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A Model for aircraft recovery problem

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the dissertation contains no material previously published or written by another person except where due reference is made in the thesis itself.

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ABSTRACT

In the airline industry, a myriad of uncertain events take place that lead to the disruption of original flight schedules. Such events include mechanical failure, technical challenges, weather changes, airport and crew related issues. Airlines therefore need a robust, dynamic way of recovering their schedules during disruptions in order to remain profitable. In recovery scenarios, aircraft recovery is given the highest priority since aircraft are the scarcest and most utilised resources in the airline.

A mathematical model for airline schedule recovery that recovers aircrafts was presented in this study. The model is based on defining a recovery scope once a fleet of aircraft has been disrupted. The model examines the possibility of delaying the flights for a short period, reassigning aircraft, ferrying aircraft and also cancelling flights. The objective of the model is to minimise costs associated with assigning a different aircraft to the disrupted flight leg, delay costs, cancellation costs for business class passengers, cancellation costs for economy class passengers and ground costs. This study uses real time data from Kenya Airways to test the proposed model. A decision support system was then developed and deployed to the Integrated Operations Control Centre in Kenya Airways for use by the duty managers to come up with optimal solutions with the least cost implications to the airline.

Keywords: airlines, disruptions, mathematical model, aircraft recovery

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ABBREVIATIONS

AEV	Adaptive Evaluated Vector
AOCC	Airline Operations Control Centre
API	Application Programming Interface
ATC	Air Traffic Controller
CG	Column Generation
CQMIP	Conic Quadratic Mixed-Integer Programming
DMO	Duty Manager Operations
DPM	Disrupted Passenger Metric Model
DSS	Decision Support Systems
GRASP	Greedy Randomised Search Procedure
IOCC	Integrated Operations Control Centre
KQ	Kenya Airways
MINLP	Mixed-Integer Non-Linear Programming
PDM	Passenger Delay Model
RTIMS	Real-Time Intermodal Substitution
UML	Unified Modelling Language
US	United States of America

CHAPTER 1 : INTRODUCTION

1.1 Background of Study

1.1.1 Introduction

The airline industry is a key beneficiary of advanced optimisation technologies. Great research and advances have been made in areas such as optimal scheduling, dynamic ticketing, crew assignment, revenue management and other areas alike (Chan et al., 2013). Most operational airlines have thus come up with optimised solutions during the planning phase. Optimised flight schedules are prepared months before the actual flight date. However, when in the operations phase, a myriad of disruptions are experienced in the airline routine caused by factors such as crew delays, passenger delays, aircraft mechanical issues, weather, airport related disruptions and much more. Such disruptions impose both hard and soft costs to the airline. Hard costs include costs of cancelling flights, passenger rebooking, compensation and costs of recovery while soft costs are related to customer experience (Cook et al., 2012).

1.1.2 Basic Concepts

A *flight schedule* is defined as a set of all the flight legs that an airline operates for a defined period of time. Flights in the schedule are defined by their flight number, destination and origin airports, flight dates, departure and arrival times. An aircraft can have a *rotation* which is a set of flights that are assigned to it. In order to have a complete rotation, the destination hub or airport of a flight must be the origin airport of the next flight and difference between the arrival time of the first flight and departure time of the second flight must be larger than or equal to the turnaround time (Bisaillon et al. 2010). *A hub and spoke network* consists of a central airport where flights are routed through and spokes are the connecting airports that link up to the hub.

A *flight leg* is a direct flight from an origin airport to destination airport. A *multi-leg flight* is a series of flight legs sharing the same flight number and operated sequentially by the same aircraft. An *aircraft fleet* is a set of all aircraft that an airline operates. Each aircraft in the fleet is described by model, unique identification number and cabin configuration. Aircraft of the same model have similar operational features such as turn-around time, transit time, range and they are grouped into families. The allocation of seats between the various classes define the cabin configuration of an aircraft.

A *flight block time* is defined as the time when a plane leaves a gate at the departure airport till it arrives at the gate of the arrival airport. A *flight ground time* is the time from when the aircraft and crew are ready for departure until the time the aircraft takes off. A *disruption,* in airlines is considered a perturbation to the planned flight schedule.

Each aircraft has a unique registration number always written on its tail, referred to as *Tail number*. *Reserve aircraft* in an airline implies the availability and utilisation of spare aircraft. *Swapping aircraft* means exchanging aircraft with other aircraft based on situations such as exchanging aircraft that have later assignments with aircraft that have earlier broken assignments. Swapping aircraft could also be referred to as *tail switching* which is switching an aircraft to fly a different route that was assigned to another aircraft. *Ferrying aircraft* means flying an empty aircraft to an airport where the aircraft is needed to carry out an assignment. *Delaying flight* schedules involves providing new arrival and departure times based on the readiness/availability of the affected aircraft. *Cancellation* is the last resolve an airline could take if no recovery solution is forthcoming within a reasonable time. In the event of a flight cancellation, the airline rebooks its passengers onto the next flights or other airlines or looks for alternative ways of transporting the passengers.

Operation costs are the costs an airline incurs to successfully cover a flight. Such costs include fuel, navigation, landing, taxing, taking off and crew wages. *Hard costs* are the quantifiable costs that an airline will incur as a result of disruption. These costs include delay costs, reassignment, passenger compensation, fines, rebooking and accommodation of passengers in case a flight is cancelled. *Soft costs* are defined by the unquantifiable costs that an airline incurs as a result of the perception formed about it by the disrupted passengers. This is based on the impact the airline disruption had to the passenger schedule.

1.1.3 Disruptions in the Airline Industry

Disruptions are grouped into three broad categories: schedule (flight), aircraft and airport disruptions. In flight disruption, a scheduled flight is either delayed or cancelled. An aircraft disruption occurs when an aircraft scheduled for a flight is unavailable temporarily or permanently. An airport disruption occurs when the arrival and departure capacities of an airport are interfered with. However, it is important to note that these three disruptions could occur in isolation or concurrently.

This research focused on flight schedule and aircraft disruption, commonly referred to as "The Flight Perturbation Problem" by Granberg & Värbrand (2004). A disruption in the aviation industry is caused by a myriad of reasons. Some reasons include:

Aircraft Malfunction: Airline uphold safety highly such that anything that seems to threaten the safety of a flight has to be resolved immediately. This causes unavailability of the affected aircraft causing a disruption.

Absent Crew: This could be due illness, delays from other flights and many other reasons.

Unpredictable weather conditions: Conditions such as fog, powerful headwinds, icing on the runway cause departure delays and in severe cases they lead to airport close down.

Air Traffic Controller related issues: The air traffic control authorities could interfere with airline plans due to several reasons such as delaying departure and arrival times of aircraft due to holding patterns, security related issues, landing clearance by heads of states and many other reasons.

In case a disruption occurs, the Airline Operations Control staff have options to manage the disruption process.

Delaying: Delaying departure of a flight affects the passengers on that flight leg and the subsequent flight legs that are dependent on that aircraft or crew.

Swapping: This is the process of assigning an aircraft to a route that was not its original. Swapping increases complexity of the problem to be solved when a swap is made to an aircraft of another fleet type. It may also lead to issues in crew planning since most crew members are certified to operate one aircraft type at a time (Liu et al., 2010).

Cancelling Flights: This is the most extreme option from the passenger's point of view. Cancelling a flight has a ripple effect to the flight legs assigned to the aircraft.

Positioning: This is flying aircraft without passengers between two airports. Happens when an aircraft needs to be at a certain airport at a particular time.

In cases of disruptions, the Airline Operations Control Centre uses a Decision Support System to bring operations back to normalcy. The recovery process is normally handled in three stages. The first stage is on aircraft recovery where aircraft are rerouted, some flights delayed and others cancelled. The second stage involves the crew where the airline can reroute crew members to other flight legs and also call in standby crew. The final stage involves passenger recovery where passengers are rescheduled to the next available flights.

1.1.4 Current Trends in the Airline Industry

On-Time performance is a key element when grading airline performance. Ryanair prides itself as one of the most punctual airline in the European Union with 90% of its 550,000 flights arriving on time between 2015 and 2016 (RyanAir, 2017). Passengers are informed of this every time a Ryanair aircraft touches down with a cheerful jingle that says, "Last year over 90% of Ryanair flights landed on time, beating every other European airline" (McDonald, 2013).

In the United States, Delta Airlines emerged the winner on On-Time Performance posting an on-time arrival rate of 89.6% of the 158,934 flights flown in the month of October 2016 (Vanessa, 2016). On flight cancellations in the US, American and United Airlines recorded the largest number with 1.3% of flights being cancelled. Southwest Airlines had the second least cancellations with 0.3% of their flights being cancelled in May 2016. Delta Airlines on the other hand had the least cancellations spanning to 0.1% of its flights being cancelled in May 2016 (Lazare, 2016). According to the U.S Department of Transportation, the reporting airlines in posted a drop in on-time arrival rate of 76.0% in January 2017 from 81.3% in January 2016. According to FlightGlobal (2017), in the Middle East and African region, Kenya Airways came fourth in On-Time Performance with 74.11% in 2016. Qatar Airways was ranked the first airline with 86.34% followed by Saudi Arabian Airlines with 79.92%.

1.2 Problem Statement

For an airline operating in a hub-and-spoke network, a disruption in any node causes a subsequent ripple effect to the entire airline network. It is expected that at the end of the recovery period, all affected aircraft and schedules should resume to normal. In the industry, it is almost impossible for an airline to avoid disruptions since they are always unplanned, and sometimes beyond human control. This calls for a mechanism to manage schedules to accommodate subtle disruptions. However, regardless of incorporating a time slack in the schedule, some disruptions extend way beyond the slack. Since aircraft are the scarcest resources in any airline, it is very important that a recovery mechanism be put in place in case an aircraft disruption occurs.

Currently, schedule recovery done in Kenya Airways is highly dependent on tacit knowledge of the operations control centre staff. The Integrated Operations Control Centre in the airline is designed in a manner where the Duty Operations Manager is at the centre of the room surrounded by other IOCC staff members who offer him updated information which will orient his decision making on the recovery problem (Vos, 2014). This leads to a slower recovery process since the process is not automated. In the end, the number of cancelled flights that the airline records are high which affects its reputation. A model that is able to offer optimised solutions with least cost impact to the airline in real time is highly desirable.

1.3 Research Objectives

The objectives of this research are:

i. To understand the challenges faced by airlines during the aircraft recovery process.
ii. To adapt a suitable mathematical model that optimises the aircraft recovery problem.
iii. To design, develop and test a system that implements the mathematical model.
iv. To validate the effectiveness of the developed system.

1.4 Research Questions

i. What challenges do airlines face in recovering aircraft schedules during a disruption?
ii. What are the current industry models in use to recover aircraft in cases of disruptions?
iii. How can a system be developed to effectively handle the aircraft recovery problem?
iv. Does the system optimise recovery of disrupted aircraft schedules?

1.5 Justification of the Research

Disruptions in airlines are inevitable and every airline has to deal with them as they occur. In order to reduce the delays and passenger inconveniences caused by disruptions, a recovery model that solves the aircraft recovery problem in the shortest time is desirable. This model will also enable the airline reduce costs associated with cancelling flights and ensure that schedules are returned to normalcy. In the end, the airline in focus will record an improvement in on-time performance which has a direct implication on its profits.

1.6 Scope of the Research

The research will entail the study of the operations research in the airline industry, the platforms used to solve recovery problems. The target industry for this study will be the airline industry, working with real data from Kenya Airways, Kenya's carrier. The model research is intended to operate in any other airline with a capacity such as the airline in this case study.

1.7 Limitations of the Research

This research focuses on aircraft recovery, working with real-time data as provided by an airline in Kenya. This means that the research will be limited to the fleet of the airline and the airline’s flight schedules. The size of the airline will also be a determining factor on the model size and applicability to other similar airlines.

CHAPTER 2 : LITERATURE REVIEW

2.1 Introduction

This literature review gives a background of how schedule recovery models have evolved over the past years. Section 2.2 discusses relevant literature in aircraft recovery. Section 2.3 focuses on attempts by previous researchers to solve the airline integrated recovery problem. Finally, section 2.4 presents brief conclusion and areas of further research.

2.2 Aircraft Recovery

Pioneer researchers on airline disruptions in schedule recovery focused on aircraft recovery. A reason could be that aircraft are the scarcest resources in an airline and also the rules that determine airline schedules are straight forward Clausen et al. (2010). Various approaches to solve the aircraft recovery problem have been presented in literature. This section categorises the problem solving approaches used in literature based on the network representation models that were developed.

2.2.1 Connection Network

The initial study of airline schedule recovery is dated to the 1980s. Teodorović & Guberinić (1984) were the first pioneers of this research who solved the problem of determining a new routing and scheduling plan after a disruption by using branch and-bound methods, with the goal of minimising total passenger delays. By this time, recovery of aircraft in the industry was small scale and involved recovering single fleet at a time. An extension of this work was presented by Teodorović & Stojković (1995), where the goal was to minimise the total number of cancelled flights and total passenger delays. They developed a heuristic algorithm and a sequential approach that enabled crew considerations. The algorithm was then tested on numerical examples.

In 2003, an optimisation model that reschedules flight legs and reroutes aircraft was presented by Rosenberger et al. (2003). The model was based on minimising an objective function to reduce rerouting, delay and flight cancellation costs. A heuristic model was then developed that selected the aircraft to be rerouted and evaluated using a simulation of airline operations. The model was further revised to minimise crew and passenger disruptions.

2.2.2 Time Line Networks

Time-line Networks base their implementation on the use of ground arcs, flight arcs and overnight arcs. Jarrah et al. (1993) presented two network flow models for minimum cost when cancelling and delaying flights after a disruption. Their decision support framework was to enable flight controllers decide when to cancel or delay flights. The possibility of swapping aircraft during the recovery period was considered where the swaps could involve spare aircraft or overnight layovers. The timeline network in this case had two node types (aircraft node and flight node) per station used to model the assignment of aircraft to flights. The research tested cases for both minor and major disruptions. The test scenarios were based on United Airlines' Boeing 737 fleet and a regional subdivision of America.

Yan & Yang (1996) developed a model that combined flight delays, cancellations and ferrying that solved the perturbations of flight schedules using a time-space network flow model. Their model used simplex method to solve pure network flow problems and Lagrangian relaxation with sub-gradient methods solved the network flow problems with side constraints. Their paper presented four variations of the model, two of which are pure network flow problems while the other two are network flow problems with side constraints. Whereas Yan & Yang (1996) focused on a single fleet, Yan & Tu (1997) advanced it to accommodate multiple fleet. Their model was further extended to address cases of airport closures and multiple aircraft fleet substitutions for a network that consisted of 24 cities, 7 fleets and 273 flights with computation time below 30 minutes.

Thengvall et al. (2000) presented a model that incorporates the concept of a protection arc where deviations from the planned schedules are penalised in the objective function allowing specification of preferences related to the recovery operations by human planners. This model aimed at reducing passenger satisfaction during reassignment of multiple flights. Real data from Continental Airlines was used. Computational results for the model were presented after schedule recovery of two homogenous fleets consisting of 16 Boeing 737's at 13 stations and 27 Boeing 737-100's at 30 stations. The model was run separately in the two fleets. Results from the computations indicated a different schedule generated when changes are introduced in the cost function, in variables such as cost of delay, cancellation and schedule deviation costs.

2.2.3 Time Band Networks

A time-band chart is defined as a chart containing two dimensions representing time intervals and airport stations respectively. In the early 2000's, the concept of time-band networks had started to take root in the research arena.

