	0	77	7
419	FFF	FFF	EBB	NBO	1800	1910	0	66	3
450	FFK	FFK	NBO	SEZ	600	910	0	58	5
451	FFK	FFK	SEZ	NBO	1000	1310	0	21	0
452a	KYT	KYT	NBO	DZA	540	810	0	77	6
452b	KYT	KYT	DZA	HAH	910	1000	0	77	6
452c	KYT	KYT	HAH	NBO	1050	1300	0	77	6
460	KYH	KYH	NBO	BJM	520	700	0	42	4
461	KYH	KYH	BJM	NBO	750	930	0	33	3
464	KYT	KYT	NBO	BJM	1400	1540	0	60	1
465	KYT	KYT	BJM	NBO	1630	1800	0	47	1
466a	FFF	FFF	KGL	NBO	2450	2620	0	34	3
466b	FFF	FFF	NBO	BJM	2050	2230	0	34	3
466c	FFF	FFF	BJM	KGL	2320	2400	0	34	3
470	FFG	FFG	NBO	KGL	450	620	0	48	1
471	FFG	FFG	KGL	NBO	710	840	0	28	0
474	FFH	KYQ	NBO	KGL	1420	1550	0	41	4
475	FFH	KYQ	KGL	NBO	1640	1810	0	35	5
480	KQE	KYP	NBO	DAR	510	630	0	63	7
481	KQE	KYP	DAR	NBO	720	840	0	37	2
482	KYN	KYQ	NBO	DAR	940	1100	0	58	8
483	KYN	KYQ	DAR	NBO	1150	1310	0	54	8
484	FFJ	FFJ	NBO	DAR	1350	1520	0	32	6
485	FFJ	FFJ	DAR	NBO	1610	1730	0	61	5
486	KYS	KYS	NBO	DAR	1540	1700	0	47	9

Cont. DAY 1

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
487	KYS	KYS	DAR	NBO	1750	1910	0	43	7
488	KYT	KYT	NBO	DAR	2000	2130	0	56	1
502	KQH	KQH	NBO	ACC	1420	2000	0	48	3
503	KQH	KQH	ACC	NBO	2100	2640	0	47	5
526	KQF	KQF	NBO	NSI	550	950	0	55	3
527	KQF	KQF	NSI	NBO	1040	1440	0	51	3
532	KYP	CYA	NBO	LOS	500	1000	0	73	9
533	KYP	CYA	LOS	NBO	1130	1630	0	60	5
554	KZF	KZF	NBO	FIH	450	820	0	117	13
555	KZF	KZF	FIH	NBO	940	1310	0	80	9
586a	KQH	KQH	NBO	FBM	530	810	0	60	10
586b	KQH	KQH	FBM	NLA	900	940	0	60	10
586c	KQH	KQH	NLA	NBO	1030	1310	0	60	10
600	FFF	FFF	NBO	MBA	300	400	0	55	7
601	FFF	FFF	MBA	NBO	440	540	0	74	3
602	KYR	KYR	NBO	MBA	530	630	0	77	10
603	KYR	KYR	MBA	NBO	710	810	0	70	3
604	FFF	FFF	NBO	MBA	630	730	0	59	10
605	FFF	FFF	MBA	NBO	810	910	0	44	4
606	KYR	KYR	NBO	MBA	900	1000	0	76	12
607	KYR	KYR	MBA	NBO	1040	1140	0	67	11
610	CYA	KYR	NBO	MBA	1230	1330	0	83	12
611	CYA	KYR	MBA	NBO	1410	1510	0	84	12
618	FFC	KYR	NBO	MBA	1600	1700	0	84	12
619	FFC	KYR	MBA	NBO	1740	1840	0	84	12
622	FFD	FFD	NBO	MBA	1720	1820	0	76	11
623	FFD	FFD	MBA	NBO	1910	2010	0	72	7
624	FFK	FFK	NBO	MBA	2000	2050	0	63	7
640	FFF	FFF	NBO	MYD	1020	1120	0	65	2
641	FFF	FFF	MYD	NBO	1210	1320	0	49	1
650	FFE	FFE	NBO	KIS	400	450	0	69	2
651	FFE	FFE	KIS	NBO	530	620	0	23	0
654	FFH	FFE	NBO	KIS	720	810	30	58	1
655	FFH	FFE	KIS	NBO	850	940	20	31	0
656	FFH	FFE	NBO	KIS	1030	1120	0	60	0
657	FFH	FFE	KIS	NBO	1200	1250	0	54	2
670	FFD	FFE	NBO	KIS	1430	1520	0	71	0
671	FFD	FFE	KIS	NBO	1610	1650	0	20	3
700	FFJ	FFJ	NBO	HRE	600	900	0	84	9
701	FFJ	FFJ	HRE	NBO	950	1250	0	36	2
704a	FFG	FFG	NBO	HRE	1000	1300	0	84	6
704b	FFG	FFG	HRE	LUN	1350	1450	0	84	6
704c	FFG	FFG	LUN	NBO	1540	1820	0	84	6
724a	KYD	KYD	NBO	LUN	500	750	0	108	14
724b	KYD	KYD	LUN	LLW	850	1000	0	108	14
724c	KYD	KYD	LLW	NBO	1100	1310	0	108	14
732a	KYP	KYP	LUN	NBO	2410	2650	0	68	2
732b	KYP	KYP	NBO	LLW	1840	2100	0	68	2
732c	KYP	KYP	LLW	LUN	2200	2310	0	68	2

Cont. DAY 1

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
756	FFD	FFH	NBO	TNR	540	900	0	51	6
757	FFD	FFH	TNR	NBO	950	1310	0	80	12
760	FFC	FFC	NBO	JNB	330	750	0	69	2
761	FFC	FFC	JNB	NBO	850	1300	0	41	9
762	KQG	KQG	NBO	JNB	540	1000	0	88	11
763	KQG	KQG	JNB	NBO	1120	1530	0	60	6
764	KQG	KQG	NBO	JNB	1730	2150	0	68	16
861a	KZA	KZA	HKG	BKK	1340	1620	0	102	4
861b	KZA	KZA	BKK	NBO	1730	2610	0	102	4
882	KZC	KZC	NBO	CAN	2150	3220	0	102	4
883	KZC	KZC	CAN	NBO	1340	2500	0	182	12
886a	KZD	KZD	BKK	CAN	750	1100	0	110	12
886b	KZD	KZD	NBO	BKK	2040	3010	0	110	12
1101	KQU	KQU	LHR	NBO	4300	5130	0	125	21
1102	KQT	KQT	NBO	LHR	4450	5340	0	129	24
1111	KQE	KQE	NBO	NBO	4000	4400	0	0	0
1113	KZB	KZB	CDG	NBO	3350	4200	0	111	10
1116	KZY	KZY	NBO	AMS	2920	3820	0	74	15
1117	KZY	KZY	AMS	NBO	4340	5200	0	201	27
1202	KQS	KQS	NBO	BOM	3810	4410	0	219	24
1203	KQS	KQS	BOM	NBO	4530	5120	0	211	10
1310	KZC	KZC	NBO	DXB	4010	4520	0	134	9
1311	KZE	KZE	DXB	NBO	4640	5150	0	134	9
1331	FFC	FFC	JED	NBO	4700	5100	0	84	9
1349	KYH	KYH	KRT	NBO	2520	2810	0	40	2
1350	FFG	FFG	NBO	JUB	2850	3030	0	49	6
1351	FFG	FFG	JUB	NBO	3120	3300	0	28	0
1352	KYJ	KYJ	NBO	JUB	3350	3530	0	48	2
1353	KYJ	KYJ	JUB	NBO	3620	3800	0	60	3
1402a	KYT	KYT	NBO	ADD	3050	3300	0	44	5
1402b	KYT	KYT	ADD	JIB	3350	3510	0	44	5
1403a	KYT	KYT	JIB	ADD	3600	3710	0	28	9
1403b	KYT	KYT	ADD	NBO	3800	4010	0	28	9
1410	KYN	KYN	NBO	EBB	2900	3010	0	86	5
1411	KYN	KYN	EBB	NBO	3100	3210	0	81	7
1412	FFK	FFK	NBO	EBB	3340	3500	0	66	3
1413	FFK	FFK	EBB	NBO	3550	3700	0	72	11
1414	FFK	FFK	NBO	EBB	3820	3940	0	69	10
1415	FFK	FFK	EBB	NBO	4030	4140	0	79	12
1416	FFJ	FFJ	NBO	EBB	4400	4510	0	79	12
1417	FFH	FFH	EBB	NBO	2600	2710	0	68	9
1418	KYS	KYS	NBO	EBB	4000	4110	0	82	10
1419	KYS	KYS	EBB	NBO	4200	4310	0	67	11
1420	KYJ	KYJ	NBO	JRO	3000	3100	0	11	2
1421	KYJ	KYJ	JRO	NBO	3150	3250	0	16	3
1446	FFF	FFF	NBO	KGL	4450	4610	0	56	5
1460	KYP	KYP	NBO	BJM	2920	3100	0	44	7
1461	KYP	KYP	BJM	NBO	3150	3330	0	29	0
1464	FFA	FFA	NBO	BJM	3800	3940	0	39	9
1465	FFA	FFA	BJM	NBO	4030	4200	0	19	6

Cont. DAY 1

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
1470	FFC	FFC	NBO	KGL	2850	3020	0	43	1
1471	FFC	FFC	KGL	NBO	3110	3240	0	43	6
1474	FFJ	FFJ	NBO	KGL	3820	3950	0	28	4
1475	FFJ	FFJ	KGL	NBO	4040	4210	0	54	8
1480	FFK	FFK	NBO	DAR	2910	3030	0	79	5
1481	FFK	FFK	DAR	NBO	3120	3240	0	62	8
1482	KYN	KYN	NBO	DAR	3340	3500	0	80	7
1483	KYN	KYN	DAR	NBO	3550	3710	0	70	6
1484	KYP	KYP	NBO	DAR	3750	3920	0	38	2
1485	KYP	KYP	DAR	NBO	4010	4130	0	61	4
1486	FFF	FFF	NBO	DAR	3940	4100	0	60	6
1487	FFF	FFF	DAR	NBO	4150	4310	0	56	1
1488	KYP	KYP	NBO	DAR	4400	4530	0	71	6
1489	KYT	KYT	DAR	NBO	2610	2730	0	56	7
1498	FFH	FFH	NBO	ZNZ	4330	4440	0	20	1
1502	KYD	KYD	NBO	ACC	3820	4400	0	67	9
1503	KYD	KYD	ACC	NBO	4500	5040	0	44	10
1512a	KQH	KQH	NBO	BKO	3010	3700	0	54	13
1512b	KQH	KQH	BKO	DKR	3800	3950	0	54	13
1513a	KQH	KQH	DKR	BKO	4050	4240	0	44	5
1513b	KQH	KQH	BKO	NBO	4340	5030	0	44	5
1526	KQE	KQE	NBO	NSI	2950	3350	0	50	4
1527	KQE	KQE	NSI	NBO	3440	3840	0	47	2
1532	CYA	CYA	NBO	LOS	2900	3400	0	103	9
1533	CYA	CYA	LOS	NBO	3530	4030	0	60	7
1536	KQG	KQG	NBO	ABV	2850	3330	0	51	5
1537	KQG	KQG	ABV	NBO	3430	3920	0	37	1
1542a	KYE	KYE	NBO	LOS	3940	4500	0	73	8
1542b	KYE	KYE	LOS	COO	4550	4630	0	73	8
1550a	KYE	KYE	NBO	BZV	2850	3230	0	83	10
1550b	KYE	KYE	BZV	FIH	3320	3410	0	83	10
1550c	KYE	KYE	FIH	NBO	3500	3840	0	83	10
1584a	FFF	FFF	NBO	NLA	2930	3210	0	52	5
1584b	FFF	FFF	NLA	FBM	3300	3340	0	52	5
1584c	FFF	FFF	FBM	NBO	3430	3700	0	52	5
1590	FFH	FFH	NBO	DLA	2920	3350	0	48	9
1591	FFH	FFH	DLA	NBO	3440	3910	0	62	6
1600	FFJ	FFJ	NBO	MBA	2700	2800	0	55	3
1601	FFJ	FFJ	MBA	NBO	2840	2940	0	55	8
1602	FFE	FFE	NBO	MBA	2930	3030	0	76	10
1603	FFE	FFE	MBA	NBO	3110	3210	0	62	12
1604	FFJ	FFJ	NBO	MBA	3030	3130	0	49	3
1605	FFJ	FFJ	MBA	NBO	3210	3310	0	53	10
1606	FFE	FFE	NBO	MBA	3300	3400	0	77	7
1607	FFE	FFE	MBA	NBO	3440	3540	0	83	12
1610	FFE	FFE	NBO	MBA	3630	3730	0	78	12
1611	FFE	FFE	MBA	NBO	3810	3910	0	84	12
1618	FFE	FFE	NBO	MBA	4000	4100	0	84	12
1619	FFE	FFE	MBA	NBO	4140	4240	0	84	12

Cont. DAY 1

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
1622	KYQ	KYQ	NBO	MBA	4120	4220	0	84	11
1623	KYQ	KYQ	MBA	NBO	4310	4410	0	75	6
1624	FFE	FFE	NBO	MBA	4400	4450	0	80	4
1625	FFK	FFK	MBA	NBO	2630	2730	0	54	5
1650	KYR	KYR	NBO	KIS	2800	2850	0	74	11
1651	KYR	KYR	KIS	NBO	2930	3020	0	34	1
1654	KYR	KYR	NBO	KIS	3120	3210	0	59	0
1655	KYR	KYR	KIS	NBO	3250	3340	0	42	0
1656	KYR	KYR	NBO	KIS	3430	3520	0	56	3
1657	KYR	KYR	KIS	NBO	3600	3650	0	65	1
1670	KYR	KYR	NBO	KIS	3830	3920	0	78	1
1671	KYR	KYR	KIS	NBO	4010	4050	0	78	10
1700	FFA	FFA	NBO	HRE	3000	3300	0	50	6
1701	FFA	FFA	HRE	NBO	3350	3650	0	59	3
1710	KYS	KYS	NBO	GBE	3020	3420	0	71	5
1711	KYS	KYS	GBE	NBO	3510	3910	0	35	3
1720	FFD	FFD	NBO	LUN	4240	4530	0	55	7
1722a	KYD	KYD	NBO	LLW	2900	3120	0	109	11
1722b	KYD	KYD	LLW	LUN	3220	3330	0	109	11
1722c	KYD	KYD	LUN	NBO	3430	3710	0	109	11
1728a	FFG	FFG	NBO	LLW	3400	3610	0	56	3
1728b	FFG	FFG	LLW	LUN	3710	3820	0	56	3
1728c	FFG	FFG	LUN	NBO	3920	4200	0	56	3
1740	KYQ	KYQ	NBO	MPM	2850	3250	0	54	4
1741	KYQ	KYQ	MPM	NBO	3340	3740	0	52	5
1760	FFD	FFD	NBO	JNB	2730	3150	0	37	3
1761	FFD	FFD	JNB	NBO	3250	3700	0	76	6
1762	KZF	KZF	NBO	JNB	2940	3400	0	82	6
1763	KZF	KZF	JNB	NBO	3520	3930	0	52	8
1764	KQG	KQG	NBO	JNB	4130	4550	0	78	15
1765	KQG	KQG	JNB	NBO	4640	5050	0	79	16
1770	KQF	KQF	NBO	LAD	3300	3700	0	58	2
1771	KQF	KQF	LAD	NBO	3800	4220	0	64	3
1780a	FFC	FFC	NBO	LVI	3320	3630	0	18	1
1780b	FFC	FFC	LVI	HRE	3720	3830	0	18	1
1780c	FFC	FFC	HRE	NBO	3920	4220	0	18	1
1860	KZB	KZB	NBO	BKK	4450	5430	0	151	20
1887	KZD	KZD	CAN	BKK	3740	4030	0	175	30

C.2 Full Day Scenario 2

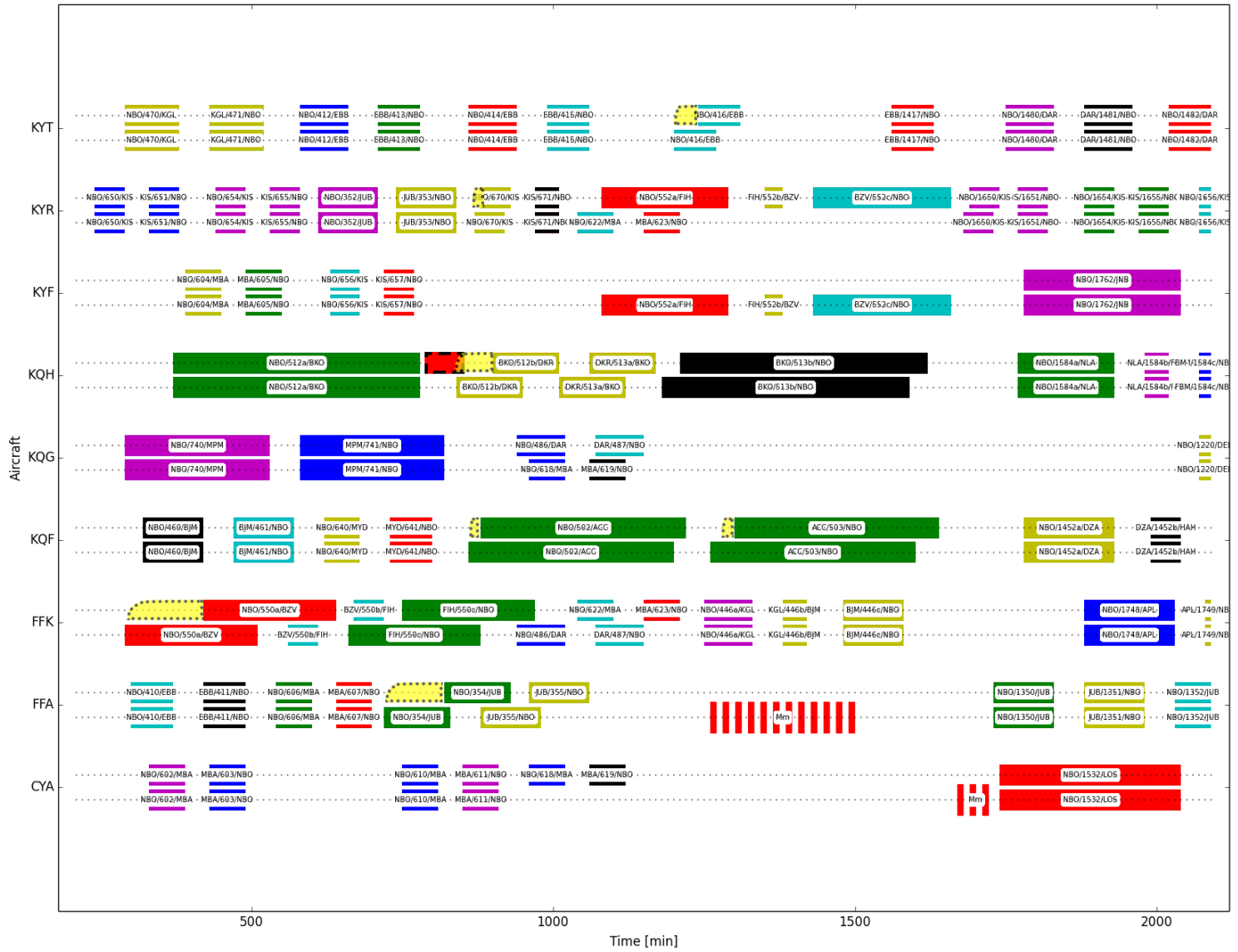


Figure C.3: Full Day scenario 2 final schedule

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
101	KQS	KQS	LHR	NBO	1900	2730	0	163	23
102	KQT	KQT	NBO	LHR	2050	2940	0	95	23
112	KZC	KZC	NBO	CDG	2040	2920	0	164	11
113	KZB	KZB	CDG	NBO	950	1800	0	164	11
116	KZF	KZF	NBO	AMS	520	1420	0	118	1
117	KZF	KZF	AMS	NBO	1940	2800	0	143	18
190	FFG	FFG	NBO	NBO	600	900	0	0	0
202	KYZ	KYZ	NBO	BOM	1410	2010	0	243	8
203	KYZ	KYZ	BOM	NBO	2130	2720	0	150	7
204	KYD	KYD	NBO	BOM	1920	2520	0	129	1
310a	KZD	KZD	NBO	DXB	1610	2120	0	82	11
310b	KZD	KZD	DXB	NBO	2240	2750	0	204	14
340	KYH	KYH	NBO	KRT	940	1230	0	25	6
341	KYH	KYH	KRT	NBO	1320	1620	0	37	4
350	KYH	KYH	NBO	JUB	450	630	0	36	4
351	KYH	KYH	JUB	NBO	720	900	0	35	1
352	KYR	KYR	NBO	JUB	950	1130	20	56	4
353	KYR	KYR	JUB	NBO	1220	1400	0	14	0
354	FFA	FFA	NBO	JUB	1200	1350	100	38	2
355	FFA	FFA	JUB	NBO	1440	1620	80	23	2
402a	FFJ	FFJ	NBO	ADD	650	900	0	59	3
402b	FFJ	FFJ	ADD	JIB	950	1110	0	33	5
403a	FFJ	FFJ	JIB	ADD	1200	1310	0	18	3
403b	FFJ	FFJ	ADD	NBO	1400	1610	0	46	4
408a	FFC	FFC	NBO	JIB	1930	2200	0	18	3
408b	FFC	FFC	JIB	ADD	2250	2410	0	25	3
408c	FFC	FFC	ADD	NBO	2510	2710	0	40	4
410	FFA	FFA	NBO	EBB	500	610	0	83	12
411	FFA	FFA	EBB	NBO	700	810	0	84	6
412	KYT	KYT	NBO	EBB	940	1100	0	58	2
413	KYT	KYT	EBB	NBO	1150	1300	0	69	5
414	KYT	KYT	NBO	EBB	1420	1540	0	41	2
415	KYT	KYT	EBB	NBO	1630	1740	0	79	7
416	KYT	KYT	NBO	EBB	2000	2110	40	38	5
417	KYR	KYR	EBB	NBO	200	310	0	84	4
418	FFE	FFE	NBO	EBB	1600	1710	0	45	2
419	FFE	FFE	EBB	NBO	1800	1910	0	38	1
420	KYP	KYP	NBO	JRO	600	700	0	40	5
421	KYP	KYP	JRO	NBO	750	850	0	32	1
446a	FFK	FFK	NBO	KGL	2050	2210	0	24	1
446b	FFK	FFK	KGL	BJM	2300	2340	0	39	1
446c	FFK	FFK	BJM	NBO	2440	2620	0	31	1
460	KQF	KQF	NBO	BJM	520	700	0	28	2
461	KQF	KQF	BJM	NBO	750	930	0	23	0
464	FFC	FFC	NBO	BJM	1400	1540	0	35	3
465	FFC	FFC	BJM	NBO	1630	1800	0	40	1
470	KYT	KYT	NBO	KGL	450	620	0	50	0
471	KYT	KYT	KGL	NBO	710	840	0	21	1
474	KYS	KYS	NBO	KGL	1420	1550	0	9	2
475	KYS	KYS	KGL	NBO	1640	1810	0	36	1