To further an initial study done by Thengvall et al. (2000), a three multi-commodity flow model based on a time- band network was presented by Thengvall et al. (2001). The model integrated cancellations, flight delays, fleet substitution, peculiar deviations to solve aircraft recovery problem in the case of a hub closure. The model consisted of three cases, the first was a pure network with side constraints, the second a generalised network and the last was a pure network with side constraints where the time horizon is discretised. The first two cases aimed at maximizing the profit function while the other cases aimed at reducing the sum of delay and cancellation costs. Computational results for a fleet of 322 aircraft divided into 12 fleets and 2921 flights was provided. After a comparison was done on computational times and solution quality of the three models, the first outperformed the others and further analysis on it was carried out. Bard et al. (2001) and Argüello et al. (1997) further advanced the time-band idea network solving the single fleet aircraft recovery problem.

2.2.4 Constraint Specific Network

Eggenberg et al. (2010) presented a modelling framework to solve aircraft recovery by allowing consideration of operational constraints within the Column Generation (CG) scheme. This column generation algorithm solved aircraft recovery problem considering maintenance planning. A time-band recovery network was constructed for each aircraft to facilitate incorporation of maintenance constraints by introducing a maintenance arc. Data generated from a real instance with 10 aircraft and 7 days maximum recovery period produced scenarios for up to 250 flights. This was an indication of the method's capability to recover the proposed disruption cases.

2.2.5 Integer Programming

In their paper, Andersson & Värbrand (2004) developed a Mixed Integer Multi-Commodity Flow model with side constraints. The model was then reformulated to a set packing model using the Dantzig-Wolfe decomposition. Their approach was based on delay management with a purpose to maximise the revenue from ticket selling. The model uses two column generation schemes to solve the model heuristically and it is tested on real data from a Swedish domestic airline. Computational tests and results show the capability of the model to provide quality optimised solutions in seconds thus recommended for industrial use.

Hu et al. (2011) presented a conference paper on aircraft recovery problem considering passenger delay, transiting and cancellation costs. In their paper, the authors developed an Integer Programming model based on the time-band network for aircraft rescheduling corresponding with passenger recovery. Solutions for single-fleet aircraft recovery were reached at by solving the linear programming relaxation then applying the rounding Heuristic Algorithm, which were then checked by the practical data. This model was tested with data that consisted of 16 aircraft and 70 flights.

2.2.6 Heuristics in Aircraft Recovery

A steady growth in aircraft recovery research led to the use of Heuristics and Metaheuristic. Argüello et al. (1997) presented a heuristic based Greedy Randomised Search Procedure (GRASP) that reconstructs aircraft routes in the occurrence of delays and aircraft groundings. Performance evaluation involved comparing the GRASP results with those from a lower bounding optimisation-based time-band network model. This model was evaluated with Boeing 757 fleet data from Continental Airlines. The method proved to be effective for some medium sized instances up to 162 flights operated by 27 aircraft.

Babić et al. (2010) presented a Decision Support System (DSS) based on a heuristic algorithm which generates a list of feasible recovery schedules based on the value of an objective function. Priority flights are defined and taken into account by addition of an unplanned flight. From the list of feasible solutions, the flight dispatcher selected and implemented one of the solutions. Løve et al. (2005) presented optimisation methods that based on local search operating on a network model. In the network, flight nodes and aircraft are defined separately. Assignment of an aircraft to a given flight was performed by selecting an edge that connects the two nodes. Data used in this model was randomly generated.

Liu et al. (2010) implemented a hybrid multi-objective genetic algorithm to try find solutions for a daily short-haul aircraft schedule recovery problem. The proposed algorithm implemented an Adaptive Evaluated Vector (AEV) to guide the search for the solution and the method of inequality-based multi-objective genetic algorithm to provide a multi-objective solution. A simulation entailing disturbance experiment, temporal airport closure was done and the hybrid method provided an efficient short-haul schedule recovery solution.

2.2.7 Advantages of Aircraft Recovery

This section describes the advantage of considering aircraft recovery in isolation in cases of disruptions. They can be summarised as:

i. Tends to be faster when generating solutions since the number of computations are lesser than in integrated recovery.
ii. The airline tends to focus on the scarcest resource (aircraft) while giving lower priority to the other parts (crew and passengers).

2.3 Integrated Airline Recovery Problem

Integrating recovery of airline aircraft, passengers and crew has always been a difficult task due to the size of the problem. Solutions generated from previous attempts have not been feasible to be used in the real time environment. This led to solving the recovery problem by isolating aircraft, crew and passenger recovery.

This section describes different approaches in literature to solve the integrated recovery problem. Section 2.3.1 focuses on integrated recovery of aircraft and passengers while section 2.3.2 covers relevant literature in integrated aircraft, crew and passenger recovery.

2.3.1 Integrated Aircraft and Passenger Recovery

Zhang and Hansen (2008) proposed the use of ground transportation of passengers as a solution to passenger recovery during disruptions in a hub and spoke network to substitute flights. This strategy, referred to as Real-Time Intermodal Substitution (RTIMS), used mathematical programming to help airlines decide how to delay, cancel or substitute flights with buses. A proposed approximation algorithm provided solutions avoiding substantial computation time required to solve non-linear integer programming. A numerical scenario for a four-hour recovery period consisting of 40 flights and 736 passengers was evaluated. After substituting transport, results showed a massive decrease in cost since the number of disrupted passengers dropped.

Jafari and Zegordi (2010) presented a mathematical model that simultaneously recovered airline schedules by recovering disrupted aircraft and passengers. The model integrated the recovery scope (the length of the recovery period) and used aircraft rotations and passenger itineraries instead of flights. The model examined possible aircraft swapping, ferrying, flight re-timing, passenger reassignment, utilisation of reserve aircraft cancellation and ferrying to generate a feasible recovered schedule. Its parameters were user specific therefore helping airlines apply their policies in the model. Outlining the recovery scope reduced the problem size ensuring the schedule resumed to normal within a certain time. The overall objective of the model was to reduce costs associated with flight cancellation, aircraft recovery, and passenger disruption related costs. A data set consisting of two disruption scenarios was used to evaluate the model. The data set contained 13 aircraft divided into 2 fleet, 100 flights, 19 airports and 223 passengers with 8 itineraries and 55 connections. The computational results were compared by those obtained by Granberg & Värbrand (2004) whose research was on aircraft recovery.

Bisaillon et al. (2010) presented a large neighbourhood heuristic for airline schedule recovery problem that combines fleet assignment, aircraft routing and passenger assignment with a goal to minimise operating costs and passenger disruption impact. The heuristic consisted of three phases, construction phase, repair phase and improvement phase. The first two phases aimed at producing an initial solution that satisfied a set of operational and functional constraints. The third phase then tried to identify an improved solution by considering the dynamism of the schedule changes while retaining original feasibility. An iteration of the whole process took place incorporating some randomness in the construction phase so as to diversify the search. Figure 2.1 demonstrates a summary of the three phases the model presented.

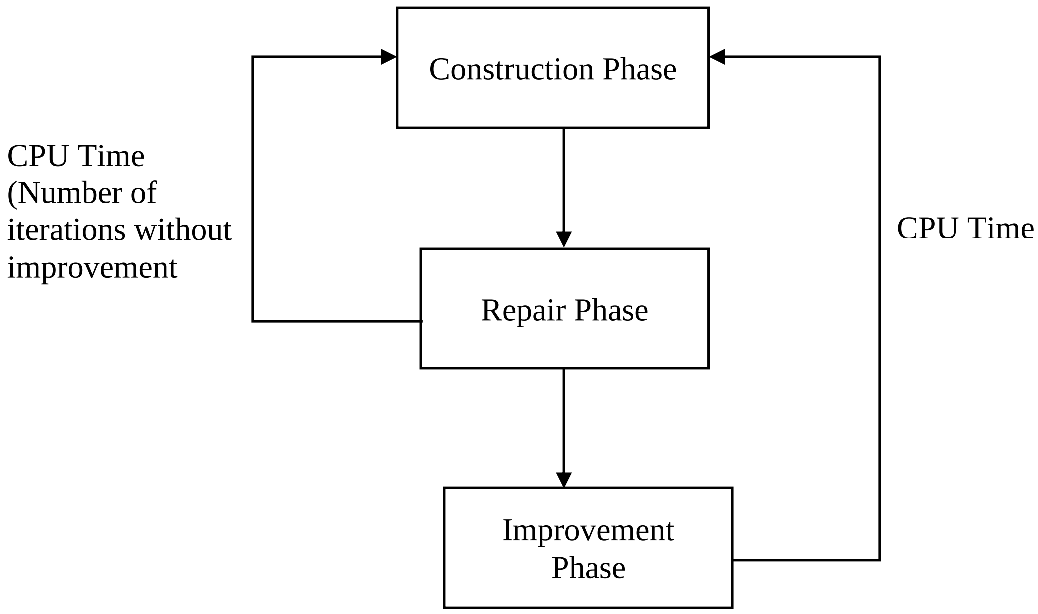

Figure 2.1 Solution Method as Given by Bisaillon et al. (2010)

In each iteration, priority was given to the generation of optimal aircraft routes then passenger itineraries are updated based on the new routes. This work won the first prize in the 2009 ROADEF Challenge, organised by the French Operational Research and Decision analysis.

This solution was improved by Sinclair et al. (2014) where they included additional steps in each phase to make it more time efficient and cost effective. The improved algorithm found 17 best solutions for 22 instances within a time limit of 10 minutes. These improvements offered a better understanding of the relation between the cost of delay and the cost of cancelling a flight. Figure 2.2 depicts the additional improvements as presented by Sinclair et al. (2014).

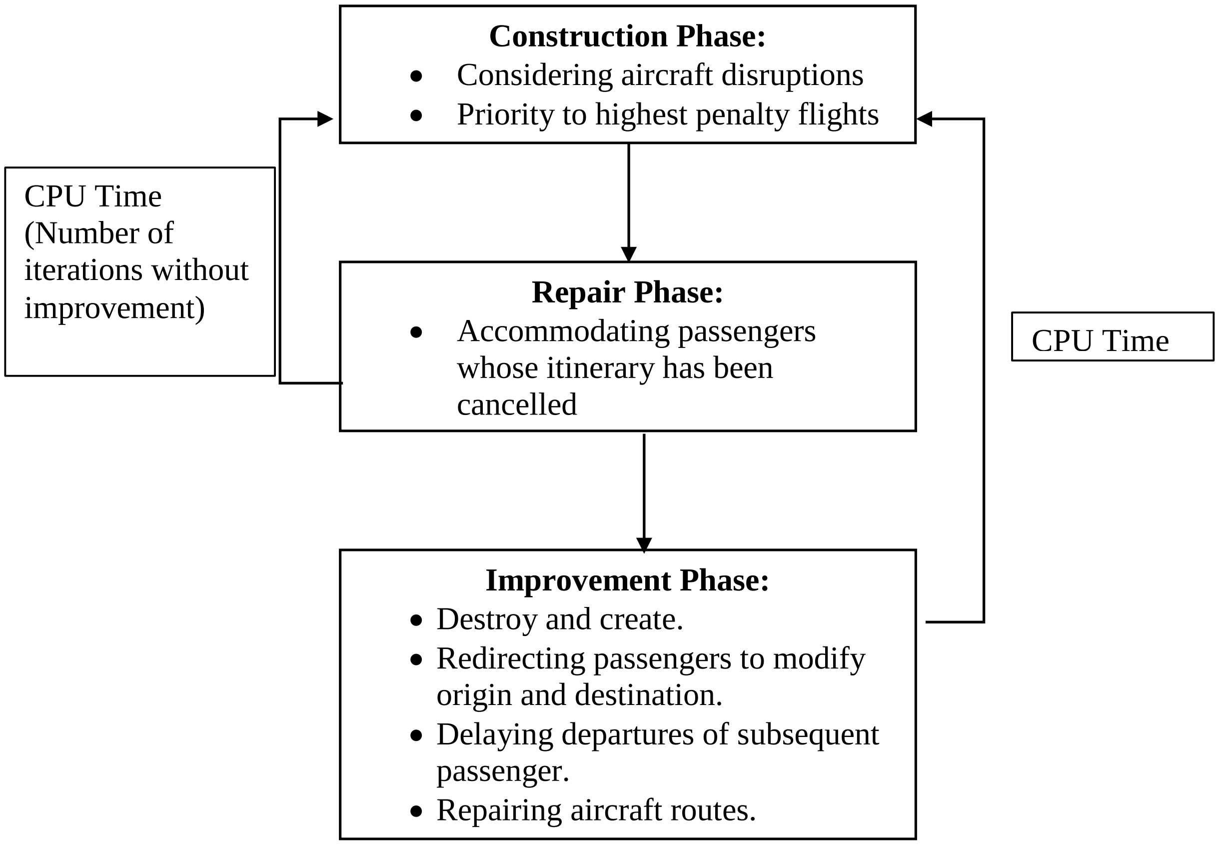

Figure 2.2 Improved Solution Presented by Sinclair et al. (2014)

Arikan et al. (2013) presented a mathematical model for integrated aircraft and passenger recovery by superimposing aircraft and passenger itinerary networks. Cruise speed control was considered to mitigate delays. This was used when trying to mitigate delays and balance fuel consumption. The problem was formulated as a Mixed-Integer Nonlinear Programming (MINLP) model and solved with IBM ILOG CPLEX, an optimisation commercial software. The authors also demonstrated that the problem could be reformulated as a Conic Quadratic Mixed-Integer Programming (CQMIP) problem and still solved with CPLEX. The computational experiments showed that the model could handle simultaneous disruptions optimally on a four-hub network within an average time of less than a minute.

Chan et al. (2013) proposed a formulation to route suitable aircraft to operate rescheduled flight legs and simultaneously generate corresponding itineraries for disrupted passengers. Through the proposed algorithm, it was expected that airlines would reassign suitable aircraft to flights in an effort to manage disruptions within a short period of time. The costs in consideration in this model was the cost of late arrivals and inconvenience costs when transferring passengers to other airline. However, no feasible solution was offered.

2.3.2 Integrated Aircraft, Crew and Passenger Recovery

In 2006, Bratu & Barnhart (2006) presented airline schedule recovery models to simultaneously develop recovery plans for aircraft, passengers and crew by determining which flight legs to postpone and which to cancel. The objective was to minimise jointly airline operation costs, disruption costs and estimated passenger delay. The models were abbreviated DPM and PDM and were based on the time-band network model developed by Bard et al. (2001). In DPM, approximate delay costs are considered together with passenger disruption costs while in PDM, delay costs are accurately computed by explicit modelling of passenger disruptions and recovery options. The model was tested using an Airline Operations Control simulator with flight information from a major US carrier. The test data included 4 aircraft types with a total of 302 aircraft, 74 airports and 3 hubs, together with 83,869 passengers following 9,925 itineraries daily. The decision model demonstrated its applicability in the real-world scenario and decisions generated from this model potentially reduce airline operating costs.

2.3.3 Advantages of Integrated Airline Recovery

Integrated aircraft recovery is desirable due to the following advantages:

i. Ability to consider passenger itinerary when recovering the schedule. This has an implication of prioritising customer experience thus reducing the soft cost that will be incurred.
ii. All factors are considered in a single computation leading to higher chances of accurate solutions.

2.3.4 Disadvantages of Integrated Airline Recovery

i. It is a slower process due to the increased complexity.

Table 2.1 depicts a summary of the advances in literature to solve the aircraft recovery problem.