Cont. DAY 2

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
480	KYS	KYS	NBO	DAR	510	630	0	84	12
481	KYS	KYS	DAR	NBO	720	840	0	60	5
482	KYS	KYS	NBO	DAR	940	1100	0	72	9
483	KYS	KYS	DAR	NBO	1150	1310	0	75	5
484	FFD	FFD	NBO	DAR	1350	1520	0	32	3
485	FFD	FFD	DAR	NBO	1610	1730	0	71	8
486	KQG	FFK	NBO	DAR	1540	1700	0	44	4
487	KQG	FFK	DAR	NBO	1750	1910	0	27	1
488	FFF	FFF	NBO	DAR	2000	2130	0	51	7
489	KYQ	KYQ	DAR	NBO	210	330	0	55	7
498	KYQ	KYQ	NBO	ZNZ	1930	2040	0	51	7
502	KQF	KQF	NBO	ACC	1420	2000	20	36	7
503	KQF	KQF	ACC	NBO	2100	2640	40	35	7
512a	KQH	KQH	NBO	BKO	610	1300	0	52	8
512b	KQH	KQH	BKO	DKR	1400	1550	60	38	4
513a	KQH	KQH	DKR	BKO	1650	1840	50	35	7
513b	KQH	KQH	BKO	NBO	1940	2630	30	44	7
528	KYH	KYH	NBO	NSI	2020	2430	0	42	6
529	KYH	KYH	NSI	NBO	2530	2930	0	52	4
532	KYQ	KYQ	NBO	LOS	500	1000	0	48	3
533	KYQ	KYQ	LOS	NBO	1130	1630	0	39	4
536	FFE	FFE	NBO	ABV	450	930	0	54	3
537	FFE	FFE	ABV	NBO	1030	1520	0	47	1
550a	FFK	FFK	NBO	BZV	450	830	130	28	2
550b	FFK	FFK	BZV	FIH	920	1010	110	52	6
550c	FFK	FFK	FIH	NBO	1100	1440	90	56	4
552a	KYR	KYF	NBO	FIH	1800	2130	0	46	6
552b	KYR	KYF	FIH	BZV	2230	2300	0	56	5
552c	KYR	KYF	BZV	NBO	2350	2740	0	35	3
586a	KYD	KYD	NBO	FBM	530	810	0	86	7
586b	KYD	KYD	FBM	NLA	900	940	0	82	7
586c	KYD	KYD	NLA	NBO	1030	1310	0	91	3
590	KQE	KQE	NBO	DLA	520	950	0	85	8
591	KQE	KQE	DLA	NBO	1040	1510	0	83	5
600	FFJ	FFJ	NBO	MBA	300	400	0	81	3
601	FFJ	FFJ	MBA	NBO	440	540	0	83	12
602	CYA	CYA	NBO	MBA	530	630	0	84	12
603	CYA	CYA	MBA	NBO	710	810	0	84	12
604	KYF	KYF	NBO	MBA	630	730	0	84	12
605	KYF	KYF	MBA	NBO	810	910	0	84	12
606	FFA	FFA	NBO	MBA	900	1000	0	84	12
607	FFA	FFA	MBA	NBO	1040	1140	0	84	12
610	CYA	CYA	NBO	MBA	1230	1330	0	81	10
611	CYA	CYA	MBA	NBO	1410	1510	0	84	12
618	CYA	KQG	NBO	MBA	1600	1700	0	78	9
619	CYA	KQG	MBA	NBO	1740	1840	0	84	11
622	FFK	KYR	NBO	MBA	1720	1820	0	77	4
623	FFK	KYR	MBA	NBO	1910	2010	0	83	12
624	FFG	FFG	NBO	MBA	2000	2050	0	65	2
625	FFA	FFA	MBA	NBO	230	330	0	84	12

Cont. DAY 2

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
640	KQF	KQF	NBO	MYD	1020	1120	0	68	3
641	KQF	KQF	MYD	NBO	1210	1320	0	69	3
650	KYR	KYR	NBO	KIS	400	450	0	61	2
651	KYR	KYR	KIS	NBO	530	620	0	82	3
654	KYR	KYR	NBO	KIS	720	810	0	68	2
655	KYR	KYR	KIS	NBO	850	940	0	71	2
656	KYF	KYF	NBO	KIS	1030	1120	0	42	0
657	KYF	KYF	KIS	NBO	1200	1250	0	70	4
670	KYR	KYR	NBO	KIS	1430	1520	10	58	2
671	KYR	KYR	KIS	NBO	1610	1650	0	75	5
700	FFD	FFD	NBO	HRE	600	900	0	78	5
701	FFD	FFD	HRE	NBO	950	1250	0	71	4
710	FFF	FFF	NBO	GBE	620	1020	0	74	2
711	FFF	FFF	GBE	NBO	1110	1510	0	79	5
720a	FFJ	FFJ	NBO	LUN	1840	2130	0	75	7
720b	FFJ	FFJ	LUN	HRE	2220	2330	0	76	4
720c	FFJ	FFJ	HRE	NBO	2420	2720	0	74	5
722a	KQU	KQU	NBO	LLW	500	720	0	61	3
722b	KQU	KQU	LLW	LUN	820	930	0	79	6
722c	KQU	KQU	LUN	NBO	1030	1310	0	73	7
728a	FFG	FFG	NBO	LLW	1000	1210	0	73	1
728b	FFG	FFG	LLW	LUN	1310	1420	0	84	1
728c	FFG	FFG	LUN	NBO	1520	1800	0	44	1
740	KQG	KQG	NBO	MPM	450	850	0	44	9
741	KQG	KQG	MPM	NBO	940	1340	0	44	9
760	FFC	FFC	NBO	JNB	330	750	0	22	3
761	FFC	FFC	JNB	NBO	850	1300	0	22	3
762	KZA	KZA	NBO	JNB	540	1000	0	54	16
763	KZA	KZA	JNB	NBO	1120	1530	0	128	15
764	KQE	KQE	NBO	JNB	1730	2150	0	64	15
765	KQE	KQE	JNB	NBO	2240	2650	0	63	9
770	KYP	KYP	NBO	LAD	900	1300	0	70	12
771	KYP	KYP	LAD	NBO	1400	1820	0	70	12
780a	FFB	FFB	NBO	LVI	920	1230	0	70	12
780b	FFB	FFB	LVI	HRE	1320	1430	0	70	12
780c	FFB	FFB	HRE	NBO	1520	1820	0	70	12
860a	KZB	KZB	NBO	BKK	2050	3030	0	185	5
860b	KZB	KZB	BKK	HKG	3230	3500	0	185	5
887a	KZE	KZE	CAN	BKK	1340	1630	0	172	15
887b	KZE	KZE	BKK	NBO	1730	2610	0	172	15
1101	KQT	KQT	LHR	NBO	4300	5130	0	213	28
1102	KYZ	KYZ	NBO	LHR	4450	5340	0	158	24
1111	KQH	KQH	NBO	NBO	4000	4300	0	100	16
1112	KZC	KZC	NBO	CDG	4440	5320	0	158	24
1113	KZC	KZC	CDG	NBO	3350	4200	0	157	12
1116	KQU	KQU	NBO	AMS	2920	3820	0	122	10
1117	KQU	KQU	AMS	NBO	4340	5200	0	284	27
1202	KZE	KZE	NBO	BOM	3810	4410	0	197	11
1203	KZE	KZE	BOM	NBO	4530	5120	0	150	7
1205	KYD	KYD	BOM	NBO	2840	3440	0	129	7

Cont. DAY 2

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
1220	KQG	KQG	NBO	DEL	3430	4200	0	100	7
1310	KZD	KZD	NBO	DXB	4010	4520	0	89	3
1311	KZD	KZD	DXB	NBO	4640	5150	0	204	14
1330	FFA	FFA	NBO	JED	4120	4520	0	84	12
1348	FFJ	FFJ	NBO	KRT	4450	4740	0	84	12
1350	FFA	FFA	NBO	JUB	2850	3030	0	71	7
1351	FFA	FFA	JUB	NBO	3120	3300	0	20	1
1352	FFA	FFA	NBO	JUB	3350	3530	0	48	5
1353	FFA	FFA	JUB	NBO	3620	3800	0	78	0
1354	FFC	FFC	NBO	JUB	3600	3750	0	78	0
1355	FFC	FFC	JUB	NBO	3840	4020	0	78	0
1406a	FFD	FFD	JIB	NBO	4930	5210	0	53	10
1406b	FFD	FFD	NBO	ADD	4420	4630	0	53	10
1406c	FFD	FFD	ADD	JIB	4720	4840	0	53	10
1410	FFE	FFE	NBO	EBB	2900	3010	0	78	9
1411	FFE	FFE	EBB	NBO	3100	3210	0	64	4
1412	FFE	FFE	NBO	EBB	3340	3500	0	54	8
1413	FFE	FFE	EBB	NBO	3550	3700	0	62	8
1414	FFE	FFE	NBO	EBB	3820	3940	0	81	5
1415	FFE	FFE	EBB	NBO	4030	4140	0	71	11
1416	FFE	FFE	NBO	EBB	4400	4510	0	75	4
1417	KYT	KYT	EBB	NBO	2600	2710	0	61	3
1418	KYP	KYP	NBO	EBB	4000	4110	0	56	7
1419	KYP	KYP	EBB	NBO	4200	4310	0	62	6
1420	FFD	FFD	NBO	JRO	3000	3100	0	49	2
1421	FFD	FFD	JRO	NBO	3150	3250	0	9	8
1442a	FFF	FFF	NBO	BJM	3350	3530	0	9	8
1442b	FFF	FFF	BJM	KGL	3620	3700	0	9	8
1442c	FFF	FFF	KGL	NBO	3750	3920	0	9	8
1450	KQE	KQE	NBO	SEZ	3000	3310	0	77	3
1451	KQE	KQE	SEZ	NBO	3400	3710	0	77	3
1452a	KQF	KQF	NBO	DZA	2940	3210	0	78	8
1452b	KQF	KQF	DZA	HAH	3310	3400	0	36	5
1452c	KQF	KQF	HAH	NBO	3450	3700	0	57	5
1460	FFC	FFC	NBO	BJM	2920	3100	0	78	8
1461	FFC	FFC	BJM	NBO	3150	3330	0	78	8
1464	FFJ	FFJ	NBO	BJM	3800	3940	0	27	4
1465	FFJ	FFJ	BJM	NBO	4030	4200	0	0	0
1466a	KYS	KYS	NBO	BJM	4450	4630	0	38	10
1466b	KYS	KYS	BJM	KGL	4720	4800	0	0	0
1466c	KYS	KYS	KGL	NBO	4850	5020	0	38	10
1470	FFF	FFF	NBO	KGL	2850	3020	0	38	10
1471	FFF	FFF	KGL	NBO	3110	3240	0	38	10
1474	KYS	KYS	NBO	KGL	3820	3950	0	24	6
1475	KYS	KYS	KGL	NBO	4040	4210	0	34	4
1480	KYT	KYT	NBO	DAR	2910	3030	0	73	5
1481	KYT	KYT	DAR	NBO	3120	3240	0	47	1
1482	KYT	KYT	NBO	DAR	3340	3500	0	48	4
1483	KYT	KYT	DAR	NBO	3550	3710	0	79	10
1484	KYT	KYT	NBO	DAR	3750	3920	0	15	4

Cont. DAY 2

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
1485	KYT	KYT	DAR	NBO	4010	4130	0	70	7
1486	FFK	FFK	NBO	DAR	3940	4100	0	38	5
1487	FFK	FFK	DAR	NBO	4150	4310	0	35	8
1488	KYT	KYT	NBO	DAR	4400	4530	0	58	4
1489	FFF	FFF	DAR	NBO	2610	2730	0	56	6
1498	FFF	FFF	NBO	ZNZ	4330	4440	0	66	1
1499	KYQ	KYQ	ZNZ	NBO	2630	2750	0	66	1
1502	KQE	KQE	NBO	ACC	3820	4400	0	50	4
1503	KQE	KQE	ACC	NBO	4500	5040	0	35	7
1520a	KYE	KYE	NBO	ABJ	3000	3600	0	72	6
1520b	KYE	KYE	ABJ	DKR	3650	3940	0	72	6
1521a	KYE	KYE	DKR	ABJ	4040	4330	0	72	6
1521b	KYE	KYE	ABJ	NBO	4420	5040	0	72	6
1532	CYA	CYA	NBO	LOS	2900	3400	0	90	13
1533	CYA	CYA	LOS	NBO	3530	4030	0	61	11
1542a	KQF	KQF	NBO	LOS	3900	4420	0	33	5
1542b	KQF	KQF	LOS	COO	4510	4550	0	33	5
1542c	KQF	KQF	COO	NBO	4640	5210	0	33	5
1554	KZA	KZA	NBO	FIH	2850	3220	0	73	9
1555	KZA	KZA	FIH	NBO	3340	3710	0	73	9
1584a	KQH	KQH	NBO	NLA	2930	3210	0	73	9
1584b	KQH	KQH	NLA	FBM	3300	3340	0	73	9
1584c	KQH	KQH	FBM	NBO	3430	3700	0	73	9
1600	KYP	KYP	NBO	MBA	2700	2800	0	65	3
1601	KYP	KYP	MBA	NBO	2840	2940	0	60	2
1602	FFG	FFG	NBO	MBA	2930	3030	0	84	12
1603	FFG	FFG	MBA	NBO	3110	3210	0	64	4
1604	KYP	KYP	NBO	MBA	3030	3130	0	64	4
1605	KYP	KYP	MBA	NBO	3210	3310	0	64	4
1606	FFG	FFG	NBO	MBA	3300	3400	0	84	12
1607	FFG	FFG	MBA	NBO	3440	3540	0	84	12
1610	FFG	FFG	NBO	MBA	3630	3730	0	84	12
1611	FFG	FFG	MBA	NBO	3810	3910	0	84	12
1618	FFG	FFG	NBO	MBA	4000	4100	0	76	8
1619	FFG	FFG	MBA	NBO	4140	4240	0	73	5
1622	KYR	KYR	NBO	MBA	4120	4220	0	84	12
1623	KYR	KYR	MBA	NBO	4310	4410	0	31	1
1624	KYQ	KYQ	NBO	MBA	4400	4450	0	83	12
1625	FFG	FFG	MBA	NBO	2630	2730	0	69	5
1640	KYP	KYP	NBO	MYD	3420	3520	0	59	6
1641	KYP	KYP	MYD	NBO	3610	3720	0	52	3
1650	KYR	KYR	NBO	KIS	2800	2850	10	62	4
1651	KYR	KYR	KIS	NBO	2930	3020	0	48	0
1654	KYR	KYR	NBO	KIS	3120	3210	0	55	0
1655	KYR	KYR	KIS	NBO	3250	3340	0	35	3
1656	KYR	KYR	NBO	KIS	3430	3520	0	34	1
1657	KYR	KYR	KIS	NBO	3600	3650	0	48	5
1670	KYQ	KYQ	NBO	KIS	3830	3920	0	67	3
1671	KYQ	KYQ	KIS	NBO	4010	4050	0	68	11

Cont. DAY 2

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
1702a	KZD	KZD	NBO	HRE	2850	3150	0	68	11
1702b	KZD	KZD	HRE	LUN	3250	3350	0	68	11
1702c	KZD	KZD	LUN	NBO	3450	3730	0	68	11
1704a	FFD	FFD	NBO	HRE	3400	3700	0	68	11
1704b	FFD	FFD	HRE	LUN	3750	3850	0	68	11
1704c	FFD	FFD	LUN	NBO	3940	4220	0	68	11
1732a	FFC	FFC	NBO	LLW	4240	4500	0	23	2
1732b	FFC	FFC	LLW	LUN	4600	4710	0	23	2
1732c	FFC	FFC	LUN	NBO	4810	5050	0	23	2
1748	FFK	FFK	NBO	APL	3120	3350	0	22	5
1749	FFK	FFK	APL	NBO	3440	3710	0	22	5
1752a	FFJ	FFJ	NBO	LLW	3000	3210	0	22	5
1752b	FFJ	FFJ	LLW	BLZ	3250	3340	0	22	5
1752c	FFJ	FFJ	BLZ	NBO	3430	3700	0	22	5
1756	KYQ	KYQ	NBO	TNR	2940	3300	0	22	5
1757	KYQ	KYQ	TNR	NBO	3350	3710	0	22	5
1760	KYS	KYS	NBO	JNB	2730	3150	0	30	4
1761	KYS	KYS	JNB	NBO	3250	3700	0	48	9
1762	KYF	KYF	NBO	JNB	2940	3400	0	101	12
1763	KYF	KYF	JNB	NBO	3520	3930	0	104	16
1764	CYA	CYA	NBO	JNB	4130	4550	0	80	14
1861a	KZB	KZB	HKG	BKK	3740	4020	0	204	10
1861b	KZB	KZB	BKK	NBO	4130	5010	0	204	10
1882	KZF	KZF	NBO	CAN	4550	5620	0	159	11
1883	KZF	KZF	CAN	NBO	6140	7300	0	159	11
1886a	KZA	KZA	NBO	BKK	4440	5410	0	152	23
1886b	KZA	KZA	BKK	CAN	5550	5900	0	152	23

C.3 Full Day Scenario 3

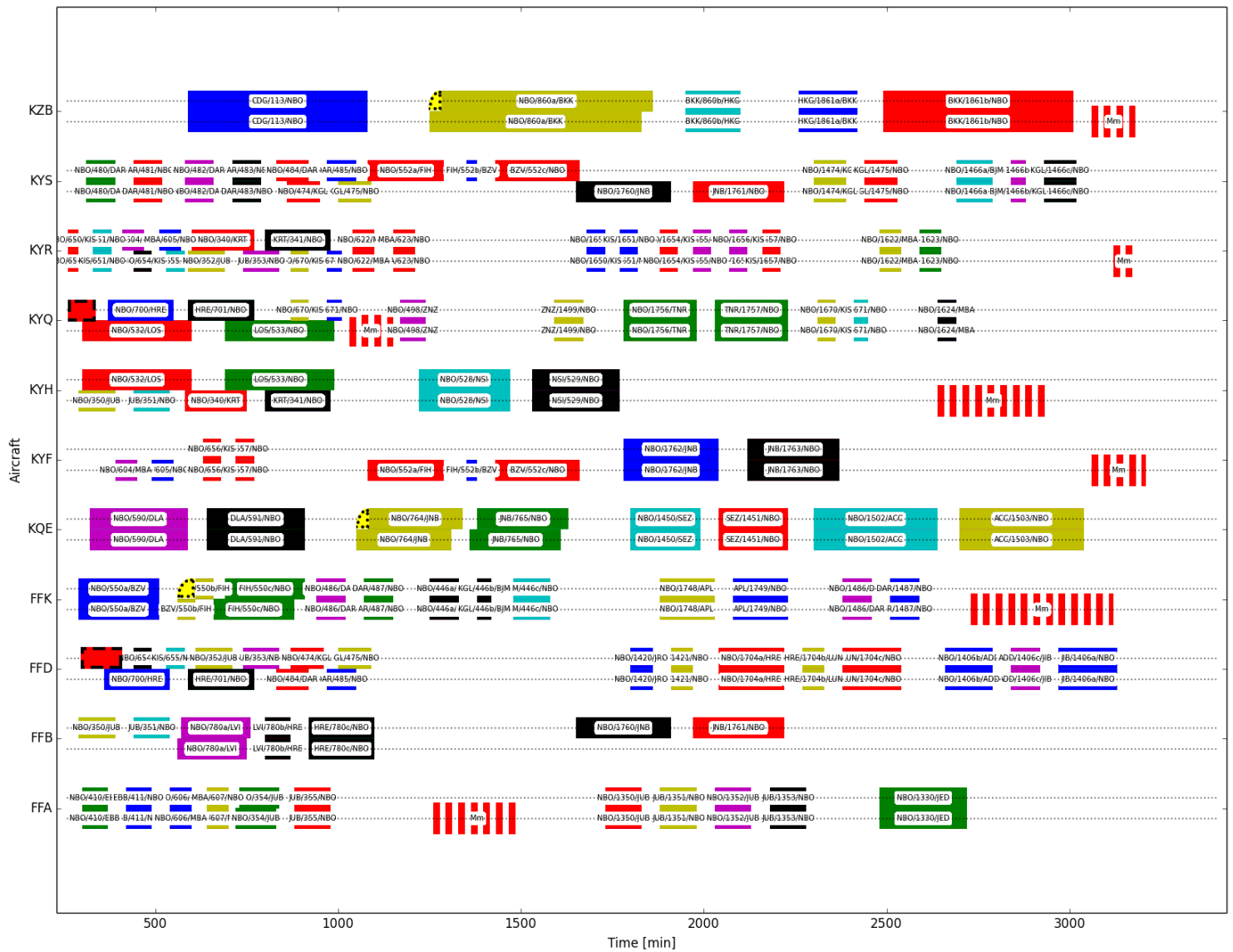


Figure C.4: Full Day scenario 3 final schedule

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
101	KQS	KQS	LHR	NBO	1900	2730	0	163	23
102	KQT	KQT	NBO	LHR	2050	2940	0	95	23
112	KZC	KZC	NBO	CDG	2040	2920	0	164	11
113	KZB	KZB	CDG	NBO	950	1800	0	164	11
116	KZF	KZF	NBO	AMS	520	1420	0	118	1
117	KZF	KZF	AMS	NBO	1940	2800	0	143	18
190	FFG	FFG	NBO	NBO	600	900	0	5	5
202	KYZ	KYZ	NBO	BOM	1410	2010	0	243	8
203	KYZ	KYZ	BOM	NBO	2130	2720	0	150	7
204	KYD	KYD	NBO	BOM	1920	2520	0	129	1
310a	KZD	KZD	NBO	DXB	1610	2120	0	82	11
310b	KZD	KZD	DXB	NBO	2240	2750	0	204	14
340	KYR	KYR	NBO	KRT	940	1230	20	25	6
341	KYR	KYR	KRT	NBO	1320	1620	0	37	4
350	FFB	FFB	NBO	JUB	450	630	0	36	4
351	FFB	FFB	JUB	NBO	720	900	0	35	1
352	FFD	FFD	NBO	JUB	950	1130	20	56	4
353	FFD	FFD	JUB	NBO	1220	1400	0	14	0
354	FFA	FFA	NBO	JUB	1200	1350	10	38	2
355	FFA	FFA	JUB	NBO	1440	1620	0	23	2
402a	FFJ	FFJ	NBO	ADD	650	900	0	59	3
402b	FFJ	FFJ	ADD	JIB	950	1110	0	33	5
403a	FFJ	FFJ	JIB	ADD	1200	1310	0	18	3
403b	FFJ	FFJ	ADD	NBO	1400	1610	0	46	4
408a	FFC	FFC	NBO	JIB	1930	2200	0	18	3
408b	FFC	FFC	JIB	ADD	2250	2410	0	25	3
408c	FFC	FFC	ADD	NBO	2510	2710	0	40	4
410	FFA	FFA	NBO	EBB	500	610	0	83	12
411	FFA	FFA	EBB	NBO	700	810	0	84	6
412	KYT	KYT	NBO	EBB	940	1100	0	58	2
413	KYT	KYT	EBB	NBO	1150	1300	0	69	5
414	KYT	KYT	NBO	EBB	1420	1540	0	41	2
415	KYT	KYT	EBB	NBO	1630	1740	0	79	7
416	KYT	KYT	NBO	EBB	2000	2110	0	38	5
417	KYR	KYR	EBB	NBO	200	310	0	84	4
418	FFE	FFE	NBO	EBB	1600	1710	0	45	2
419	FFE	FFE	EBB	NBO	1800	1910	0	38	1
420	KYP	KYP	NBO	JRO	600	700	0	40	5
421	KYP	KYP	JRO	NBO	750	850	0	32	1
446a	FFK	FFK	NBO	KGL	2050	2210	0	24	1
446b	FFK	FFK	KGL	BJM	2300	2340	0	39	1
446c	FFK	FFK	BJM	NBO	2440	2620	0	31	1
460	KQF	KQF	NBO	BJM	520	700	0	28	2
461	KQF	KQF	BJM	NBO	750	930	0	23	0
464	FFC	FFC	NBO	BJM	1400	1540	0	35	3
465	FFC	FFC	BJM	NBO	1630	1800	0	40	1
470	KYT	KYT	NBO	KGL	450	620	0	50	0
471	KYT	KYT	KGL	NBO	710	840	0	21	1
474	FFD	FFD	NBO	KGL	1420	1550	10	9	2
475	FFD	FFD	KGL	NBO	1640	1810	0	36	1
480	KYS	KYS	NBO	DAR	510	630	0	84	12