Year	Authors	Network Model	Objective Function	Solution Approach
1984	Teodorović & Guberinić	CN[1]	**Min**: passenger delay	Branch & Bound
1993	Jarrah et al.	TLN[2]	**Min**: Delay, swap and cancellation costs	Busacker-Gowen's Dual algorithm.
1995	Teodorović & Stojkovic	CN	**Min**: Total number of cancelled flights and passenger delays	Greedy Heuristics Goal programming
1996	Yan and Yang	TLN	**Max**: Revenue	Lagrarian relaxation
1997	Cao and Kanafani	TLN	**Max**: Revenue	Quadratic programming
1997	Argüello et al.	TBN[3]	**Min**: Rerouting and cancellation costs	Greedy Randomised Adaptive Search Procedure (GRASP)
1997	Lou and Yu	Integer Programming	**Min**: Flight delays for more than 15 minutes	LP Relaxation[4]
2000	Thengvall et al.	TLN	**Max**: Revenue	LP Relaxation, Rounding Heuristic
2000	Bard et al.	TBN	**Min**: Delay and Cancellation costs	LP Relaxation , Branch and Bound
2003	Rosenberger et al.	CN	**Min**: Rerouting, delay and cancellation costs	Aircraft Selection Heuristic
2004	Anderson and Varbrand	Mixed Integer Programming	**Max**: Revenue Costs	Column Generation
2010	Jafari and Zegordi	Mixed integer Programming	**Min**: Operating, Cancellation and passenger inconvenience costs.	
2010	Eggenberg et al.	CSN[5]	**Min**: Operating, Cancellation, passenger inconvenience costs	Column Generation Dynamic Programming
2011	Hu et al.	Interger programming	**Min**: Passenger Delays, transiting and cancellation costs	Linear programming relaxtaion rounding heuristc algorithm

Table 2.1 Summary of Aircraft Recovery literature

[1] CN: Connection Network
[2] TLN: Time-Line Network
[3] TBN: Time-Band Network
[4] LP Relaxation: Linear Programming Relaxation
[5] CSN: Constraint Specific Network

Table 2.2 is a summary of the advances in literature to solve the integrated airline recovery problem.

Year	Authors	Objective Function	Solution Approach
		Integrated Aircraft and Passenger Recovery	
2008	Zhang and Hansen	**Min**: Passenger inconvenience costs	Real-Time intermodal Substitution (RTIMS)
2010	Jafari and Zegordi	**Min**: Flight cancellation, Aircraft recovery, passanger disrution related costs	
2010	Bisaillon et al.	**Min**: Total number of cancelled flights and passenger delays	Heuristics
2013	Chan et al.	**Min:** Disruption associated costs	
2013	Arikan et al.	**Min:** Delays	MINLP IBM ILOG CPLEX Optimisation
2014	Sinclair et al	**Min**: Total number of cancelled flights and passenger delays	Heuristics
		Integrated Aircraft, Crew and Passenger Recovery	
2006	Bratu & Barnhart	**Min**: Airline operation costs, disruption costs, total passenger delays	DPM &PDM

Table 2.2 Summary of Integrated Airline Recovery Problem Literature

2.4 Conclusions

From above sections, it is evident that there has been extensive growth in disruption management for the airline industry in the last decade, coupled with the introduction of commercial tools to aid in disruption management. However, the airline industry demands more capability from the available commercial tools making this an area of interest to research. While reviewing the different techniques that have been presented in literature, different methods could be used to solve the aircraft recovery problem. However, the use of time-band networks as presented by Bard et al. (2001), Thengvall et al. (2003) and Eggenberg et al. (2007) provide computation times that can be adapted for real life situations. This study found mathematical models presented by Vos (2014) and Jafari & Zegordi (2010) useful. Jafari & Zegordi (2010) minimise assignment, delay, cancellation, passenger reassignment, cost of refund to disrupted passengers' itinerary and cost of passengers who are not reassigned. Vos (2014) considers minimising costs of operation to which a recovery aircraft is assigned, costs of delay, costs of cancellation for passengers with economy tickets and the ground costs for where an aircraft is when the disruption occurs.

This study proposes an improved model to the existing models which considers the different passenger itinerary in its recovery process. Further, the researcher intended to fill the gap in the industry which is characterized by lack of an implemented model that offers optimal aircraft recovery solutions in feasible time frames.

CHAPTER 3 : RESEARCH METHODOLOGY

3.1 Introduction

This chapter discusses the methodology the research used to answer the research questions.

3.2 Agile Software Development Methodology

Agile Methodology is an industry standard methodology applied to produce high quality software in a shorter period of time. This approach offers an opportunity to build software while keeping user requirements in mind. The methodology involves a highly iterative process, effective communication and stakeholder collaboration during the system development phases allowing productivity in short periods of time, Rover et al. (2014).

This methodology will be considered for this research due to the following reasons:

- Agile Methodology can accommodate evolving user requirements.
- This methodology also allows continuous modification, according to feedback received from the user.
- Unlike other software development methodologies, agile enables development teams stay competitive throughout long projects.
- Agile methodology enables a faster time to market strategy.

Agile Methodology has five major phases which include planning, requirements analysis, design, development and testing, Rover et al. (2014). Figure 3.1 depicts the phases of Agile Methodology and the subsequent iterations involved during the software development lifecycle.

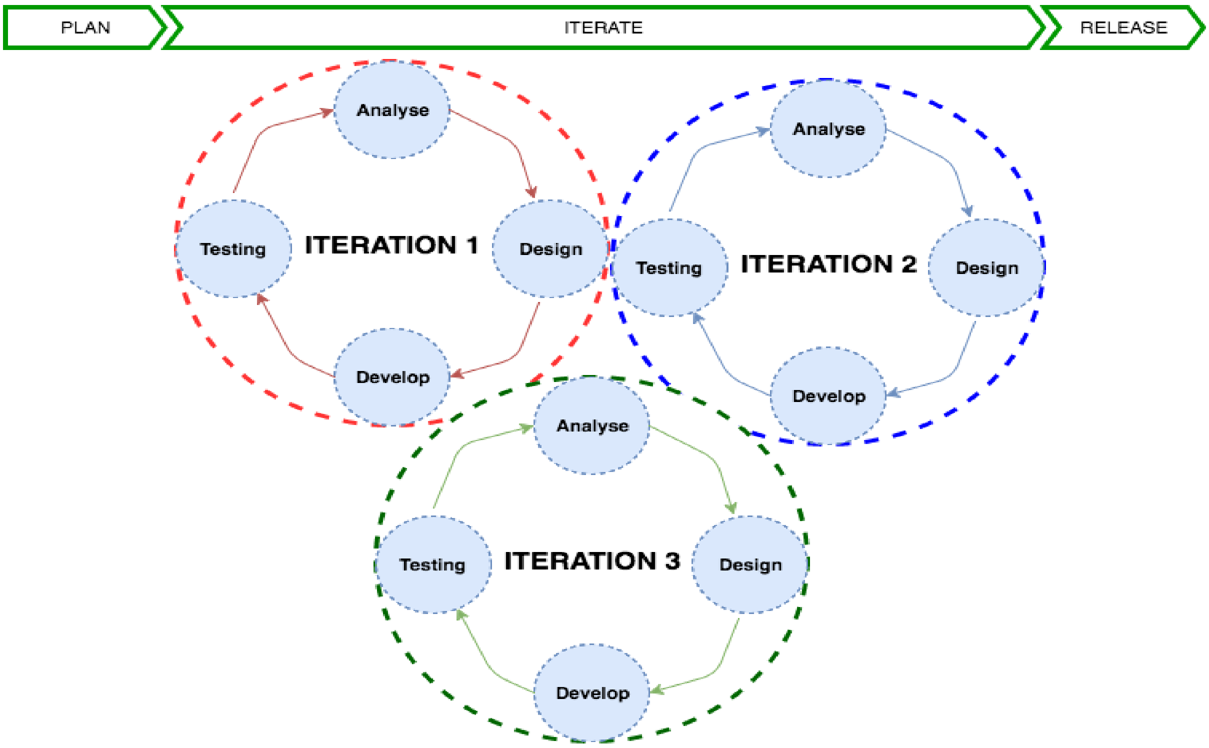

Figure 3.1 Agile Methodology Steps by Rover et al. (2014)

3.2.1 Planning Phase

The planning phase was the initial phase of the software development lifecycle and it was kept at a very high level. The major goal of this step was to outline the project scope (Duka, 2013).

3.2.2 Requirements Analysis Phase

This phase involved understanding what the system was expected to accomplish. During this phase, the researcher wanted to acquire various information such as the functional requirements and the non- functional requirements of the system.

Sample Population

The research used Kenya Airways as a case study, working with real data and staff from the airline. The sample population for this research consisted of staff members from the operations control centre. This population consisted of 22 staff members working in different departments in recovery management. Out of the 22 staff members, a total of 12 members was selected as the target population. This target population was ideal for the research since they are going to be the end users of the system that will be deployed.

Data Collection

The data was collected using interviews, questionnaires and literature survey. These methods were chosen because they have a high chance of providing accurate information.

At the system design phase, a questionnaire was handed over to 12 respondents working at the operations control centre in Kenya Airways. The goal for this questionnaire was to understand how they currently handle aircraft schedule recovery management in order to outline the system requirements. A sample questionnaire detailing this was captured in Appendix A. Once the system had been developed, the same users were handed a post questionnaire, detailed in Appendix A, to evaluate whether their requirements were met by the proposed system.

Two interviews were conducted with two duty manager operations. The choice of interview respondents was based on their experience level. The goal of these interviews was to understand an overview of the decision making process since it is the duty managers who make the final decisions on the course of action to be taken. A sample interview that was administered is captured in Appendix B.

A survey of existing literature was also used by the researcher to gain in-depth knowledge of linear programming and optimisation models. Previous work by Vos (2014) and Jafari & Zegordi (2010) formed the basis of the literature survey.

3.2.3 Design Phase

Once all the software requirements had been understood in the requirements analysis stage, the system design took place. This involved employing system design methods to represent the architectural design of the system. Unified Modelling Language was used to diagrammatically model the requirements of the system, and also the relationships between the various components (Rumbaugh et al., 2005). The following will be the steps to design the application.

Use Case Analysis: Use cases were used to describe and document the user interaction with the system (Bond, 2007). In this step, a use case diagram was draw and a corresponding use case description was also defined to detail the various actors and use cases. From the use case diagrams, an activity diagram was drawn to show the sequence of activities in the system and the interaction between the various entities.

Process Modelling: This was a formal way to represent how the system will operate in the organisation. Logical processes and physical processes were identified which aided in drawing

data flow diagrams (Rumbaugh et al., 2005). For this case, a context diagram, level 0, level 1 and level 2 data flow diagrams were drawn. A sequence diagram was also drawn to depict the sequence of the events in the system.
Data Modelling: This is a representation of the organisation data (Bond, 2007). In this phase, a conceptual data modelling took place which resulted in the drawing of an Entity Relationship Diagram.

Wireframes: An initial prototype of the application was designed. This was in the form of low fidelity mock-ups that were designed to mimic the final system. An online tool, Draw.io was used to draw the mock-ups.

Mathematical modelling: This research developed an improved model based on previous work done by Vos (2014) and Jafari & Zegordi (2010). This step was based on Linear Programming to develop the optimised model which works with a set of parameters and constraints. The model contained an objective function as discussed in Chapter 4 whose main aim was to minimise costs when carrying out recovery operations.

3.2.4 Development Phase

This was the phase where the system was developed based on the architectures that were developed in the design phase. During this development phase, a series of steps were followed. They include:

Model Optimisation: Once the model had been developed, it was expected that it will be run in an optimiser. IBM Cplex (IBM, 2014) was the chosen optimiser for this model since it enabled optimisation of models using mathematical, linear and constraint programming. The mathematical model was run through a solver using Python programming language libraries. Results from the optimized model were saved on the database as well displayed on a web interface.

Web Application Development: The web application was developed using Python programming language which enabled the users interact with the system. This also served as an interface where parameters pertaining the disruption were input so that the model could generate an optimised solution.
Database: MySQL Database Management System was used to create entities and store data used that would be used by the model and also to store the results generated after a successful computation. The database was hosted on an online Apache Hypertext Transfer Protocol

(HTTP) server. MySQL database was chosen for its ease of use and its availability since it is an open source software.

3.2.5 Verification

When the system modules were ready, they underwent a series of tests to ascertain that the model was working correctly and the objectives of the research met. The testing phase was done by both the end user and researcher. For the users, a questionnaire was issued and the responses recorded. They were given the system to use for a day then fill the questionnaire afterwards. The questionnaire covered aspects on usability testing, compatibility testing and performance testing. Appendix A captures the questions the users were asked.

The study involved a series of verification stages which include:

Usability testing: This was done to determine how user friendly the system is. The major focus of this test was to ensure that the users had a minimalistic interface that enabled them accomplish tasks with minimal effort. The test involved giving users the prototype to interact with and followed by a subsequent questionnaire in order to get feedback as well as having talks with them to understand their experience. A sample questionnaire used for usability testing is captured in Appendix A. A total of 12 staff members in the Operations Control Office at Kenya Airways formed the test users and the respondents of the questionnaire.

Compatibility testing: The system was expected to be used in different web browsers. This testing was to ensure that there is seamless interoperability between the browsers and the experience was the same regardless of which browser or which version was used.

Performance Testing: Since the completed system was expected to be used in critical scenarios, its performance was expected to be top notch. This was to guarantee high degree of performance when working. This test was carried out by using test scenarios to be able to determine how long the model would take. Sample test cases used for performance testing are outlined in Appendix C.

3.2.6 Validation

The evaluation and validation was done to ascertain whether the system optimised recovered aircraft schedules. To validate the developed system, a flight schedule with real disruptions were run and the results recorded. The results of the model were then compared with the results that were produced by the manual process in Kenya Airways.

3.3 Conclusions

This chapter provides a detailed description of the methods used to analyse and design the aircraft recovery model and system that was used to answer the research questions. Through the methodology, the research was able to draw a roadmap of the implementation process taking into account all the required tools and technologies and also software development methodologies.

CHAPTER 4 : SYSTEM DESIGN

4.1 Introduction

This section describes the mathematical model developed, analysis and design for the system developed as proof of concept. The major source of data for this research was from Kenya Airways staff who were the intended users for the system. The system design covers how the platform was developed and tested. The research uses use case diagrams to depict user interaction with the system, and a context diagram to demonstrate the flow of data between the different components.

4.2 Requirements Analysis

Based on the interaction with Kenya Airways staff to understand their problem and the responses from the questionnaires administered, the study came up with the following functional and non-functional requirements.

4.2.1 Functional Requirements

In order for the system developed to add value to the organisation, the Duty Manager operations and the directors needed to accomplish certain tasks, referred to as the functional requirements. They include:

a. **User Login**

   This is useful when tracking user activities. Every user of the system will be required to login. Since the end users will be making critical decisions that affect the airline operations, accountability should be enforced so that everyone is responsible for their decisions.

b. **Load Schedule**

   The user has the ability to view the current schedules for all the aircraft. This information will be retrieved from existing scheduling systems that the airline already has. An overview of the current schedule is important for the duty manager to understand the current situation in the airline.

c. **Enter Model Parameters**

   For the model to execute and return results, there are a set of parameters and constraints that it requires. Some of the parameters are constant such as aircraft capability while others vary depending on other factors. Cost is one parameter that keeps varying over time since it is dependent on market forces.

d. Run Model

In order to get feasible solutions for the problem at hand, the user is expected to run the model and pass parameters to it in order to obtain results.

e. View Results

A user has the ability to view a set of results from the model which will be informative to the decision making process.

4.2.2 Non-Functional Requirements

The following are the main non-functional requirements that would make the system solve its intended purposes.

a. Performance

In the aircraft recovery period, system performance was key since the matter at hand is crucial to the airline's reputation. The system was thus designed with performance aspects in mind such as processing speeds, throughput and utilization. Different scenarios are expected to be delivered to the Duty Manager so that they could make quick decisions immediately.

b. Availability, Reliability, Fault Tolerant and Recoverability

The duty managers heavily rely on the system to make critical decisions in times of disruptions, making it necessary that the system be available always, carrying out its intended task. The system is also designed to be fault tolerant as well as be able to recover from in cases where faults are experienced.

c. Security

Since the system processes sensitive organizational data, security mechanisms are put in place to safeguard the airline's interests. The use of user sessions was implemented to ensure that user activity is tracked as well as only authorized users can be able to consume services offered in the system. For communication between the client application and organisation server, OAuth2 was used.

4.3 System Architecture

The system architecture represents the various components of the system and their roles. The system adopts the client server system architecture model. This is due to the fact that decentralisation of various entities has an advantage on performance and maintenance of the system. Figure 4.1 depicts the system architecture.

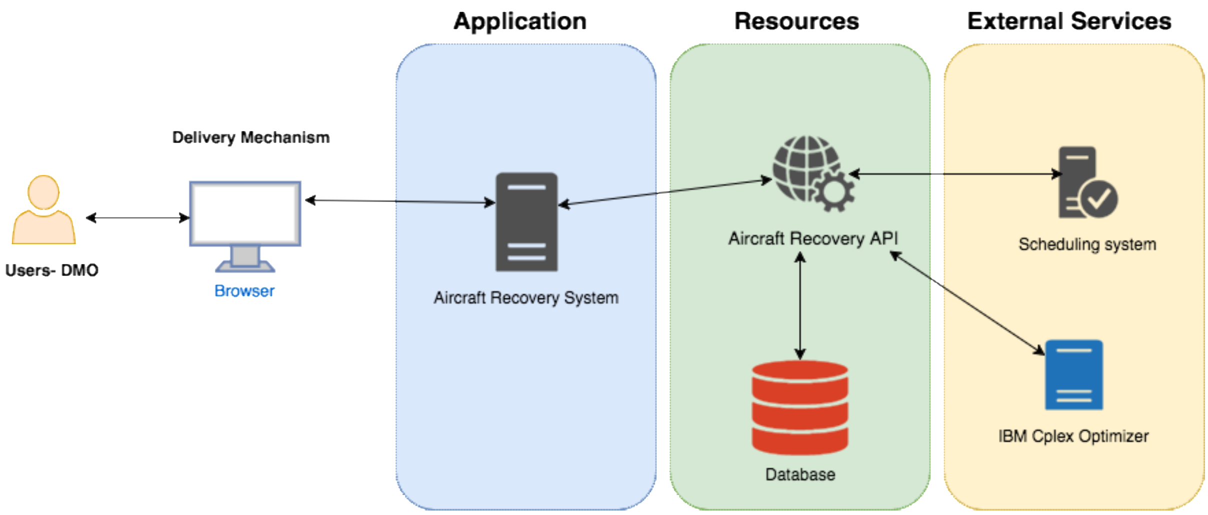

Figure 4.1 System Architecture

The users are the Kenya Airways staff and they can be able to access the system through a web browser on their computer or mobile phone. The Aircraft Recovery System services their requests with the help of an API. Through the API, the system is able to access other external systems and also the database. External systems critical to Aircraft Recovery System are the IBM Cplex Optimiser and the Airline Scheduling System. The optimiser if takes parameters as inputs for the model after which it runs the model to produce results. The results are then stored on a database where they can be retrieved by an API to the web portal to be displayed to the end users.

4.4 Mathematical Model

This research presented an improved model based on previous works done by Vos (2014) and Jafari & Zegordi (2010). The two models aim at minimising recovery management costs. Jafari & Zegordi (2010) minimise assignment, delay, cancellation, passenger reassignment, cost of refund to disrupted passengers' itinerary and cost of passengers' who are not reassigned. Vos (2014) on the other hand considers minimising costs of operation to which a recovery aircraft is assigned, costs of delay, costs of cancellation for passengers with economy tickets and the ground costs for where an aircraft is when the disruption occurs.

This research aimed at coming up with an improved model which considers reassignment costs for a recovery aircraft, cost of flight delay based on the duration spent in the disruption, cancellation costs for business class passengers, cancellation costs for economy class passengers and ground costs.

4.4.1 Sets

This section describes the sets of data used in the mathematical model. These input sets defined here contain real data from Kenya Airways. The model requires a set of all airports (N_n)with which the airline operates from. This would be useful to determine the ground arc costs since every airport has ground fees. A set of all fights (F_r) in the recovery scope incorporates all the flights that have been affected or will likely be affected by the disruption. Set K_r defines all aircraft that are affected by the disruption and need to be recovered.

N_n Sets of all the nodes (airports) where the airline operates

F_r Set of all flights in the recovery scope

K_r Set of all aircraft to be used in the recovery scope

4.4.2 Parameters

The parameters for this model are mainly geared towards the cost implications of decisions by the duty managers. Assignment costs (C_{kf}) for aircraft to a flight is necessary especially when considering tail switching. The assignment cost, as described in chapter 1 is a summation of different costs. In case of a delay, the cost of delay (CD_f) must be determined, where passengers will be paid for the delays caused. Scheduled (Ts_f) and actual departure (Td_f) times of a flight are necessary to determine the delay that resulted from the disruption. In cases of cancelling flights, there is always a cost implication to the airline. Such cost could be incurred when the airline has to rebook passengers or accommodate them in hotels.

C_{kf} Cost of assigning an aircraft to a flight

CD_f Cost of delay for flight

Td_f Actual departure time for flight

Ts_f Scheduled departure time for flight

NP_f Total number of passengers in flight f

CC_f Cost of cancelling flight f with passenger itinerary.

CG_n Cost of ground delays in airports

A_{kf} Aircraft ready time

4.4.3 Decision Variables

Using the decision variables, the objective function becomes the choice of each of the variables multiplied by the value of selecting each of the variables.

X_{kf} Assigned 1 if aircraft *k* is assigned to flight *f* and 0 otherwise

δCan_f Assigned 1 if flight *f* is cancelled and 0 otherwise

δAG_{nk} Assigned 1 if ground *n* is used by aircraft *k* and 0 otherwise

4.4.4 Objective Function

The objective function aims at minimising the associated costs incurred in the event of a disruption. The function first gets the assignment costs in case an aircraft is assigned to a flight. If this is not the case ($X_{kf} = 0$), the value of that cost is assigned zero. The assignment cost is then summed with the delay cost. Delay cost is a product of the set cost of delay of a flight by the number of passengers (NP_f) by the number of minutes the delay has been experienced. In case a flight is cancelled, the cancellation costs are also considered. This cost is a product of the set cancellation cost of all flights and the number of passengers involved. For business class passengers, their refund will be three times an economy passenger. The ground costs (CG_n) are also factored in the model especially if an aircraft disruption takes place away from the base airport.

MIN:

$$\left\{ \sum_{f \in F_r} \sum_{k \in K_r} C_{kf} X_{kf} + \sum_{f \in F_r} CD_f \, [Td_f - Ts_f] \, NP_f + \sum_{f \in F_r} \delta Canc_f \, CC_f \, NP_f + \sum_{n \in N} \delta AG_{nk} CG_n \right\}$$

4.4.5 Constraints

The constraints are used in the linear program ensuring that only valid solution are given after valid cases have been considered.

1. Flight cancellation

Constraints in 1 is to ensure that when a flight *f* is cancelled (when $\delta Can_f = 1$), no aircraft in F_r is assigned to it.

$$(1-\delta Can_f) = \sum_{k \in K_r} X_{kf} \qquad \forall f \in F_r \qquad (1)$$

2. Departure

time in Recovered Schedule

Constraint in 2 specifies that the departure time for a flight *f* after a recovery should not be earlier than the aircraft ready time.

$$Td_f \geq A_{kf} \qquad (2)$$

4.5 Use Case Modelling

The use cases discussed below are used to depict the processes in the system and their interactions. Actors comprise of Duty Manager Operations (DMOs) and directors.

4.5.1 Use Case Diagram

Figure 4.2 is a visual representation of the use cases depicting various functionalities of the system and the relationship between the functions and the users.

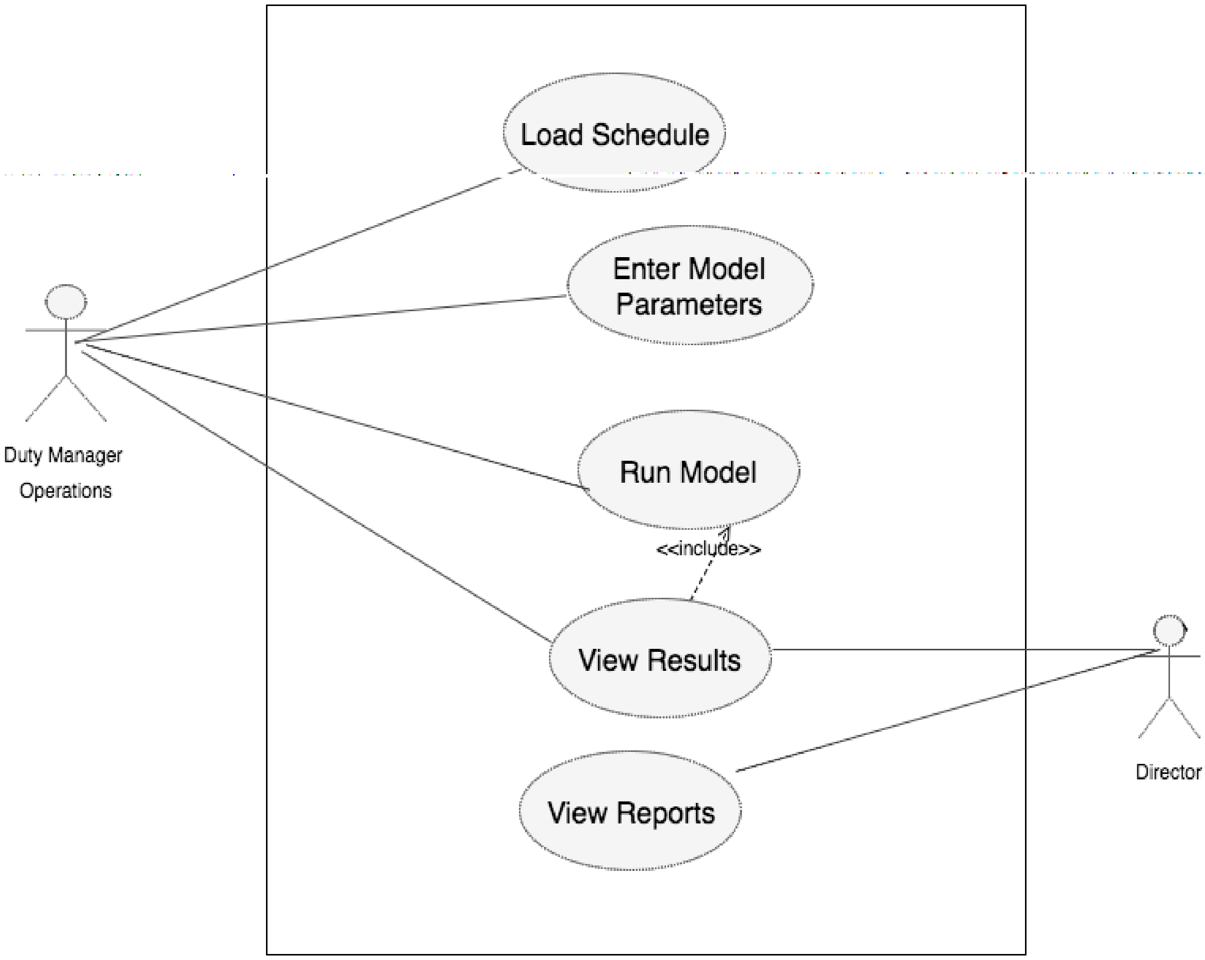

Figure 4.2 Use Case Diagram

4.5.2 Use Case Description

The main use cases in the system that will be considered for description from the use case diagram are load aircraft schedule, enter model parameters, run model, view results and view reports

The load aircraft schedule use case is important for the model and DMO as well to be able to get an overview of the state of the schedules. Since the major use for this system is to recover the schedule, it would be important to first be able to understand the current situation of the schedule. Table 4.1 describes the Load aircraft schedule use case.

Use Case	Load Aircraft Schedule
Actor	Duty Manager Operations(DMO)
Purpose	To load aircraft schedule from the scheduling system
Overview	This use case starts every time this page is loaded. The system is designed to retrieve this data from an excel file provided by the airline.
Cross References	Login use case
Pre-Conditions	The user must be logged in. The user must either be a DMO or a director
Post Conditions	The aircraft schedule is loaded to the page displaying all the aircraft and their current state as well as their planned schedules.

Table 4.1 Load Aircraft Schedule

In case a disruption occurs, a set of parameters which are run through a mathematical model are entered. This is done by the Duty Manager Operations. Table 4.2 describes the use case for loading model parameters by the duty manager operations.

Use Case	Enter Model Parameters
Actor	Duty Manager Operations(DMO)
Purpose	To enter the parameters and constraints that the model will work with in order to come up with a feasible solution.
Overview	This use case is triggered in case a disruption is witnessed in the airline and the DMO needs to find a suitable solution to recover the current challenge.
Cross References	Login use case
Pre-Conditions	The user must be logged in. The user must either be a DMO or a director There must be a schedule disruption reported
Post Conditions	The model parameters are input for processing in the model.

Table 4.2 Enter Model Parameters

Once the parameters for the model are entered, the Duty Manager Operations runs the model to come up with a list of possible solutions. Table 4.3 discusses the run model use case.

Use Case	Run Model
Actor	Duty Manager Operations(DMO)
Purpose	To perform computations that necessitate the development of feasible solutions for the aircraft recovery problem
Overview	This use case is triggered in case a disruption is witnessed in the airline and the DMO needs to find a suitable solution to recover the current challenge.
Cross References	Enter Model Parameters
Pre-Conditions	The user must be logged in. The user must either be a DMO or a director All necessary parameters must be entered.
Post Conditions	The model is executed and a list of possible solutions to the problem at hand is generated.

Table 4.3 Run Model

Once the mathematical model is run through Cplex Optimiser, it is expected to come up with a list of possible solutions. The results are then displayed to the Duty manager operations through a reporting table. Table 4.4 is a brief description for the view results use case.

Use Case	View Results
Actor	Duty Manager Operations(DMO)
Purpose	To display a list of possible solutions to be considered in order to help in decision making by the DMO.
Overview	This use case is triggered once a successful run of the model has taken place.
Cross References	Run Model
Pre-Conditions	The user must be logged in. The user must either be a DMO or a director The model must execute successfully
Post Conditions	A list of possible solutions is generated and displayed for the DMO to visualize the scenario.

Table 4.4 View Results

4.6 Sequence Diagram

The sequence diagram illustrates how the users interact with the system and the responses they get from their requests. Figure 4.3 depicts the whole sequence of events from when the Duty Manager Operations logs into the system, loads the current affected schedule, and enters parameters to the model, Executes the model through an optimiser till the point when results are delivers. In Figure 4.3, the sequence of events with which a director accesses the system and views reports is also depicted.