Cont. DAY 3

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
481	KYS	KYS	DAR	NBO	720	840	0	60	5
482	KYS	KYS	NBO	DAR	940	1100	0	72	9
483	KYS	KYS	DAR	NBO	1150	1310	0	75	5
484	KYS	KYS	NBO	DAR	1350	1520	0	32	3
485	KYS	KYS	DAR	NBO	1610	1730	0	71	8
486	FFK	FFK	NBO	DAR	1540	1700	0	44	4
487	FFK	FFK	DAR	NBO	1750	1910	0	27	1
488	FFF	FFF	NBO	DAR	2000	2130	0	51	7
489	KYQ	KYQ	DAR	NBO	210	330	0	55	7
498	KYQ	KYQ	NBO	ZNZ	1930	2040	0	51	7
502	KQF	KQF	NBO	ACC	1420	2000	0	36	7
503	KQF	KQF	ACC	NBO	2100	2640	0	35	7
512a	KQH	KQH	NBO	BKO	610	1300	0	52	8
512b	KQH	KQH	BKO	DKR	1400	1550	0	38	4
513a	KQH	KQH	DKR	BKO	1650	1840	0	35	7
513b	KQH	KQH	BKO	NBO	1940	2630	0	44	7
528	KYH	KYH	NBO	NSI	2020	2430	0	42	6
529	KYH	KYH	NSI	NBO	2530	2930	0	52	4
532	KYH	KYH	NBO	LOS	500	1000	0	48	3
533	KYH	KYH	LOS	NBO	1130	1630	0	39	4
536	FFE	FFE	NBO	ABV	450	930	0	54	3
537	FFE	FFE	ABV	NBO	1030	1520	0	47	1
550a	FFK	FFK	NBO	BZV	450	830	0	28	2
550b	FFK	FFK	BZV	FIH	920	1010	50	52	6
550c	FFK	FFK	FIH	NBO	1100	1440	30	56	4
552a	KYS	KYS	NBO	FIH	1800	2130	0	46	6
552b	KYS	KYS	FIH	BZV	2230	2300	0	56	5
552c	KYS	KYS	BZV	NBO	2350	2740	0	35	3
586a	KYD	KYD	NBO	FBM	530	810	0	86	7
586b	KYD	KYD	FBM	NLA	900	940	0	82	7
586c	KYD	KYD	NLA	NBO	1030	1310	0	91	3
590	KQE	KQE	NBO	DLA	520	950	0	85	8
591	KQE	KQE	DLA	NBO	1040	1510	0	83	5
600	FFJ	FFJ	NBO	MBA	300	400	0	81	3
601	FFJ	FFJ	MBA	NBO	440	540	0	83	12
602	CYA	CYA	NBO	MBA	530	630	0	84	12
603	CYA	CYA	MBA	NBO	710	810	0	84	12
604	KYR	KYR	NBO	MBA	630	730	20	84	12
605	KYR	KYR	MBA	NBO	810	910	20	84	12
606	FFA	FFA	NBO	MBA	900	1000	0	84	12
607	FFA	FFA	MBA	NBO	1040	1140	0	84	12
610	CYA	CYA	NBO	MBA	1230	1330	0	81	10
611	CYA	CYA	MBA	NBO	1410	1510	0	84	12
618	KQG	KQG	NBO	MBA	1600	1700	0	78	9
619	KQG	KQG	MBA	NBO	1740	1840	0	84	11
622	KYR	KYR	NBO	MBA	1720	1820	0	77	4
623	KYR	KYR	MBA	NBO	1910	2010	0	83	12
624	FFG	FFG	NBO	MBA	2000	2050	0	65	2
625	FFA	FFA	MBA	NBO	230	330	0	84	12
640	KQF	KQF	NBO	MYD	1020	1120	0	68	3

Cont. DAY 3

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
641	KQF	KQF	MYD	NBO	1210	1320	0	69	3
650	KYR	KYR	NBO	KIS	400	450	0	61	2
651	KYR	KYR	KIS	NBO	530	620	0	82	3
654	FFD	FFD	NBO	KIS	720	810	0	68	2
655	FFD	FFD	KIS	NBO	850	940	0	71	2
656	KYF	KYF	NBO	KIS	1030	1120	0	42	0
657	KYF	KYF	KIS	NBO	1200	1250	0	70	4
670	KYQ	KYQ	NBO	KIS	1430	1520	0	58	2
671	KYQ	KYQ	KIS	NBO	1610	1650	0	75	5
700	KYQ	KYQ	NBO	HRE	600	900	10	78	5
701	KYQ	KYQ	HRE	NBO	950	1250	0	71	4
710	FFF	FFF	NBO	GBE	620	1020	0	74	2
711	FFF	FFF	GBE	NBO	1110	1510	0	79	5
720a	FFJ	FFJ	NBO	LUN	1840	2130	0	75	7
720b	FFJ	FFJ	LUN	HRE	2220	2330	0	76	4
720c	FFJ	FFJ	HRE	NBO	2420	2720	0	74	5
722a	KQU	KQU	NBO	LLW	500	720	0	61	3
722b	KQU	KQU	LLW	LUN	820	930	0	79	6
722c	KQU	KQU	LUN	NBO	1030	1310	0	73	7
728a	FFG	FFG	NBO	LLW	1000	1210	0	73	1
728b	FFG	FFG	LLW	LUN	1310	1420	0	84	1
728c	FFG	FFG	LUN	NBO	1520	1800	0	44	1
740	KQG	KQG	NBO	MPM	450	850	0	44	9
741	KQG	KQG	MPM	NBO	940	1340	0	44	9
760	FFC	FFC	NBO	JNB	330	750	0	22	3
761	FFC	FFC	JNB	NBO	850	1300	0	22	3
762	KZA	KZA	NBO	JNB	540	1000	0	54	16
763	KZA	KZA	JNB	NBO	1120	1530	0	128	15
764	KQE	KQE	NBO	JNB	1730	2150	30	64	15
765	KQE	KQE	JNB	NBO	2240	2650	20	63	9
770	KYP	KYP	NBO	LAD	900	1300	0	70	12
771	KYP	KYP	LAD	NBO	1400	1820	0	70	12
780a	FFB	FFB	NBO	LVI	920	1230	10	70	12
780b	FFB	FFB	LVI	HRE	1320	1430	0	70	12
780c	FFB	FFB	HRE	NBO	1520	1820	0	70	12
860a	KZB	KZB	NBO	BKK	2050	3030	30	185	5
860b	KZB	KZB	BKK	HKG	3230	3500	0	185	5
887a	KZE	KZE	CAN	BKK	1340	1630	0	172	15
887b	KZE	KZE	BKK	NBO	1730	2610	0	172	15
1101	KQT	KQT	LHR	NBO	4300	5130	0	213	28
1102	KYZ	KYZ	NBO	LHR	4450	5340	0	158	24
1111	KQH	KQH	NBO	NBO	4000	4300	0	100	16
1112	KZC	KZC	NBO	CDG	4440	5320	0	158	24
1113	KZC	KZC	CDG	NBO	3350	4200	0	157	12
1116	KQU	KQU	NBO	AMS	2920	3820	0	122	10
1117	KQU	KQU	AMS	NBO	4340	5200	0	284	27
1202	KZE	KZE	NBO	BOM	3810	4410	0	197	11
1203	KZE	KZE	BOM	NBO	4530	5120	0	150	7
1205	KYD	KYD	BOM	NBO	2840	3440	0	129	7
1220	KQG	KQG	NBO	DEL	3430	4200	0	100	7

Cont. DAY 3

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
1310	KZD	KZD	NBO	DXB	4010	4520	0	89	3
1311	KZD	KZD	DXB	NBO	4640	5150	0	204	14
1330	FFA	FFA	NBO	JED	4120	4520	0	84	12
1348	FFJ	FFJ	NBO	KRT	4450	4740	0	84	12
1350	FFA	FFA	NBO	JUB	2850	3030	0	71	7
1351	FFA	FFA	JUB	NBO	3120	3300	0	20	1
1352	FFA	FFA	NBO	JUB	3350	3530	0	48	5
1353	FFA	FFA	JUB	NBO	3620	3800	0	78	0
1354	FFC	FFC	NBO	JUB	3600	3750	0	78	0
1355	FFC	FFC	JUB	NBO	3840	4020	0	78	0
1406a	FFD	FFD	JIB	NBO	4930	5210	0	53	10
1406b	FFD	FFD	NBO	ADD	4420	4630	0	53	10
1406c	FFD	FFD	ADD	JIB	4720	4840	0	53	10
1410	FFE	FFE	NBO	EBB	2900	3010	0	78	9
1411	FFE	FFE	EBB	NBO	3100	3210	0	64	4
1412	FFE	FFE	NBO	EBB	3340	3500	0	54	8
1413	FFE	FFE	EBB	NBO	3550	3700	0	62	8
1414	FFE	FFE	NBO	EBB	3820	3940	0	81	5
1415	FFE	FFE	EBB	NBO	4030	4140	0	71	11
1416	FFE	FFE	NBO	EBB	4400	4510	0	75	4
1417	KYT	KYT	EBB	NBO	2600	2710	0	61	3
1418	KYP	KYP	NBO	EBB	4000	4110	0	56	7
1419	KYP	KYP	EBB	NBO	4200	4310	0	62	6
1420	FFD	FFD	NBO	JRO	3000	3100	0	49	2
1421	FFD	FFD	JRO	NBO	3150	3250	0	9	8
1442a	FFF	FFF	NBO	BJM	3350	3530	0	9	8
1442b	FFF	FFF	BJM	KGL	3620	3700	0	9	8
1442c	FFF	FFF	KGL	NBO	3750	3920	0	9	8
1450	KQE	KQE	NBO	SEZ	3000	3310	0	77	3
1451	KQE	KQE	SEZ	NBO	3400	3710	0	77	3
1452a	KQF	KQF	NBO	DZA	2940	3210	0	78	8
1452b	KQF	KQF	DZA	HAH	3310	3400	0	36	5
1452c	KQF	KQF	HAH	NBO	3450	3700	0	57	5
1460	FFC	FFC	NBO	BJM	2920	3100	0	78	8
1461	FFC	FFC	BJM	NBO	3150	3330	0	78	8
1464	FFJ	FFJ	NBO	BJM	3800	3940	0	27	4
1465	FFJ	FFJ	BJM	NBO	4030	4200	0	0	0
1466a	KYS	KYS	NBO	BJM	4450	4630	0	38	10
1466b	KYS	KYS	BJM	KGL	4720	4800	0	0	0
1466c	KYS	KYS	KGL	NBO	4850	5020	0	38	10
1470	FFF	FFF	NBO	KGL	2850	3020	0	38	10
1471	FFF	FFF	KGL	NBO	3110	3240	0	38	10
1474	KYS	KYS	NBO	KGL	3820	3950	0	24	6
1475	KYS	KYS	KGL	NBO	4040	4210	0	34	4
1480	KYT	KYT	NBO	DAR	2910	3030	0	73	5
1481	KYT	KYT	DAR	NBO	3120	3240	0	47	1
1482	KYT	KYT	NBO	DAR	3340	3500	0	48	4
1483	KYT	KYT	DAR	NBO	3550	3710	0	79	10
1484	KYT	KYT	NBO	DAR	3750	3920	0	15	4
1485	KYT	KYT	DAR	NBO	4010	4130	0	70	7
1486	FFK	FFK	NBO	DAR	3940	4100	0	38	5