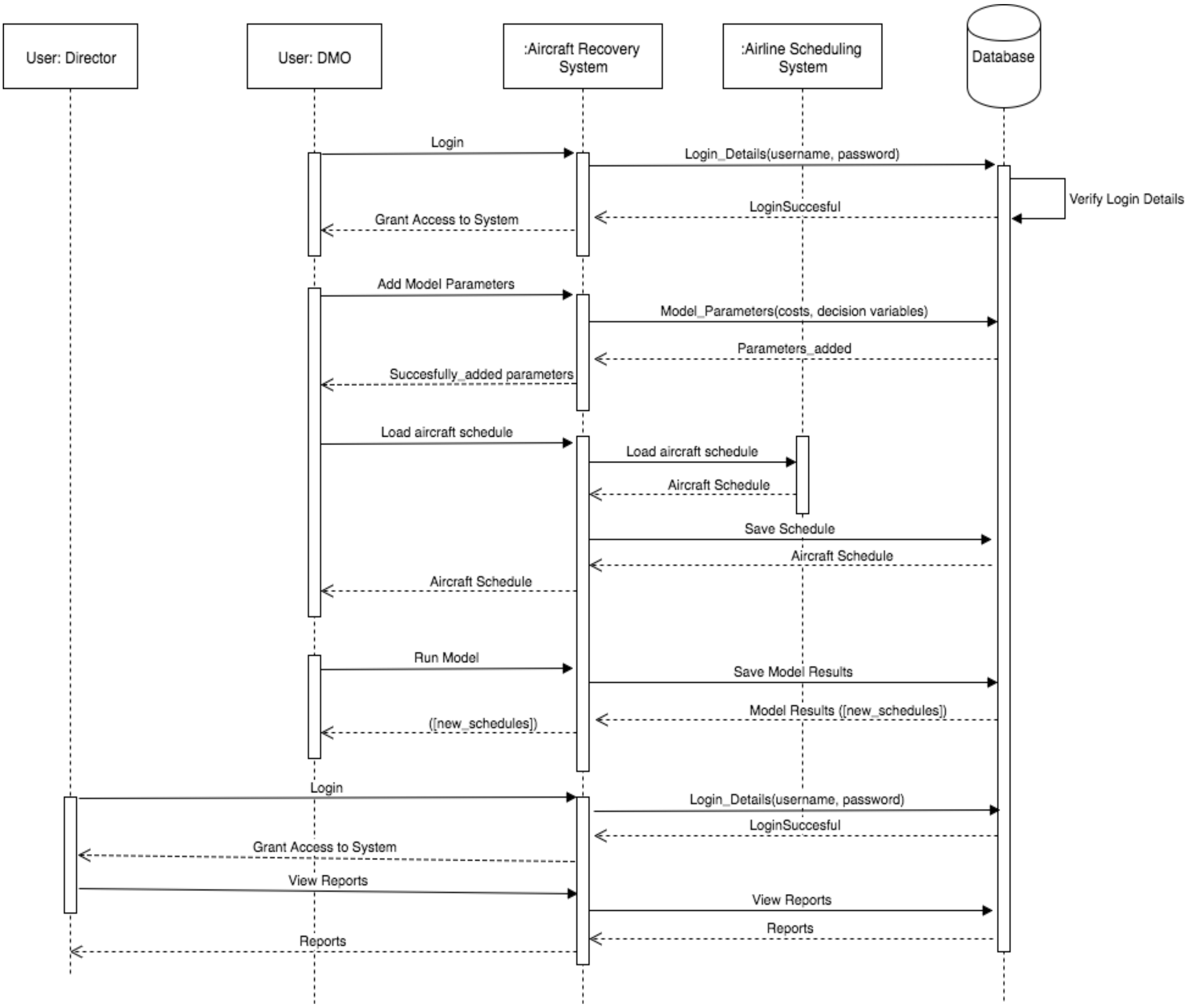

Figure 4.3 System Sequence Diagram

4.7 Data Flow Diagrams

Data flow diagrams depicted below show the movement of data between different processes in the application

4.7.1 Context Diagram

Figure 4.4 illustrates at a high level how various users and applications interact with the Aircraft Recovery Management system and data sent and retrieved from these interactions. The scheduling system loads schedule data to the recovery management system. The Duty Manager Operations, who is the major actor in the system preforms a set of operations that aid in decision making process in cases of aircraft disruption.

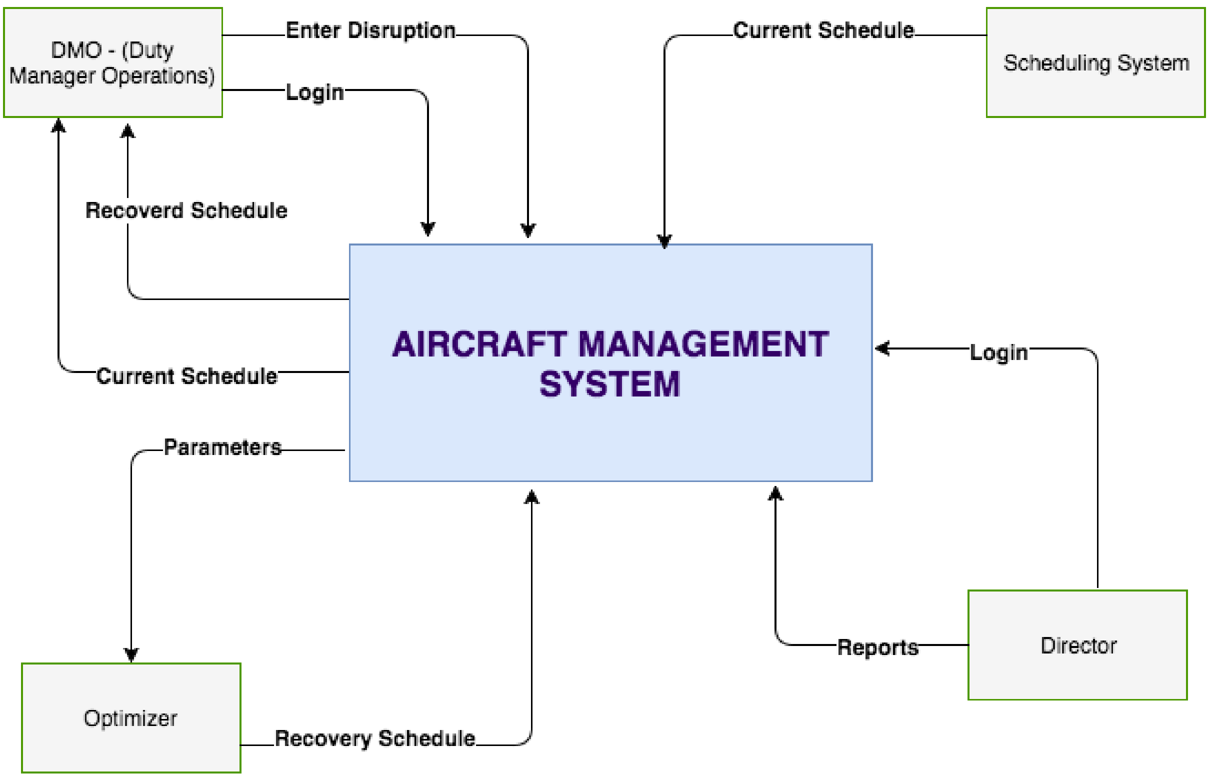

Figure 4.4 Context Diagram

4.8 Database Design

This section describes the structure of the database that the system used.

4.8.1 Entity Relationship Diagram

The entity relationship diagram depicts the correlation between the different entities in the database. For aircraft recovery system, the database has a total of eight entities and Figure 4.5 below illustrates how they are related.

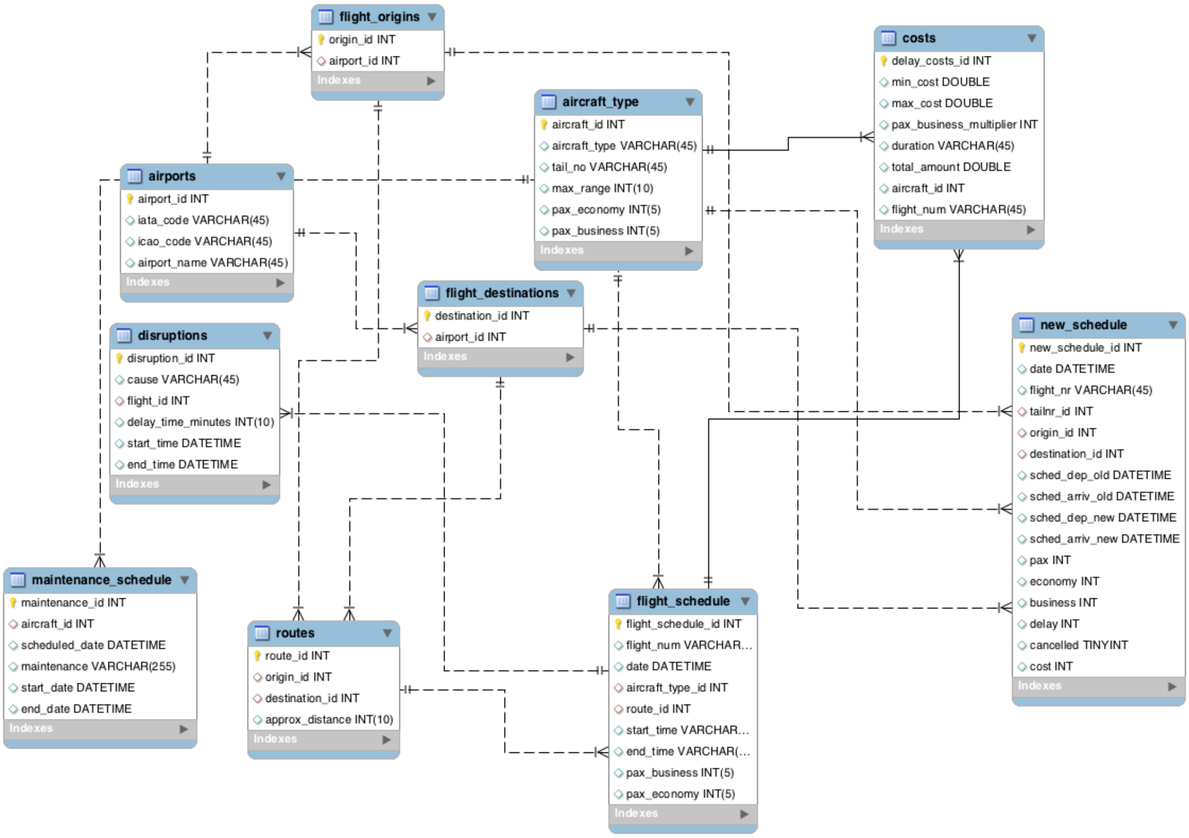

Figure 4.5 Entity Relationship Diagram

4.8.2 Database Schema

Aircraft Type

Table 4.5 stores data on all the types of aircrafts that the airline has. The aircraft type field specifies the fleet to which an aircraft belongs, while the tail number field is a unique identifier for every aircraft. The table also stores the maximum range an aircraft can cover in kilometres as well as the number of passengers the plane can accommodate. Data contained in this table is useful especially when one of the options is tail switching. The model has to consider the capability of a certain aircraft before assigning it to a new route that was not in its initial schedule.

Column Name	**Data type**	**Index**
aircraft_type_id	Int	Primary Key
aircraft_type	Varchar(45)	
tail_no	Varchar(45)	
max_range	Int(10)	
pax_business	Int(5)	
pax_economy	Int(5)	

Table 4.5 Aircraft Type Table

Flight Schedule

Table 4.6 stores data about all initial flight schedules for the airline. An overview of the planned schedule is important in determining the impact a disruption will have to the entire airline network.

Column Name	Data type	Index
flight_schedule_id	Int	Primary Key
flight_num	Varchar(45)	
date	DateTime	
aircraft_id	Int(10)	Foreign Key
route_id	Int(5)	Foreign Key
start_time	Varchar(45)	
end_time	Varchar(45)	
pax_business	Int(5)	
pax_economy	Int(5)	

Table 4.6 Flight Schedules Table

Routes

A route is formed by an origin to destination pair. The two can never be the same when creating a route. Table 4.7 holds data on routes flown by the airline. Attributes such as destination and origin of a route enable the model get to know the distance thereby enabling it assign aircraft that can handle that range.

Column Name	Data type	Index
route_id	Int	Primary Key
origin_id	Int	Foreign Key
destination_id	Int	Foreign Key
approx_distance	Int(10)	

Table 4.7 Routes Table

Disruptions Table

All disruptions that are solved by the model are solved on the database. The most important aspects of a disruption are the time it is known, the time the disruption occurs and the time it will end. This times are important since they will determine the delay caused by the disruption and subsequently the cost implication to the airline.

Column Name	Data type	Index
disruption_id	Int	Primary Key
type	Int	
flight_id	Int	Foreign Key
start_time	DateTime	
end_time	DateTime	

time_known	DateTime	
delay_time_minutes	Int(10)	

Table 4.8 Disruptions Table

Costs Table

Table 4.9 stores all the costs that the model will incorporate in its operation. The costs include assignments costs, operation costs, delay costs

Column Name	**Data type**	**Index**
delay_costs_id	Int	Primary Key
min_cost	Double	
max_cost	Double	
pax_business_multiplier	Int	
duration_minutes	Int	
total_amount	Double	
flight_num	Varchar	Foreign Key

Table 4.9 Costs Table

Airports

Table 4.10 stores data on all airports that the airline operates. The various codes used in the airline industry by international organisations is also saved.

Column Name	**Data type**	**Index**
airport_id	Int	Primary Key
iata_code	Varchar(45)	
icao_code	Varchar(45)	
airport_name	Varchar(45)	

Table 4.10 Airports

Origins Table

Table 4.11 stores data on all flight origins in the flight schedules.

Column Name	**Data type**	**Index**
origin_id	Int	Primary Key
airport_id	Varchar(45)	Foreign Key

Table 4.11 Origins Table

Destinations Table

Table 4.12 stores data on all flight destinations in the flight schedules. A destination could as well be an origin for the next flight.

Column Name	**Data type**	**Index**
destination_id	Int	Primary Key
airport_id	Varchar(45)	Foreign Key

Table 4.12 Destinations Table

Maintenance Schedule

All aircraft undergo scheduled maintenance to ensure they are safe for flying. The schedule is always prepared in advance and regulated by the Kenya Civil Aviation Authority. Table 4.13 is used to store maintenance schedules data for all the aircraft

Column Name	**Data type**	**Index**
maintenance_id	Int	Primary Key
aircraft_type_id	Int	Foreign Key
scheduled_date	DateTime	
maintenance	Varchar(255)	
start_date	DateTime	
end_date	DateTime	

Table 4.13 Maintenance Schedule

New Schedule

After a successful run, the model generates a new flight schedule with cost implications of that flight. The cost is calculated based on various factors such as the operation costs, navigation costs, assignment costs and delay costs in case there was a delay. Table 4.14 shows the various fields that will be saved in the new schedule table.

Column Name	**Data type**	**Index**
new_schedule_id	Int	Primary Key
date	DateTime	
flight_nr	Varchar(25)	
tail_no_id	Int	Foreign Key
origin_id	Int	Foreign Key
destination_id	Int	Foreign Key
sched_dep_old	DateTime	
sched_arriv_old	DateTime	
sched_dep_new	DateTime	
sched_arriv_new	DateTime	
pax	Int	
economy	Int	
business	Int	
delay	Int	
cancelled	Yes/No	
cost	Double	

Table 4.14 New Schedule

4.8.3 Model and Optimiser Integration

The mathematical model relies on inputs from the database to optimise the schedule. The initial parameters are saved in a database and retrieved by the model using a Python library called numpy. The data from the database is first converted to a numpy file format which will be interpreted by the model. The model, will then use inbuilt Cplex libraries to extract the data from the numpy file, perform operations and generate an output numpy file. This file will then be converted to an SQL readable format and saved on the database. Once the data is on the database, a request by the web interface will fetch the data and display it in a user friendly format on the web portal.

4.9 System Wireframes

Once the Duty manager operations logs into the system, they are able to see the current schedule for the aircraft. There is an option to update schedule once they are notified of a disruption in order to be able to see the affected aircraft. Figure 4.6 shows the wireframe or the load schedule page.

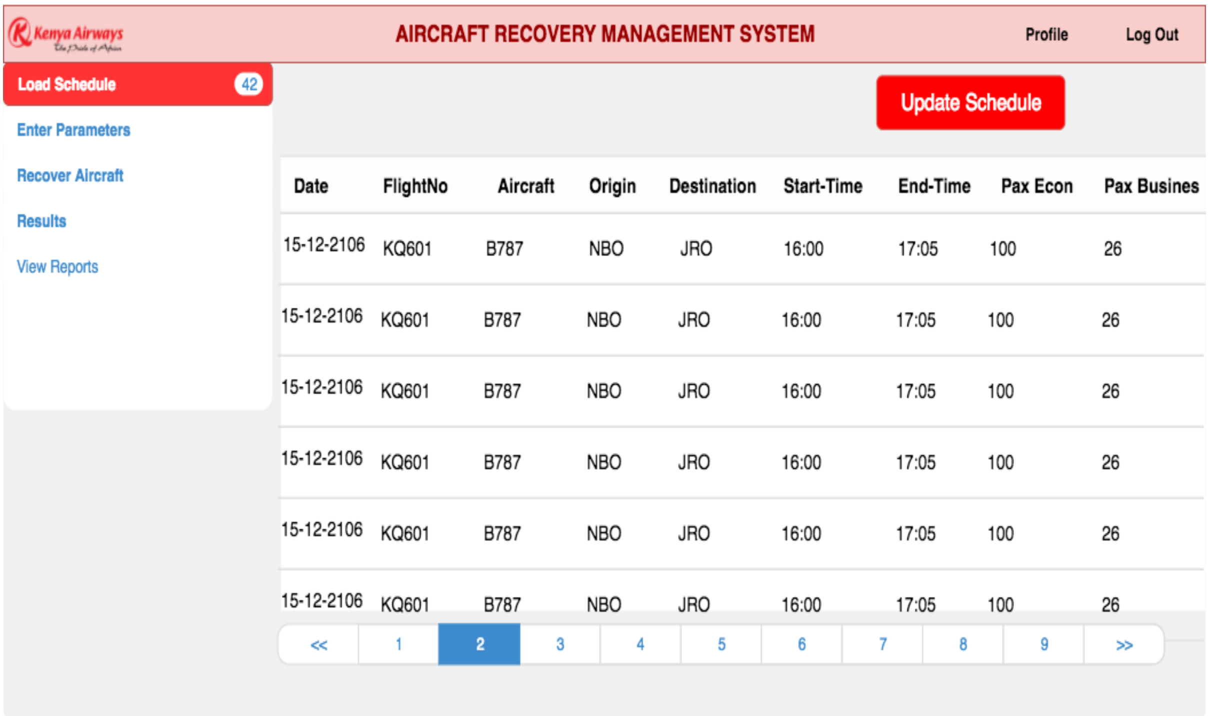

Figure 4.6 Load Schedule Wireframe

Once the duty manager has an idea of the current state of the airline schedule, they can be able to resolve disruptions in case there is one. There are parameters needed in the decision making process in case a disruption is recorded. These parameters keep changing since they are dictated by market forces, thus a page to update their current values is necessary to ensure that the model is run, with updated decision variables. Figure 4.7 illustrates the page which the duty manager operations will enter the model parameters.

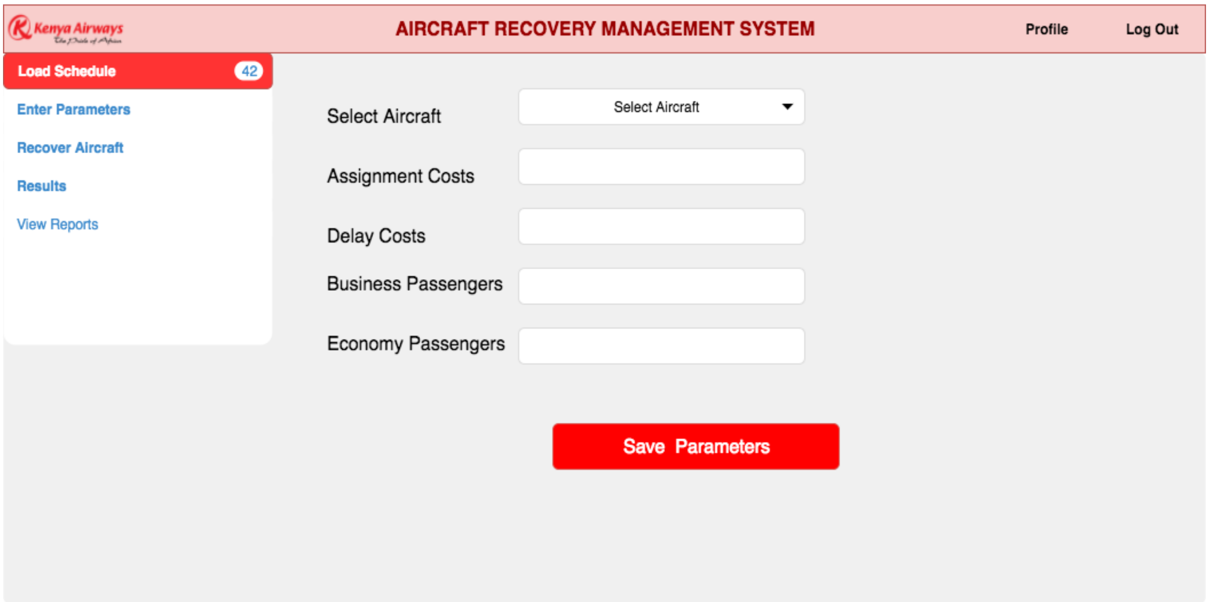

Figure 4.7 Enter Model Parameters Wireframe

Having updated model parameters guarantees accuracy of the solutions generated by the optimiser. The duty manager can then run the model by pressing a button which will trigger the optimiser. Figure 4.8 illustrates the screen to where the model is executed from.

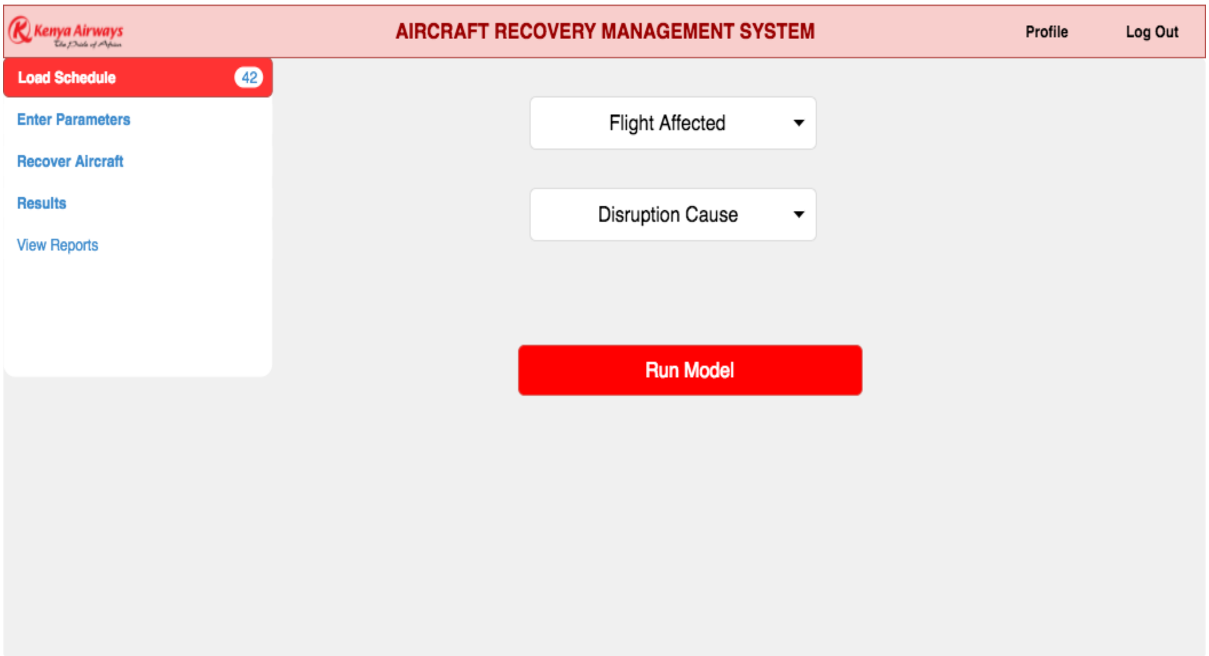

Figure 4.8 Run Model Wireframe

Once the model has been run successfully, it is expected to generate a new flight schedule with the associated cost implications. The new schedule can then be updated to be the current operation schedule in the scheduling system. Figure 4.9 illustrates the wireframe for the generated schedule page.

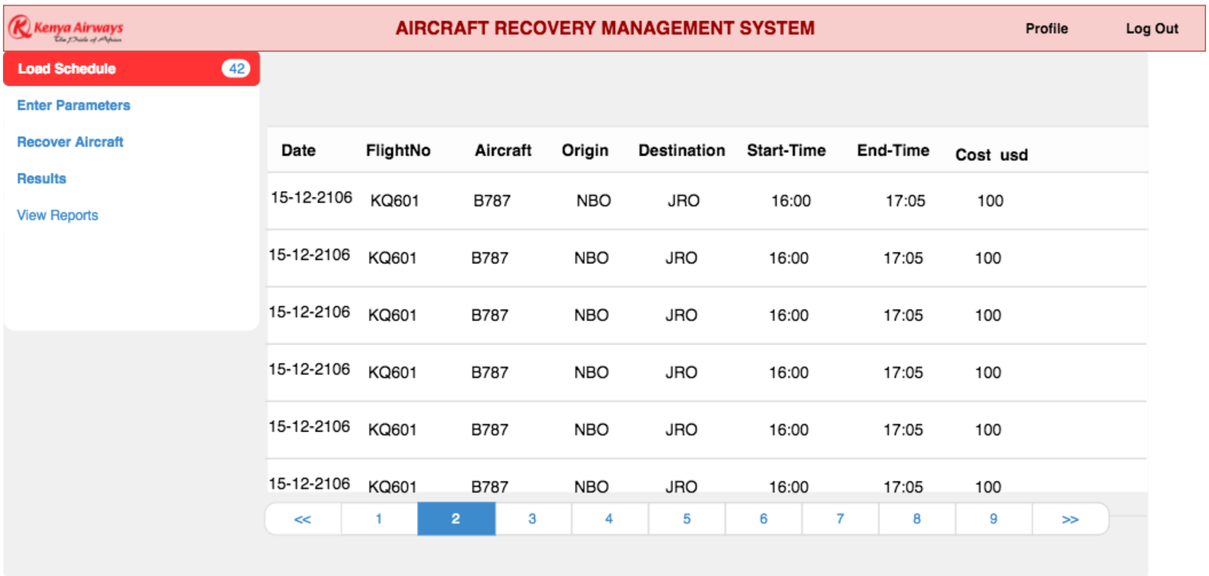

Figure 4.9 New Schedule Wireframe

CHAPTER 5 : SYSTEM IMPLEMENTATION AND TESTING

5.1 Introduction

In line with the analysis done and the designs developed in Chapter 4, the end product was developed to ensure its functional requirements and non- functional requirements were met. This section discusses the developed solution by this research.

5.2 Web Portal

A web portal served as a platform for proof of concept for the model developed. The users of the system can be able to perform all the functional requirements using the web portal. A Duty Manager Operations can be able to see the current schedule, run the model in case a disruption is witnessed, enter and update model parameters and view the proposed new schedules. A director on the other hand gets a dashboard with reports of what has been happening in the airline network regarding disruption management.

5.2.1 Load Schedule

Once authenticated, the Duty Manager Operations proceeds to load the current schedule for all the aircraft. This schedule is generated from Sabre Scheduling System and stored on the database. In case a disruption has occurred, the current schedule will inform the Duty Manager the affected aircraft and the reasons for the disruption. Figure 5.1 is an illustration of the web page that the DMO will be interacting with when loading the current schedule.

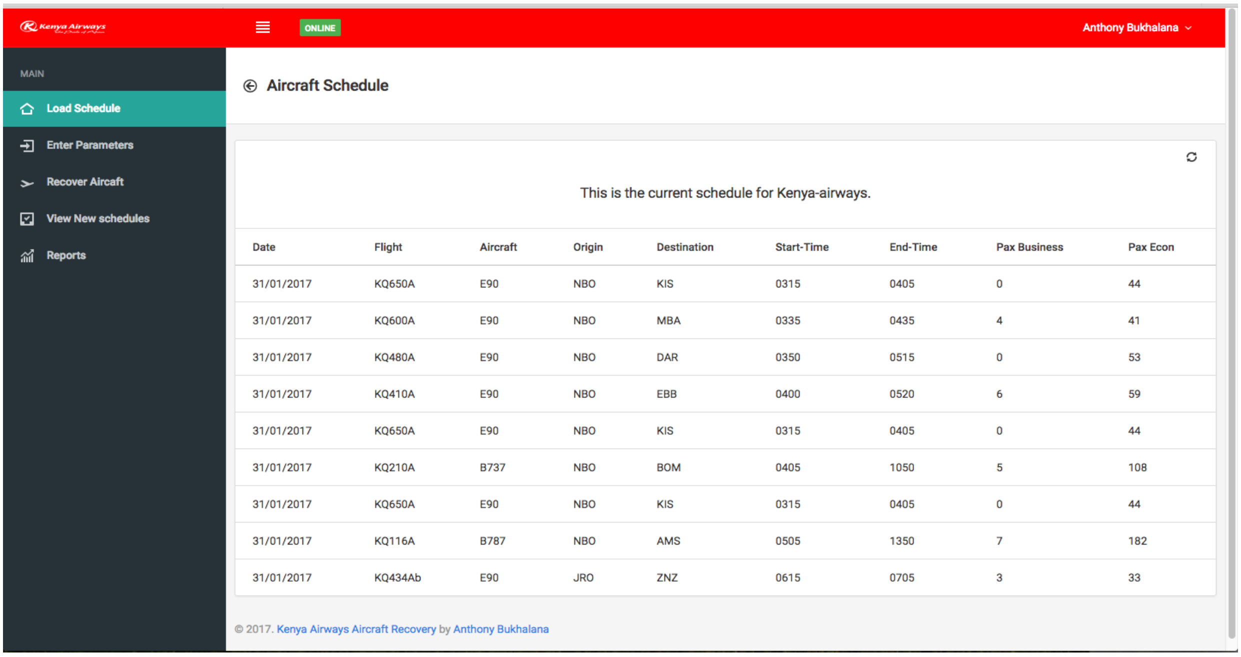

Figure 5.1 Load Airline Schedule

5.2.2 Add Model Parameters

The mathematical model developed in this research depends on a set of constant and variable parameters. For parameters that are constant such an aircraft specification will be defined as variable in the code for the model. However, there are parameters such as assignment costs, aircraft operation costs that vary according to market forces. This page will enable the DMO to update the parameters as they are in the market. Figure 5.2 displays the add model parameters page.