Cont. DAY 3

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
1487	FFK	FFK	DAR	NBO	4150	4310	0	35	8
1488	KYT	KYT	NBO	DAR	4400	4530	0	58	4
1489	FFF	FFF	DAR	NBO	2610	2730	0	56	6
1498	FFF	FFF	NBO	ZNZ	4330	4440	0	66	1
1499	KYQ	KYQ	ZNZ	NBO	2630	2750	0	66	1
1502	KQE	KQE	NBO	ACC	3820	4400	0	50	4
1503	KQE	KQE	ACC	NBO	4500	5040	0	35	7
1520a	KYE	KYE	NBO	ABJ	3000	3600	0	72	6
1520b	KYE	KYE	ABJ	DKR	3650	3940	0	72	6
1521a	KYE	KYE	DKR	ABJ	4040	4330	0	72	6
1521b	KYE	KYE	ABJ	NBO	4420	5040	0	72	6
1532	CYA	CYA	NBO	LOS	2900	3400	0	90	13
1533	CYA	CYA	LOS	NBO	3530	4030	0	61	11
1542a	KQF	KQF	NBO	LOS	3900	4420	0	33	5
1542b	KQF	KQF	LOS	COO	4510	4550	0	33	5
1542c	KQF	KQF	COO	NBO	4640	5210	0	33	5
1554	KZA	KZA	NBO	FIH	2850	3220	0	73	9
1555	KZA	KZA	FIH	NBO	3340	3710	0	73	9
1584a	KQH	KQH	NBO	NLA	2930	3210	0	73	9
1584b	KQH	KQH	NLA	FBM	3300	3340	0	73	9
1584c	KQH	KQH	FBM	NBO	3430	3700	0	73	9
1600	KYP	KYP	NBO	MBA	2700	2800	0	65	3
1601	KYP	KYP	MBA	NBO	2840	2940	0	60	2
1602	FFG	FFG	NBO	MBA	2930	3030	0	84	12
1603	FFG	FFG	MBA	NBO	3110	3210	0	64	4
1604	KYP	KYP	NBO	MBA	3030	3130	0	64	4
1605	KYP	KYP	MBA	NBO	3210	3310	0	64	4
1606	FFG	FFG	NBO	MBA	3300	3400	0	84	12
1607	FFG	FFG	MBA	NBO	3440	3540	0	84	12
1610	FFG	FFG	NBO	MBA	3630	3730	0	84	12
1611	FFG	FFG	MBA	NBO	3810	3910	0	84	12
1618	FFG	FFG	NBO	MBA	4000	4100	0	76	8
1619	FFG	FFG	MBA	NBO	4140	4240	0	73	5
1622	KYR	KYR	NBO	MBA	4120	4220	0	84	12
1623	KYR	KYR	MBA	NBO	4310	4410	0	31	1
1624	KYQ	KYQ	NBO	MBA	4400	4450	0	83	12
1625	FFG	FFG	MBA	NBO	2630	2730	0	69	5
1640	KYP	KYP	NBO	MYD	3420	3520	0	59	6
1641	KYP	KYP	MYD	NBO	3610	3720	0	52	3
1650	KYR	KYR	NBO	KIS	2800	2850	0	62	4
1651	KYR	KYR	KIS	NBO	2930	3020	0	48	0
1654	KYR	KYR	NBO	KIS	3120	3210	0	55	0
1655	KYR	KYR	KIS	NBO	3250	3340	0	35	3
1656	KYR	KYR	NBO	KIS	3430	3520	0	34	1
1657	KYR	KYR	KIS	NBO	3600	3650	0	48	5
1670	KYQ	KYQ	NBO	KIS	3830	3920	0	67	3
1671	KYQ	KYQ	KIS	NBO	4010	4050	0	68	11
1702a	KZD	KZD	NBO	HRE	2850	3150	0	68	11
1702b	KZD	KZD	HRE	LUN	3250	3350	0	68	11
1702c	KZD	KZD	LUN	NBO	3450	3730	0	68	11
1704a	FFD	FFD	NBO	HRE	3400	3700	0	68	11

Cont. DAY 3

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
1704b	FFD	FFD	HRE	LUN	3750	3850	0	68	11
1704c	FFD	FFD	LUN	NBO	3940	4220	0	68	11
1732a	FFC	FFC	NBO	LLW	4240	4500	0	23	2
1732b	FFC	FFC	LLW	LUN	4600	4710	0	23	2
1732c	FFC	FFC	LUN	NBO	4810	5050	0	23	2
1748	FFK	FFK	NBO	APL	3120	3350	0	22	5
1749	FFK	FFK	APL	NBO	3440	3710	0	22	5
1752a	FFJ	FFJ	NBO	LLW	3000	3210	0	22	5
1752b	FFJ	FFJ	LLW	BLZ	3250	3340	0	22	5
1752c	FFJ	FFJ	BLZ	NBO	3430	3700	0	22	5
1756	KYQ	KYQ	NBO	TNR	2940	3300	0	22	5
1757	KYQ	KYQ	TNR	NBO	3350	3710	0	22	5
1760	FFB	FFB	NBO	JNB	2730	3150	0	30	4
1761	FFB	FFB	JNB	NBO	3250	3700	0	48	9
1762	KYF	KYF	NBO	JNB	2940	3400	0	101	12
1763	KYF	KYF	JNB	NBO	3520	3930	0	104	16
1764	CYA	CYA	NBO	JNB	4130	4550	0	80	14
1861a	KZB	KZB	HKG	BKK	3740	4020	0	204	10
1861b	KZB	KZB	BKK	NBO	4130	5010	0	204	10
1882	KZF	KZF	NBO	CAN	4550	5620	0	159	11
1883	KZF	KZF	CAN	NBO	6140	7300	0	159	11
1886a	KZA	KZA	NBO	BKK	4440	5410	0	152	23
1886b	KZA	KZA	BKK	CAN	5550	5900	0	152	23

C.4 Full Day Scenario 4

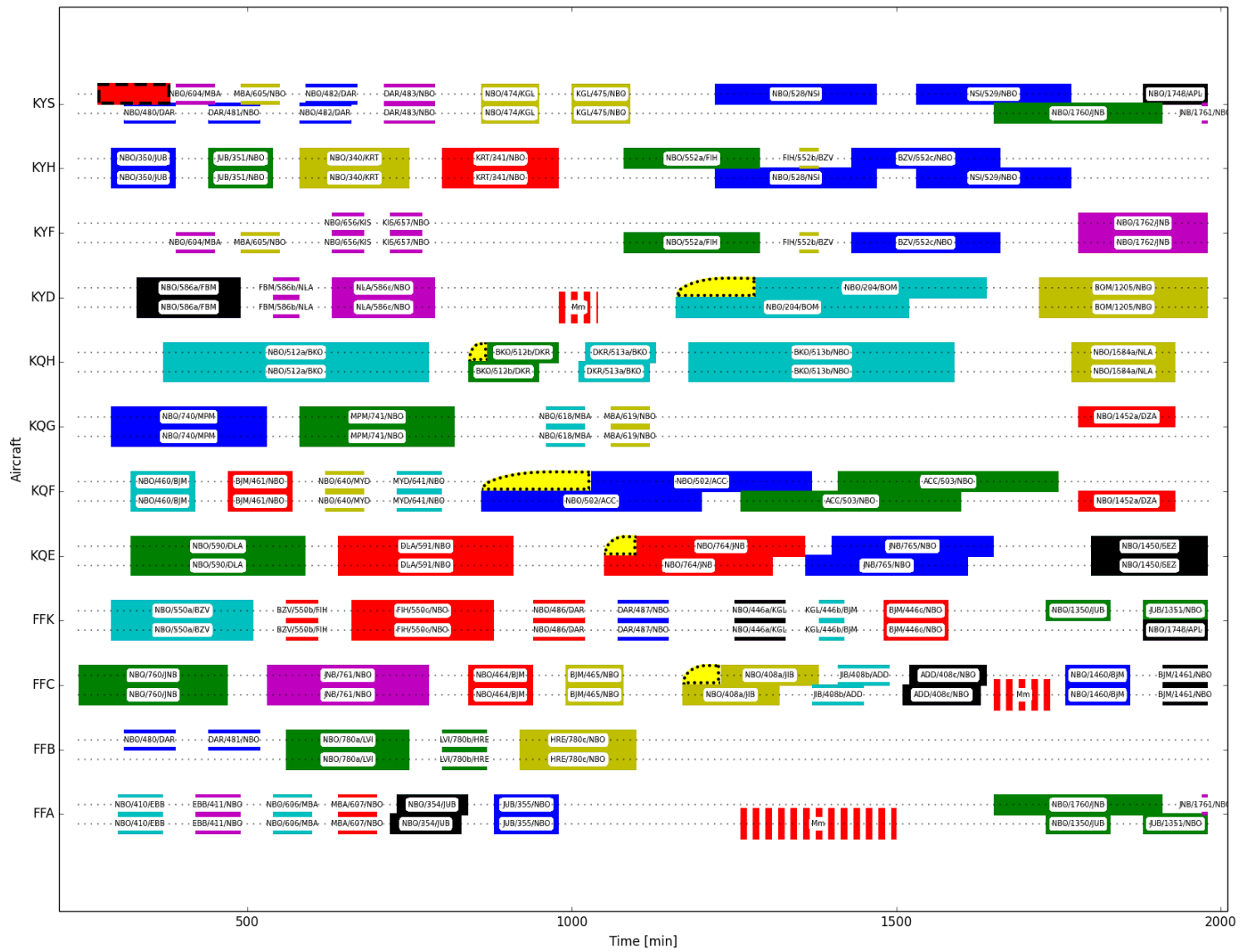


Figure C.5: Full Day scenario 4 final schedule

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
101	KQS	KQS	LHR	NBO	1900	2730	0	163	23
102	KQT	KQT	NBO	LHR	2050	2940	0	95	23
112	KZC	KZC	NBO	CDG	2040	2920	0	164	11
113	KZB	KZB	CDG	NBO	950	1800	0	164	11
116	KZF	KZF	NBO	AMS	520	1420	0	118	1
117	KZF	KZF	AMS	NBO	1940	2800	0	143	18
190	FFG	FFG	NBO	NBO	600	900	0	5	5
202	KYZ	KYZ	NBO	BOM	1410	2010	0	243	8
203	KYZ	KYZ	BOM	NBO	2130	2720	0	150	7
204	KYD	KYD	NBO	BOM	1920	2520	120	129	1
310a	KZD	KZD	NBO	DXB	1610	2120	0	82	11
310b	KZD	KZD	DXB	NBO	2240	2750	0	204	14
340	KYH	KYH	NBO	KRT	940	1230	0	25	6
341	KYH	KYH	KRT	NBO	1320	1620	0	37	4
350	KYH	KYH	NBO	JUB	450	630	0	36	4
351	KYH	KYH	JUB	NBO	720	900	0	35	1
352	KYR	KYR	NBO	JUB	950	1130	0	56	4
353	KYR	KYR	JUB	NBO	1220	1400	0	14	0
354	FFA	FFA	NBO	JUB	1200	1350	10	38	2
355	FFA	FFA	JUB	NBO	1440	1620	0	23	2
402a	FFJ	FFJ	NBO	ADD	650	900	0	59	3
402b	FFJ	FFJ	ADD	JIB	950	1110	0	33	5
403a	FFJ	FFJ	JIB	ADD	1200	1310	0	18	3
403b	FFJ	FFJ	ADD	NBO	1400	1610	0	46	4
408a	FFC	FFC	NBO	JIB	1930	2200	60	18	3
408b	FFC	FFC	JIB	ADD	2250	2410	40	25	3
408c	FFC	FFC	ADD	NBO	2510	2710	10	40	4
410	FFA	FFA	NBO	EBB	500	610	0	83	12
411	FFA	FFA	EBB	NBO	700	810	0	84	6
412	KYT	KYT	NBO	EBB	940	1100	0	58	2
413	KYT	KYT	EBB	NBO	1150	1300	0	69	5
414	KYT	KYT	NBO	EBB	1420	1540	0	41	2
415	KYT	KYT	EBB	NBO	1630	1740	0	79	7
416	KYT	KYT	NBO	EBB	2000	2110	0	38	5
417	KYR	KYR	EBB	NBO	200	310	0	84	4
418	FFE	FFE	NBO	EBB	1600	1710	0	45	2
419	FFE	FFE	EBB	NBO	1800	1910	0	38	1
420	KYP	KYP	NBO	JRO	600	700	0	40	5
421	KYP	KYP	JRO	NBO	750	850	0	32	1
446a	FFK	FFK	NBO	KGL	2050	2210	0	24	1
446b	FFK	FFK	KGL	BJM	2300	2340	0	39	1
446c	FFK	FFK	BJM	NBO	2440	2620	0	31	1
460	KQF	KQF	NBO	BJM	520	700	0	28	2
461	KQF	KQF	BJM	NBO	750	930	0	23	0
464	FFC	FFC	NBO	BJM	1400	1540	0	35	3
465	FFC	FFC	BJM	NBO	1630	1800	0	40	1
470	KYT	KYT	NBO	KGL	450	620	0	50	0
471	KYT	KYT	KGL	NBO	710	840	0	21	1
474	KYS	KYS	NBO	KGL	1420	1550	0	9	2
475	KYS	KYS	KGL	NBO	1640	1810	0	36	1
480	FFB	KYS	NBO	DAR	510	630	0	84	12

Cont. DAY 4

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
481	FFB	KYS	DAR	NBO	720	840	0	60	5
482	KYS	KYS	NBO	DAR	940	1100	10	72	9
483	KYS	KYS	DAR	NBO	1150	1310	0	75	5
484	FFD	FFD	NBO	DAR	1350	1520	0	32	3
485	FFD	FFD	DAR	NBO	1610	1730	0	71	8
486	FFK	FFK	NBO	DAR	1540	1700	0	44	4
487	FFK	FFK	DAR	NBO	1750	1910	0	27	1
488	FFF	FFF	NBO	DAR	2000	2130	0	51	7
489	KYQ	KYQ	DAR	NBO	210	330	0	55	7
498	KYQ	KYQ	NBO	ZNZ	1930	2040	0	51	7
502	KQF	KQF	NBO	ACC	1420	2000	170	36	7
503	KQF	KQF	ACC	NBO	2100	2640	150	35	7
512a	KQH	KQH	NBO	BKO	610	1300	0	52	8
512b	KQH	KQH	BKO	DKR	1400	1550	30	38	4
513a	KQH	KQH	DKR	BKO	1650	1840	10	35	7
513b	KQH	KQH	BKO	NBO	1940	2630	0	44	7
528	KYS	KYH	NBO	NSI	2020	2430	0	42	6
529	KYS	KYH	NSI	NBO	2530	2930	0	52	4
532	KYQ	KYQ	NBO	LOS	500	1000	0	48	3
533	KYQ	KYQ	LOS	NBO	1130	1630	0	39	4
536	FFE	FFE	NBO	ABV	450	930	0	54	3
537	FFE	FFE	ABV	NBO	1030	1520	0	47	1
550a	FFK	FFK	NBO	BZV	450	830	0	28	2
550b	FFK	FFK	BZV	FIH	920	1010	0	52	6
550c	FFK	FFK	FIH	NBO	1100	1440	0	56	4
552a	KYH	KYF	NBO	FIH	1800	2130	0	46	6
552b	KYH	KYF	FIH	BZV	2230	2300	0	56	5
552c	KYH	KYF	BZV	NBO	2350	2740	0	35	3
586a	KYD	KYD	NBO	FBM	530	810	0	86	7
586b	KYD	KYD	FBM	NLA	900	940	0	82	7
586c	KYD	KYD	NLA	NBO	1030	1310	0	91	3
590	KQE	KQE	NBO	DLA	520	950	0	85	8
591	KQE	KQE	DLA	NBO	1040	1510	0	83	5
600	FFJ	FFJ	NBO	MBA	300	400	0	81	3
601	FFJ	FFJ	MBA	NBO	440	540	0	83	12
602	CYA	CYA	NBO	MBA	530	630	0	84	12
603	CYA	CYA	MBA	NBO	710	810	0	84	12
604	KYS	KYF	NBO	MBA	630	730	0	84	12
605	KYS	KYF	MBA	NBO	810	910	0	84	12
606	FFA	FFA	NBO	MBA	900	1000	0	84	12
607	FFA	FFA	MBA	NBO	1040	1140	0	84	12
610	CYA	CYA	NBO	MBA	1230	1330	0	81	10
611	CYA	CYA	MBA	NBO	1410	1510	0	84	12
618	KQG	KQG	NBO	MBA	1600	1700	0	78	9
619	KQG	KQG	MBA	NBO	1740	1840	0	84	11
622	KYR	KYR	NBO	MBA	1720	1820	0	77	4
623	KYR	KYR	MBA	NBO	1910	2010	0	83	12
624	FFG	FFG	NBO	MBA	2000	2050	0	65	2
625	FFA	FFA	MBA	NBO	230	330	0	84	12
640	KQF	KQF	NBO	MYD	1020	1120	0	68	3
641	KQF	KQF	MYD	NBO	1210	1320	0	69	3

Cont. DAY 4

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
650	KYR	KYR	NBO	KIS	400	450	0	61	2
651	KYR	KYR	KIS	NBO	530	620	0	82	3
654	KYR	KYR	NBO	KIS	720	810	0	68	2
655	KYR	KYR	KIS	NBO	850	940	0	71	2
656	KYF	KYF	NBO	KIS	1030	1120	0	42	0
657	KYF	KYF	KIS	NBO	1200	1250	0	70	4
670	KYR	KYR	NBO	KIS	1430	1520	0	58	2
671	KYR	KYR	KIS	NBO	1610	1650	0	75	5
700	FFD	FFD	NBO	HRE	600	900	0	78	5
701	FFD	FFD	HRE	NBO	950	1250	0	71	4
710	FFF	FFF	NBO	GBE	620	1020	0	74	2
711	FFF	FFF	GBE	NBO	1110	1510	0	79	5
720a	FFJ	FFJ	NBO	LUN	1840	2130	0	75	7
720b	FFJ	FFJ	LUN	HRE	2220	2330	0	76	4
720c	FFJ	FFJ	HRE	NBO	2420	2720	0	74	5
722a	KQU	KQU	NBO	LLW	500	720	0	61	3
722b	KQU	KQU	LLW	LUN	820	930	0	79	6
722c	KQU	KQU	LUN	NBO	1030	1310	0	73	7
728a	FFG	FFG	NBO	LLW	1000	1210	0	73	1
728b	FFG	FFG	LLW	LUN	1310	1420	0	84	1
728c	FFG	FFG	LUN	NBO	1520	1800	0	44	1
740	KQG	KQG	NBO	MPM	450	850	0	44	9
741	KQG	KQG	MPM	NBO	940	1340	0	44	9
760	FFC	FFC	NBO	JNB	330	750	0	22	3
761	FFC	FFC	JNB	NBO	850	1300	0	22	3
762	KZA	KZA	NBO	JNB	540	1000	0	54	16
763	KZA	KZA	JNB	NBO	1120	1530	0	128	15
764	KQE	KQE	NBO	JNB	1730	2150	50	64	15
765	KQE	KQE	JNB	NBO	2240	2650	40	63	9
770	KYP	KYP	NBO	LAD	900	1300	0	70	12
771	KYP	KYP	LAD	NBO	1400	1820	0	70	12
780a	FFB	FFB	NBO	LVI	920	1230	0	70	12
780b	FFB	FFB	LVI	HRE	1320	1430	0	70	12
780c	FFB	FFB	HRE	NBO	1520	1820	0	70	12
860a	KZB	KZB	NBO	BKK	2050	3030	0	185	5
860b	KZB	KZB	BKK	HKG	3230	3500	0	185	5
887a	KZE	KZE	CAN	BKK	1340	1630	0	172	15
887b	KZE	KZE	BKK	NBO	1730	2610	0	172	15
1101	KQT	KQT	LHR	NBO	4300	5130	0	213	28
1102	KYZ	KYZ	NBO	LHR	4450	5340	0	158	24
1111	KQH	KQH	NBO	NBO	4000	4300	0	100	16
1112	KZC	KZC	NBO	CDG	4440	5320	0	158	24
1113	KZC	KZC	CDG	NBO	3350	4200	0	157	12
1116	KQU	KQU	NBO	AMS	2920	3820	0	122	10
1117	KQU	KQU	AMS	NBO	4340	5200	0	284	27
1202	KZE	KZE	NBO	BOM	3810	4410	0	197	11
1203	KZE	KZE	BOM	NBO	4530	5120	0	150	7
1205	KYD	KYD	BOM	NBO	2840	3440	0	129	7
1220	KQF	KQG	NBO	DEL	3430	4200	0	100	7

Cont. DAY 4

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
1310	KZD	KZD	NBO	DXB	4010	4520	0	89	3
1311	KZD	KZD	DXB	NBO	4640	5150	0	204	14
1330	FFK	FFA	NBO	JED	4120	4520	0	84	12
1348	FFJ	FFJ	NBO	KRT	4450	4740	0	84	12
1350	FFK	FFA	NBO	JUB	2850	3030	0	71	7
1351	FFK	FFA	JUB	NBO	3120	3300	0	20	1
1352	FFK	FFA	NBO	JUB	3350	3530	0	48	5
1353	FFK	FFA	JUB	NBO	3620	3800	0	78	0
1354	FFC	FFC	NBO	JUB	3600	3750	0	78	0
1355	FFC	FFC	JUB	NBO	3840	4020	0	78	0
1406a	FFD	FFD	JIB	NBO	4930	5210	0	53	10
1406b	FFD	FFD	NBO	ADD	4420	4630	0	53	10
1406c	FFD	FFD	ADD	JIB	4720	4840	0	53	10
1410	FFE	FFE	NBO	EBB	2900	3010	0	78	9
1411	FFE	FFE	EBB	NBO	3100	3210	0	64	4
1412	FFE	FFE	NBO	EBB	3340	3500	0	54	8
1413	FFE	FFE	EBB	NBO	3550	3700	0	62	8
1414	FFE	FFE	NBO	EBB	3820	3940	0	81	5
1415	FFE	FFE	EBB	NBO	4030	4140	0	71	11
1416	FFE	FFE	NBO	EBB	4400	4510	0	75	4
1417	KYT	KYT	EBB	NBO	2600	2710	0	61	3
1418	KYP	KYP	NBO	EBB	4000	4110	0	56	7
1419	KYP	KYP	EBB	NBO	4200	4310	0	62	6
1420	FFD	FFD	NBO	JRO	3000	3100	0	49	2
1421	FFD	FFD	JRO	NBO	3150	3250	0	9	8
1442a	FFF	FFF	NBO	BJM	3350	3530	0	9	8
1442b	FFF	FFF	BJM	KGL	3620	3700	0	9	8
1442c	FFF	FFF	KGL	NBO	3750	3920	0	9	8
1450	KQE	KQE	NBO	SEZ	3000	3310	0	77	3
1451	KQE	KQE	SEZ	NBO	3400	3710	0	77	3
1452a	KQG	KQF	NBO	DZA	2940	3210	0	78	8
1452b	KQG	KQF	DZA	HAH	3310	3400	0	36	5
1452c	KQG	KQF	HAH	NBO	3450	3700	0	57	5
1460	FFC	FFC	NBO	BJM	2920	3100	0	78	8
1461	FFC	FFC	BJM	NBO	3150	3330	0	78	8
1464	FFJ	FFJ	NBO	BJM	3800	3940	0	27	4
1465	FFJ	FFJ	BJM	NBO	4030	4200	0	0	0
1466a	FFA	KYS	NBO	BJM	4450	4630	0	38	10
1466b	FFA	KYS	BJM	KGL	4720	4800	0	0	0
1466c	FFA	KYS	KGL	NBO	4850	5020	0	38	10
1470	FFF	FFF	NBO	KGL	2850	3020	0	38	10
1471	FFF	FFF	KGL	NBO	3110	3240	0	38	10
1474	FFA	KYS	NBO	KGL	3820	3950	0	24	6
1475	FFA	KYS	KGL	NBO	4040	4210	0	34	4
1480	KYT	KYT	NBO	DAR	2910	3030	0	73	5
1481	KYT	KYT	DAR	NBO	3120	3240	0	47	1
1482	KYT	KYT	NBO	DAR	3340	3500	0	48	4
1483	KYT	KYT	DAR	NBO	3550	3710	0	79	10
1484	KYT	KYT	NBO	DAR	3750	3920	0	15	4
1485	KYT	KYT	DAR	NBO	4010	4130	0	70	7
1486	KYS	FFK	NBO	DAR	3940	4100	0	38	5