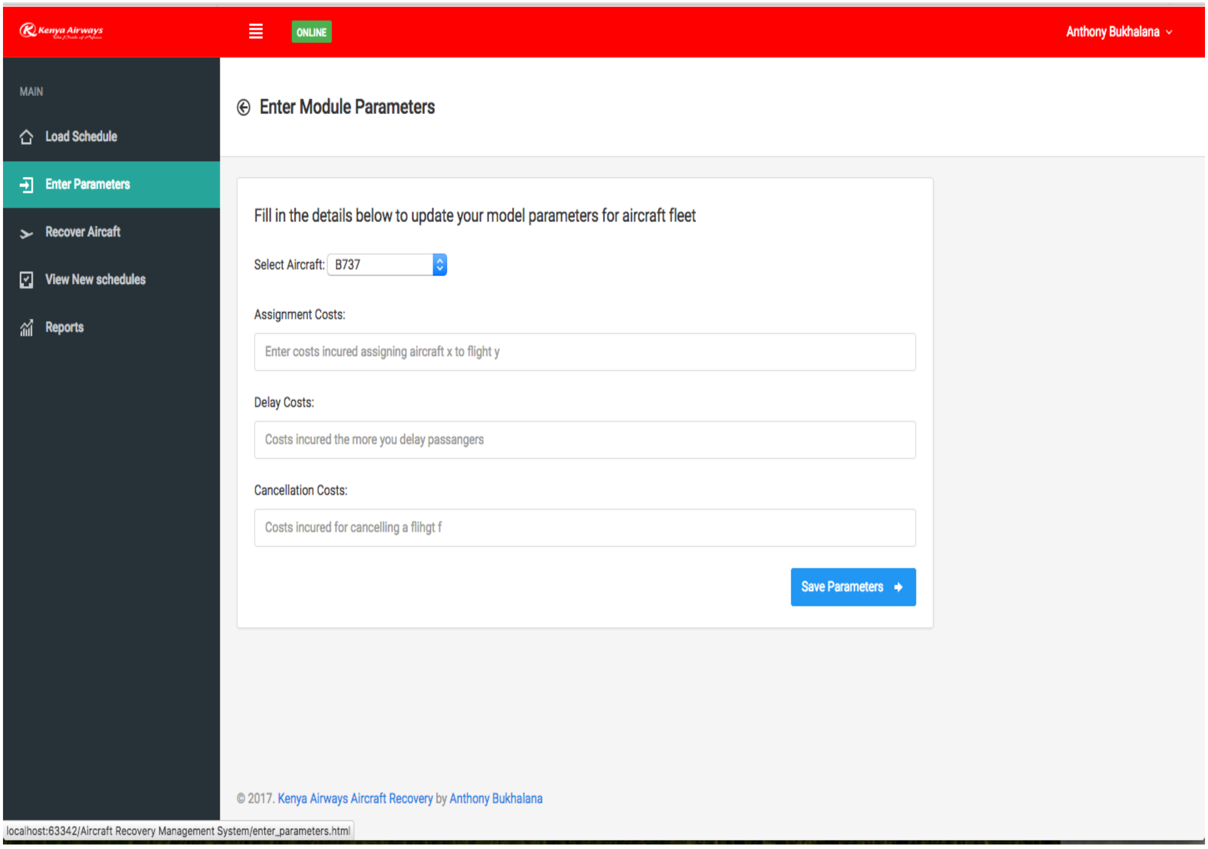

Figure 5.2 Add Model Parameters

5.2.3 Run Model

In order to retrieve new schedules, the DMO needs to run the model, which invokes Cplex to perform optimisations to the mathematical model and come up with the most feasible solution. The model then executes and provides a set of results. Figure 5.3 illustrates the Run Model Page.

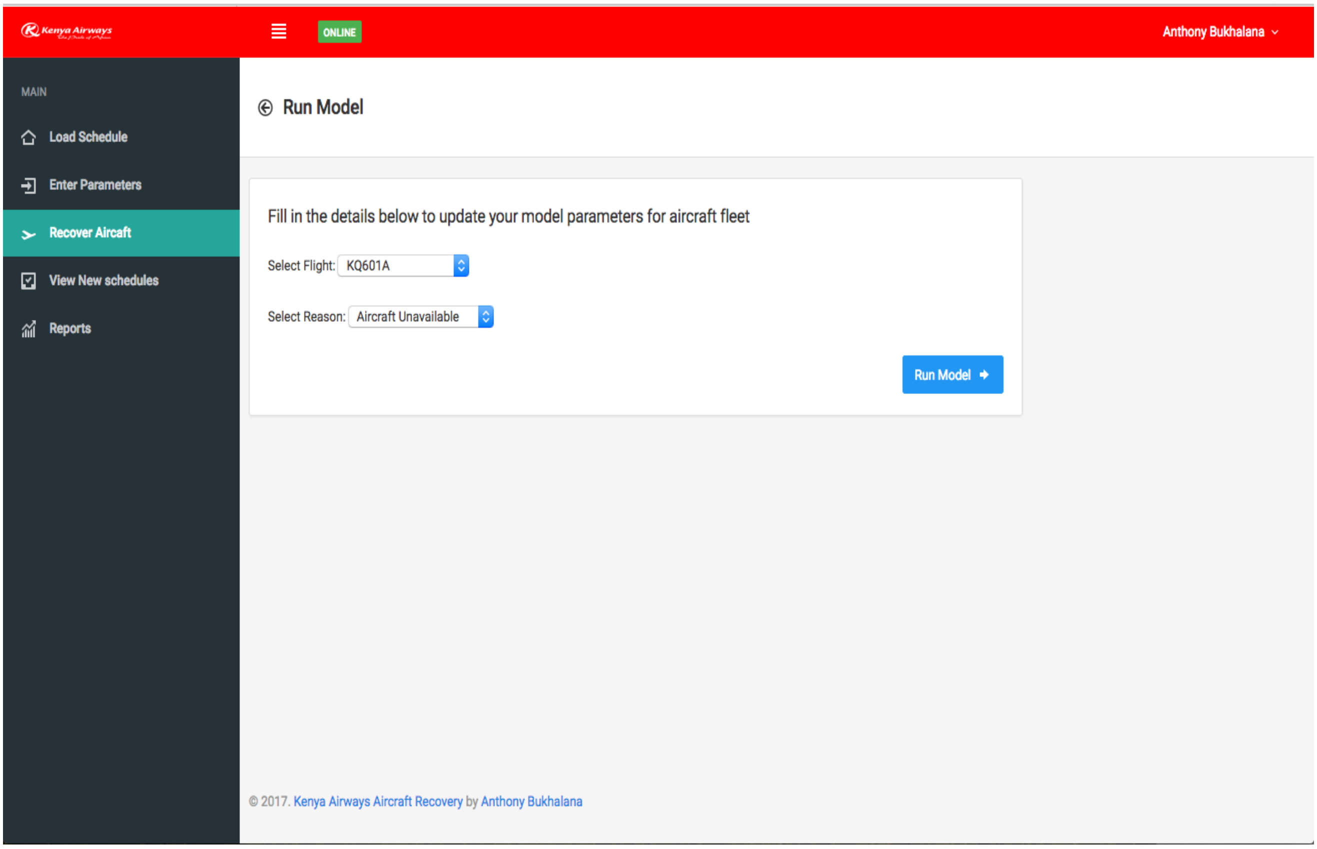

Figure 5.3 Run Model Screen

5.2.4 View Results

On successful run through the optimiser, the model should generate results, which are displayed on to the web portal. The results simulate a recovered schedule with possible suggestions and cost implications. Figure 5.4 shows the expected results from the model.

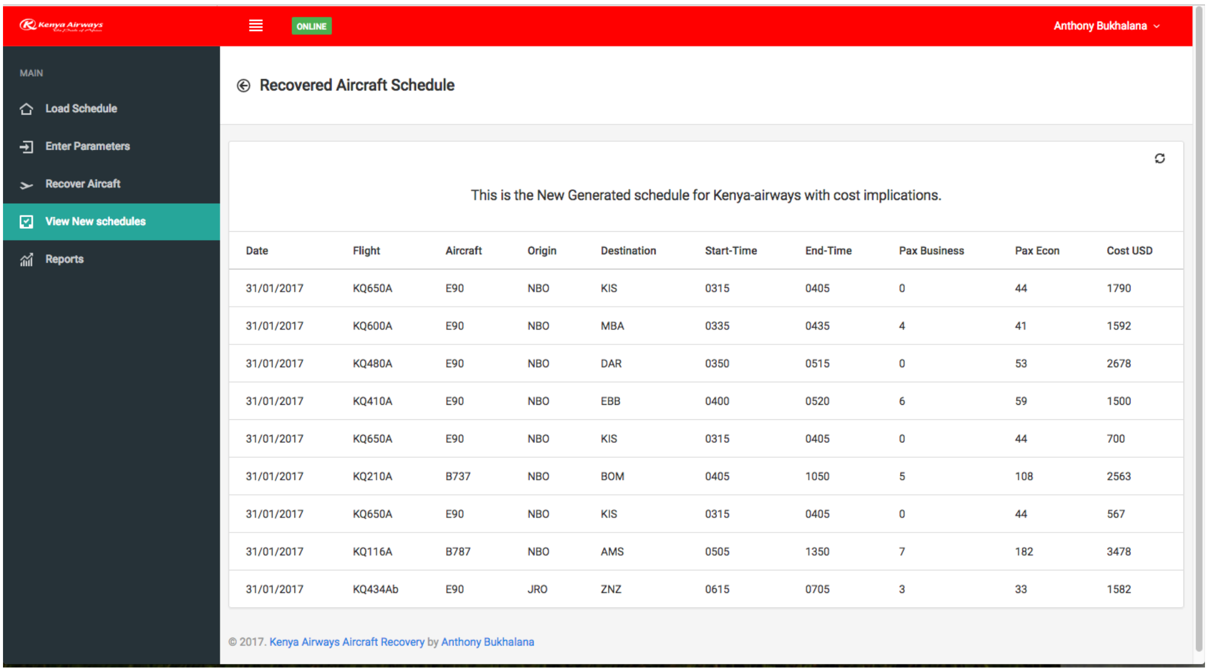

Figure 5.4 View Recovered Schedule

5.2.5 View Reports

The Duty Managers Operations can also access the system and get a dashboard that summarises all the activities that have been taking place in the airline. Once the model is executed, results are stored in a database and queried appropriately to generate the relevant reports. Reports on the On-Time performance for the airline will be calculated and displayed. Figure 5.5 illustrates the reports tab that will be displayed to the system users.

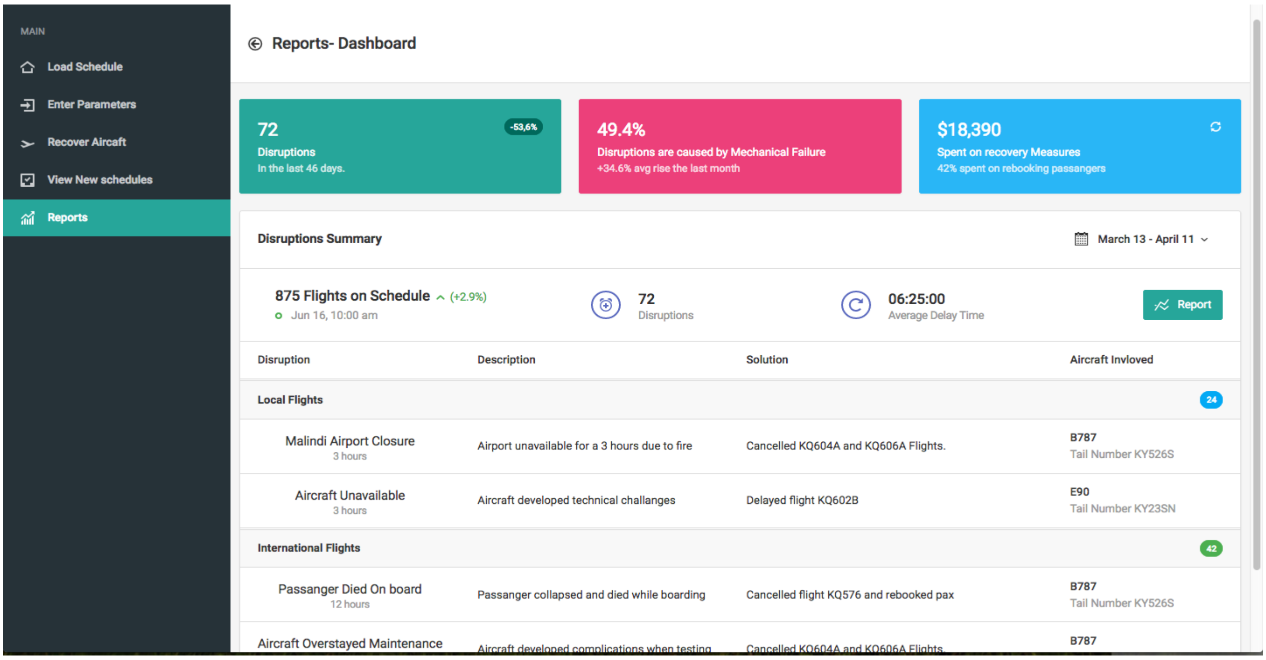

Figure 5.5 View Reports

5.3 System Testing

In order to deploy the application for commercial use in the airline, it was important to carry out a series of tests to ascertain that it is fit. The tests were done with Duty Manager Operations, who are the proposed users of the system.

5.3.1 Compatibility Testing

The application was developed to be used on a browser client. Compatibility tests were carried out in two forms, user testing and developer testing. To test its compatibility, the same application was run on different browsers and it was evaluated how it performed on them. The browsers that were used to carry out the test were Firefox, Internet explorer, Google Chrome and Apple Safari. Much consideration was put to support older versions on these browsers. The application was also tested on mobile browsers to enable users to access the application on their phones and tablets. The study carried out compatibility tests for the application across all the browsers and tabulated the results below

Table 5.1 Compatibility Test Results

Test Case Name: Compatibility Testing **Date Tested: 28th March 2017**				
Preconditions: The computer must have a browser client installed				
Post Conditions				
Steps	Action	Expected Response	Result	Comment
1	Check if multiple browsers efficiently on a desktop computer can support the application. Firefox version 8 and above Google Chrome (all versions) Internet Explorer version 4 and above Apple Safari version 6 and above	The application should be able to load and perform its functions regardless of the browser type and version	Pass	Well supported in all browsers. Internet explorer was not swift compared to the other browsers
2	Check if the application can be supported by browsers run on mobile phones and tablets	The application should be responsive thus easily accessible on mobile browser	Pass	Functions as expected. Though with some delays due to mobile performance.

After the application was tested by the developer, it was given to the end users to test with their computers. A questionnaire, captured in Appendix A was then handed to them in order to get feedback on their test cases.

5.3.2 Performance Testing

This system developed is used in critical decision-making process when there is a disaster in the airline. The system thus needed to provide a set of solutions within a limited amount of time, preferable less than ten minutes. The major process that was being tested to ascertain that the system had passed the performance test was running the model with a set of parameters to give you a solution. The results for this test are tabulated in Table 5.2 below.

Table 5.2 Performance Testing

Test Case Name: Performance Testing **Date Tested: 28th March 2017**				
Preconditions: There is a disruption, which the model will be run to provide a solution.				
Post Conditions: The model will run successfully and provide an optimised solution in a short time				
Steps	Action	Expected Response	Result	Comment
1	Enter all necessary model parameters	Model parameters entered successfully	Pass	Model parameters entered successfully
2	Run model and wait for results	The model will run within 15 minutes and come up with optimised solutions for decision-making.	Pass	Model run for 21 minutes and provided around five solution scenarios.