Cont. DAY 4

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
1487	KYS	FFK	DAR	NBO	4150	4310	0	35	8
1488	KYT	KYT	NBO	DAR	4400	4530	0	58	4
1489	FFF	FFF	DAR	NBO	2610	2730	0	56	6
1498	FFF	FFF	NBO	ZNZ	4330	4440	0	66	1
1499	KYQ	KYQ	ZNZ	NBO	2630	2750	0	66	1
1502	KQE	KQE	NBO	ACC	3820	4400	0	50	4
1503	KQE	KQE	ACC	NBO	4500	5040	0	35	7
1520a	KYE	KYE	NBO	ABJ	3000	3600	0	72	6
1520b	KYE	KYE	ABJ	DKR	3650	3940	0	72	6
1521a	KYE	KYE	DKR	ABJ	4040	4330	0	72	6
1521b	KYE	KYE	ABJ	NBO	4420	5040	0	72	6
1532	CYA	CYA	NBO	LOS	2900	3400	0	90	13
1533	CYA	CYA	LOS	NBO	3530	4030	0	61	11
1542a	KQG	KQF	NBO	LOS	3900	4420	0	33	5
1542b	KQG	KQF	LOS	COO	4510	4550	0	33	5
1542c	KQG	KQF	COO	NBO	4640	5210	0	33	5
1554	KZA	KZA	NBO	FIH	2850	3220	0	73	9
1555	KZA	KZA	FIH	NBO	3340	3710	0	73	9
1584a	KQH	KQH	NBO	NLA	2930	3210	0	73	9
1584b	KQH	KQH	NLA	FBM	3300	3340	0	73	9
1584c	KQH	KQH	FBM	NBO	3430	3700	0	73	9
1600	KYP	KYP	NBO	MBA	2700	2800	0	65	3
1601	KYP	KYP	MBA	NBO	2840	2940	0	60	2
1602	FFG	FFG	NBO	MBA	2930	3030	0	84	12
1603	FFG	FFG	MBA	NBO	3110	3210	0	64	4
1604	KYP	KYP	NBO	MBA	3030	3130	0	64	4
1605	KYP	KYP	MBA	NBO	3210	3310	0	64	4
1606	FFG	FFG	NBO	MBA	3300	3400	0	84	12
1607	FFG	FFG	MBA	NBO	3440	3540	0	84	12
1610	FFG	FFG	NBO	MBA	3630	3730	0	84	12
1611	FFG	FFG	MBA	NBO	3810	3910	0	84	12
1618	FFG	FFG	NBO	MBA	4000	4100	0	76	8
1619	FFG	FFG	MBA	NBO	4140	4240	0	73	5
1622	KYR	KYR	NBO	MBA	4120	4220	0	84	12
1623	KYR	KYR	MBA	NBO	4310	4410	0	31	1
1624	KYQ	KYQ	NBO	MBA	4400	4450	0	83	12
1625	FFG	FFG	MBA	NBO	2630	2730	0	69	5
1640	KYP	KYP	NBO	MYD	3420	3520	0	59	6
1641	KYP	KYP	MYD	NBO	3610	3720	0	52	3
1650	KYR	KYR	NBO	KIS	2800	2850	0	62	4
1651	KYR	KYR	KIS	NBO	2930	3020	0	48	0
1654	KYR	KYR	NBO	KIS	3120	3210	0	55	0
1655	KYR	KYR	KIS	NBO	3250	3340	0	35	3
1656	KYR	KYR	NBO	KIS	3430	3520	0	34	1
1657	KYR	KYR	KIS	NBO	3600	3650	0	48	5
1670	KYQ	KYQ	NBO	KIS	3830	3920	0	67	3
1671	KYQ	KYQ	KIS	NBO	4010	4050	0	68	11

Cont. DAY 4

Flight nr	Tail nr	Tail nr Original	Origin	Destination	STD	STA	Delay	Economy	Business
1702a	KZD	KZD	NBO	HRE	2850	3150	0	68	11
1702b	KZD	KZD	HRE	LUN	3250	3350	0	68	11
1702c	KZD	KZD	LUN	NBO	3450	3730	0	68	11
1704a	FFD	FFD	NBO	HRE	3400	3700	0	68	11
1704b	FFD	FFD	HRE	LUN	3750	3850	0	68	11
1704c	FFD	FFD	LUN	NBO	3940	4220	0	68	11
1732a	FFC	FFC	NBO	LLW	4240	4500	0	23	2
1732b	FFC	FFC	LLW	LUN	4600	4710	0	23	2
1732c	FFC	FFC	LUN	NBO	4810	5050	0	23	2
1748	KYS	FFK	NBO	APL	3120	3350	0	22	5
1749	KYS	FFK	APL	NBO	3440	3710	0	22	5
1752a	FFJ	FFJ	NBO	LLW	3000	3210	0	22	5
1752b	FFJ	FFJ	LLW	BLZ	3250	3340	0	22	5
1752c	FFJ	FFJ	BLZ	NBO	3430	3700	0	22	5
1756	KYQ	KYQ	NBO	TNR	2940	3300	0	22	5
1757	KYQ	KYQ	TNR	NBO	3350	3710	0	22	5
1760	FFA	KYS	NBO	JNB	2730	3150	0	30	4
1761	FFA	KYS	JNB	NBO	3250	3700	0	48	9
1762	KYF	KYF	NBO	JNB	2940	3400	0	101	12
1763	KYF	KYF	JNB	NBO	3520	3930	0	104	16
1764	CYA	CYA	NBO	JNB	4130	4550	0	80	14
1861a	KZB	KZB	HKG	BKK	3740	4020	0	204	10
1861b	KZB	KZB	BKK	NBO	4130	5010	0	204	10
1882	KZF	KZF	NBO	CAN	4550	5620	0	159	11
1883	KZF	KZF	CAN	NBO	6140	7300	0	159	11
1886a	KZA	KZA	NBO	BKK	4440	5410	0	152	23
1886b	KZA	KZA	BKK	CAN	5550	5900	0	152	23

Appendix D

List of aircraft

Tail Nr.	Type	Type Short	Business	Economy	Total Pax
5Y-KYN	Boeing 737-306	B73L	16	100	116
5Y-KQC	Boeing 737-3U8(SF)	B737-Cargo	-	-	-
5Y-KQD	Boeing 737-3U8(SF)	B737-Cargo	-	-	-
5Y-KQE	Boeing 737-76N(WL)	B73W	16	100	116
5Y-KQF	Boeing 737-76N(WL)	B73W	16	100	116
5Y-KQG	Boeing 737-7U8(WL)	B73W	16	100	116
5Y-KQH	Boeing 737-7U8(WL)	B73W	16	100	116
5Y-KYD	Boeing 737-86N(WL)	B738	16	129	145
5Y-KYF	Boeing 737-86N(WL)	B738	16	129	145
5Y-KYB	Boeing 737-8AL(WL)	B738	16	129	145
5Y-KYC	Boeing 737-8AL(WL)	B738	16	129	145
5Y-CYA	Boeing 737-8HX(WL)	B738	16	129	145
5Y-CYB	Boeing 737-8HX(WL)	B738	16	129	145
5Y-KYE	Boeing 737-8Q8(WL)	B738	16	129	145
5Y-KYW	Boeing 767-319(ER)	B767	20	196	216
5Y-KQX	Boeing 767-36N(ER)	B767	20	196	216
5Y-KQY	Boeing 767-36N(ER)	B767	20	196	216
5Y-KQZ	Boeing 767-36N(ER)	B767	20	196	216
5Y-KYX	Boeing 767-3P6(ER)	B767	20	196	216
5Y-KYV	Boeing 767-3Q8(ER)	B767	24	211	235
5Y-KQS	Boeing 777-2U8(ER)	B772	28	294	322
5Y-KQT	Boeing 777-2U8(ER)	B772	28	294	322
5Y-KQU	Boeing 777-2U8(ER)	B772	28	294	322
5Y-KYZ	Boeing 777-2U8(ER)	B772	28	294	322
5Y-KZY	Boeing 777-36N(ER)	B773	28	372	400
5Y-KZZ	Boeing 777-36N(ER)	B773	28	372	400
5Y-KZX	Boeing 777-3U8(ER)	B773	28	372	400
5Y-KZA	Boeing 787-8 Dreamliner	B788	30	204	234
5Y-KZB	Boeing 787-8 Dreamliner	B788	30	204	234
5Y-KZC	Boeing 787-8 Dreamliner	B788	30	204	234
5Y-KZD	Boeing 787-8 Dreamliner	B788	30	204	234
5Y-KZE	Boeing 787-8 Dreamliner	B788	30	204	234
5Y-KZF	Boeing 787-8 Dreamliner	B788	30	204	234
5Y-KYH	Embraer ERJ-170LR (ERJ-170-100 LR)	E70	8	64	72
5Y-KYJ	Embraer ERJ-170LR (ERJ-170-100 LR)	E70	8	64	72
5Y-KYK	Embraer ERJ-170LR (ERJ-170-100 LR)	E70	8	64	72
5Y-KYG	Embraer ERJ-170STD (ERJ-170-100)	E70	8	64	72
5Y-KYL	Embraer ERJ-170STD (ERJ-170-100)	E70	8	64	72

Tail Nr.	Type	Type Short	Business	Economy	Total Pax
5Y-FFA	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-FFB	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-FFC	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-FFD	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-FFE	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-FFF	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-FFG	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-FFH	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-FFJ	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-FFK	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-KYP	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-KYQ	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-KYR	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-KYS	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96
5Y-KYT	Embraer ERJ-190AR (ERJ-190-100 IGW)	E90	12	84	96

Appendix E

Airport List

Code	City	Country	Code	City	Country
ABJ	Abidjan	Côte d'Ivoire	HAH	Moroni	Comores
ABV	Abudja	Nigeria	HKG	Hong Kong	Hong Kong
ACC	Accra	Ghana	HRE	Harare	Zimbabwe
ADD	Addis Abbaba	Ethiopia	JED	Jeddah	Saudi Arabia
AMS	Amsterdam	The Netherlands	JIB	Djibouti	Djibouti
APL	Nampula	Mozambique	JNB	Johannesburg	South Africa
BGF	Bangui	Central African Republic	JRO	Kilimanjaro	Tanzania
BJM	Bujumbura	Burundi	JUB	Juba	South Sudan
BKK	Bangkok	Thailand	KGL	Kigali	Rwanda
BKO	Bamako	Mali	KIS	Kisumu	Kenya
BLZ	Blantyre	Malawi	KRT	Khartoum	Sudan
BOM	Mumbai	India	LAD	Luanda	Angola
BZV	Brazzaville	Congo	LHR	London	United Kingdom
CAI	Cairo	Egypt	LLW	Lilongwe	Malawi
CAN	Guangzhou	China	LOS	Lagos	Nigeria
CDG	Paris	France	LUN	Lusaka	Zambia
COO	Cotonou	Benin	LVI	Livingstone	Zambia
DAR	Dar Es Salaam	Tanzania	MBA	Mombasa	Kenya
DEL	Delhi	India	MPM	Maputa	Mozambique
DKR	Dakar	Senegal	MYD	Malindi	Kenya
DLA	Douala	Cameroon	NBO	Nairobi	Kenya
DXB	Dubai	United Arab Emirates	NDJ	N'djamena	Chad
DZA	Dzaoudzi	Comores	NLA	Ndola	Zambia
EBB	Entebbe	Uganda	NSI	Yaoundé	Cameroon
EDL	Eldoret	Kenya	OUA	Ouagadougou	Burkina Faso
FBM	Lubumbashi	DR Congo	ROB	Monrovia	Liberia
FIH	Kinshasa	DR Congo	SEZ	Mahe Island	Seychelles
FKI	Kisangani	DR Congo	TNR	Antanavarivo	Madagascar
FNA	Freetown	Sierra Leone	ZNZ	Zanzibar	Tanzania
GBE	Gaborone	Botswana			

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