5.3.3 Functional Testing

Functional tests were done based on the functional requirements to determine the success or failure of the system design and also the implementation. The tests were carried out in the airline premises with the Duty Manager Operations and the director in charge of airline operations. The tables below illustrate the major use cases and their test cases.

Table 5.3 Load Schedule Test Case

Identifier	1
Test Case	Load Schedule
Description	DMO is able to load the current schedule to view the state of the schedule
Utilized Use Case	Load Schedule
Results	The schedule was loaded successfully displaying the current status of the airline's aircraft. Data on available aircrafts was also displayed.
Pass/Fail	Pass

Table 5.4 Enter Model Parameters Test Case

Identifier	2
Test Case	Enter Model Parameters
Description	In case there is a disruption, the DMO inputs the parameters for the model in order to be able to run it.
Utilized Use Case	Enter Parameters
Results	The necessary parameters for the model were input successfully and stored in the database. Updates were made successfully.
Pass/Fail	Pass

Table 5.5 Run Model Test Case

Identifier	3
Test Case	Run Model
Description	This is done in case there is a disruption and the system needs to generate solutions
Utilized Use Case	Run Model
Results	The model was run and produced a set of possible recovered schedule options. The cost implications of every suggestion is indicated.
Pass/Fail	Pass

5.3.4 Integration Testing

This test was done to ascertain that the various components of the system work together. The test was conducted to see whether the optimiser was able to optimise the model and send the results back to the web portal. This test was successful since a set of suggested optimised schedules were displayed on the results page.

5.4 User Testing

As defined in the research methodology, the system development process employed agile methodology. This implied end user involvement in the development process. User testing was carried out to determine an application's user friendliness, user acceptance and its aesthetics.

5.4.1 User Friendliness

The study sought out to find how user friendly the system was. A questionnaire, detailed in Appendix A, was sent out whose respondents got to use the system with minimal training in order to gauge how easy it was to learn and get work done. 90% of the respondents could be able to smoothly operate the system with minimal help. 10% required help to carry out the core functionality of the application. Figure 5.6 below shows the response received from the respondents.

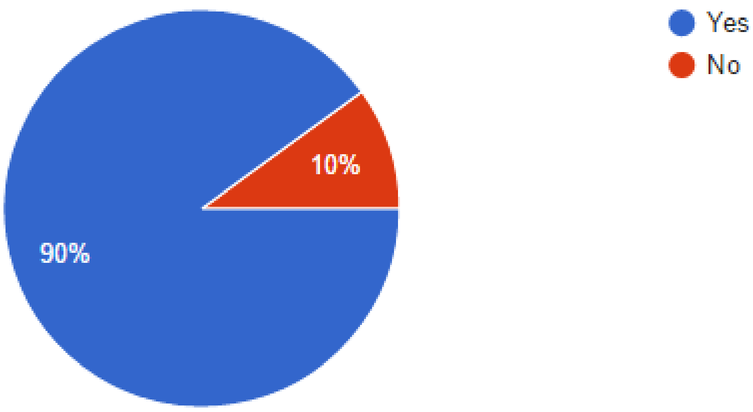

Figure 5.6 Users Able to Use the System Without Help

5.4.2 Aesthetics

This test was set up to determine the impression the system created to the users. During development, the research sort to operate within the airline's brand colours, so as to emulate already existing systems. The advantage with this approach was that the similarity of the system with the current existing systems made the users feel at home. Out of all the people who filled the online questionnaire, 80% appreciated its aesthetics while the remaining 20% were of the opinion that something better could be done.

5.4.3 User Acceptance

In order to evaluate the success of the system it was important that the users acknowledge its importance to their daily operations. 87% of the intended users of the application found it relevant to assist in decision making in cases of aircraft disruptions. 5% of the respondents were not certain on the value proposition that was given by the system. The remaining 7% rejected the system since they preferred to continue using their tacit knowledge to come up with solutions.

5.5 Validation

5.5.1 Schedule and Disruption Scenarios

The validation of the model was done by running actual disruptions captured in a two-day schedule consisting of a total of 277 flights between 21st and 22nd November 2017, detailed in Appendix D. The schedule used was obtained from Sabre scheduling software which is used by the airline to schedule flights.

Disruption Scenarios

Kenya Airways does not always record and review the times which disruptions were reported. In order to acquire this information, two days were spent at the operations control room taking note of disruptions that took place. Below is a list detailing the disruptions which were 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 06:30, found out at 3:00

• Scenario 3: No crew available resulting in flight cancellation

– Flight KQ860 cancelled at 20:20, found out at 19:00

• Scenario 4: Technical 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 airport closure for 4 hours

– Airport MBA unavailable from 10:00 until 14:00 found out 9:00

In addition to these time-spaced disruptions, the model was also tested with full day disruption cases that occurred in the airline. The list below details some of these disruptions:

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 04:10 until 07:30, found out at 04:00

– Aircraft 5Y-KYR unavailable from 11:40 until 24:00, found out at 09:30

• Full day 2:

– Aircraft 5Y-KYQ unavailable from 04:10 until 16:30, found out at 04:00

– Aircraft 5Y-FFH unavailable from 04:10 until 07:30, found out at 04:00

– Flight KQ550a unavailable until 07:00, found out at 04:30

– Flight KQ512b unavailable until 15:00, found out at 13:50

– Flight KQ502 unavailable until 14:40, found out at 13:40

– Flight KQ670 unavailable until 14:40 found out at 13:40

– Flight KQ416 unavailable until 20:40 found out at 19:20

– Flight KQ503 unavailable until 21:40 found out at 20:50

5.5.2 Validation with Duty Operations Managers

The validation of the model is done by checking the results found by the model with industry expert John Nalyanya, all of who is the head of operations control at Kenya Airways with experience in solving disruptions. Three of the scenarios are full days of disruptions from the Kenya Airways network in November 2017 each selected for the high number of reactionary delays. All of these scenarios have been applied to the schedule of 21-23 November 2017. The reason that this is done is because the operations as scheduled (including tail numbers) as planned at a given point in the past 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.

The final scenario is an actual disrupted day of operations at Kenya Airways 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 Centre and the final solution could be compared with the one implemented.

The conclusions from the validation sessions that were held with the duty operations manager were the following:

Cost Implications: Based on the responses of the validation interview in Appendix C, the study concluded that the model generated solutions with lower cost implications. The costs incurred from the disrupted schedules, detailed in Appendix E were concluded as lower than the average costs incurred. It was however difficult to determine the exact cost difference since the airline splits the costs to various departments’ budgets. Also at times the research noted that the costs incurred in fines are wavered by the government bodies such as Kenya Civil Aviation Authorities. Costs incurred as a result of passenger reimbursement are as well not structured or predetermined since most passengers do not claim to be reimbursed. It is therefore varied from disruption to disruption.

Time: Computational time was of essence since an increase in delay time implied an increase in recovery cost. The model run times, detailed in Appendix E were compared with the manual operations. Based on feedback from the DMO through an interview detailed in Appendix C, it was noted that the model solved the problem faster that the average time taken. It was however noted that an increase in computing power could reduce the computational time for the model. For a new Staff member in the operations control centre, such disruption scenarios could take a minimum of three hours to solve for a time spaced disruption, and a whole day for a full day disruption. For an experienced staff member, the process could take up to five to six hours for a full day disruption. The model run for a total of 52 minutes with a total of 38 possible runs to generate solutions for a time spaced disruption. For a full day disruption, the model run for a maximum of three hours. This was desirable compared to the manual disruption especially when a new staff member is involved.

Crew issues: Though the DMO's agree that the operational cost should be kept low, the amount of tail switches that are done between fleet types are quite numerous. In these scenarios the number of flights flown by Embraer increases and the number of flights by Boeing 737's, decreases. This will mean that the scheduled crews for Embraer are required to fly more flights, which could cause problem from a crew perspective. This issue is one which 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.

5.5.3 Computational Performance

In airline recovery operation, handling speed of the operations control center makes the difference between having to delay or cancel flights. Decisions 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 study is set up with the goal of being implemented as a decision support tool for real time operations. Interview with Kenya Airways DMO's captured in Appendix B, determines that depending on the disruption, final decision on what to do should be made in a time-span of 30 to 60 minutes.

In the created model the module which will work as a decision support tool is the optimiser. This is the element which solves for all the disruptions known at a given moment in time. For time spaced disruption, this disruption set solver meets the 60-minute requirement in all of the 38 runs of DSS in the tested scenarios. Appendix E details the results of the runs.

The solver runs two different parts: the first part is the running through the selected fleet in which aircraft have been put in a specific order and saving the selection of aircraft providing the best solution. The second part is run with the best solution in the previous step, running through the same selected fleet same in random order in search of a better selection of aircraft providing a better solution. When the solution is no longer improving the stopping condition is met and the best solution is printed.

5.6 Conclusions

The system requirements coupled with agile development methodology provided a stable base for efficient, user-centred development of the system. The system was developed with functional and non-functional requirements in mind. A series of tests were carried out by an independent testers and users to verify that the system was ready for deployment to the industry. Results produced by the mathematical model were compared with the manual process being carried out in Kenya Airways and it was concluded that the model provided timely and cost effective solutions.

CHAPTER 6 : DISCUSSIONS

6.1 Introduction

The purpose of this research was to identify challenges faced by airlines during the aircraft recovery process, to adapt a suitable mathematical model that solves the aircraft recovery problem then to design and test a system that implements the mathematical model. Finally, to validate the developed system.

This was in order to adapt a suitable technique to be used to recover aircraft from schedule disruptions. The literature review offered a deep dive into the airline schedule recovery management domain. The research findings helped develop a system that offers possible schedule recovery solutions in such cases.

Once the design, development and testing process of the system was complete, the study sort out to find out whether the set objectives of the research were accomplished and the relevance of the proposed system to solve the current problem. The research delved into the airline current recovery operations with an intention to develop an efficient, easy to use system.

6.2 Explanation of Findings

The researcher issued online questionnaires to duty managers in Kenya Airways, and interviewed one director. From the mentioned sources, it was evident that aircraft schedule recovery management needed to be improved. This is because the current recovery management measures put in place were not accurate since they relied on human experience and tacit knowledge. Data was collected and analysed to provide answers to the research questions.

6.3 Discussions

This dissertation aimed at identifying challenges faced in the airline industry especially on schedule recovery management. An aircraft recovery management system was developed to help duty managers in the airline make informed decisions when recovering disrupted aircraft schedules.

The research's first objective in Section 1.3 identify challenges in faced by airlines during the aircraft recovery process. The study identified the major challenge being reliance on human experience in the decision making process which was not necessarily the most efficient method. Allowing the duty manager to make decision had an implication of not having the bigger picture in mind from the onset. For instance, it could not be possible to compare the cost implication of recovering an aircraft schedule when presented with two possible solutions. The system developed offered an option to come up with a suggested solution and also its get to know its implications making it possible to make informed decisions.

The second objective was to adapt a suitable mathematical model that solves the aircraft recovery problem in Section 1.3. From literature, different mathematical models had been designed but not necessarily implemented. The researcher thus developed a mathematical model that advanced the already existing models.

The third objective was to design and test a system that implements the mathematical model. This was an extension to what previous researchers had done. The system was able to get parameters from the users, optimise the model and provide a set of suggested solutions. For this case, the expected output from the system would be a revised schedule that would be cost effective as well as try to adhere to the initial schedule. The research focused on optimising the proposed model. The researcher further displayed the results of the optimisation process to a web portal.

The final objective was to validate the developed system. This was to determine the relevance of the system to the airline. Validation was conducted by the various tests that were done. How the proposed system integrated with the existing airline operations systems was critical, especially the scheduling system. Compatibility tests were done to ascertain that the system was supported by different browsers.

6.4 Advantages of the Proposed System

The developed system has the following advantages over the existing ways of recovering aircraft currently in use:

i. The system, running the model through an optimiser, generates solutions in relatively shorter periods of time compared to human experience. Optimising a full day schedule, with 100 flights, the schedule can generate a solution in 1hr 13 minutes. Running the schedules in time windows allow faster turnaround of the model solution, with an average time span of 16 minutes for a quarter a day.

ii. The application allows easy modification of decision variables that are necessary to generate optimal solution. Data can be fed to

iii. The application is designed to integrate with other systems receiving up to date information with a click of a button.

6.5 Disadvantages of the Proposed System

i. The system could take quite some time to come up with a solution especially when the decision variables are too many.

ii. The application is reliant on the internet in order to communicate with other systems. In case of a network connection challenge then the application is rendered obsolete.

6.6 Conclusions

Feedback received during testing phase indicated that the developed platform had a positive impact to the organisation. Its ability to generate more than one possible solution was its most desirable feature since it gave the Duty Manager Operations the ability to make informed decisions with implications in mind.

CHAPTER 7 : CONCLUSIONS, RECOMMENDATIONS

7.1 Conclusions

Technology has been much appreciated in airline recovery management the past decade. Information gathered from literature illustrated the evolving of mathematical models since 1993. However, from literature it was evident that most mathematical models developed did not go the extent of creating computerised systems. There was therefore a high demand for a computerised system which relied on linear programming principles and optimisation to create new airline schedule after disruptions. From the analysis carried out, it was evident that there are major problems in recovering schedules. For the sample airline this research worked with, the use of human experience did not necessarily end up with the best approaches.

The result was the development of an aircraft schedule recovery management system. The key features of the system were to load the current schedule in order to see the source of the disruption; to run the model to come up with optimised solutions and finally to view reports of previous disruptions and solutions. The main aim of the system was to regenerate an optimised aircraft schedule after disruptions. The system was developed, tested and is awaiting adoption to the industry. Once adopted, the airline will be able to regenerate their schedules in case of disruptions with much ease, and pick an option that has less cost implications to the organisation.

7.2 Recommendations

Schedule recovery optimisation is at the heart of airline operations. My recommendations therefore, for the system to work better in the industry would be to automate the process. Currently the proposed system takes inputs manually, including current schedules. Automation can be achieved by integrating the system with Sabre Scheduling System currently in use. This can be achieved by developing a communication API between the two systems to ensure that there is real time communication among them.

Secondly, the airline would need to invest in powerful computers that would be able to run the optimiser faster and generate results in a shorter period of time.

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APPENDICES

Appendix A: User Questionnaire

Pre-Questionnaire

This questionnaire intends to gather information on Aircraft recovery management process. The information you provide will benefit the researcher in accomplishing academic goals and developing a reliable Aircraft schedule recovery system. Please note that there is no right or wrong answer and no personal details are required.

(Please answer the questions to the best of your ability)

1. Do you take part in schedule recovery process?

    () Yes () No

2. Please describe your role in the recovery management process

____

3. What type of browser do use on your computer?

    ( ) Internet Explorer ( ) Mozilla Firefox ( ) Google Chrome

4. What operation system is your computer running?

    ( ) Windows ( ) Mac OS () Linux

5. How long on average does it take to recover an aircraft schedule?

    ( ) 1 hour ( ) 30 minutes ( ) 10 minutes ( ) Not sure

6. Please describe the greatest challenge you face when recovering aircraft schedule.

____

7. Please describe the how you would prefer the challenge stated above be solved using technology.

____

Post Questionnaire

This questionnaire was designed to get your feedback on the system and help improve or address any features of concern. The application provided is a prototype and the data presented is dummy. The web application link has been attached in this email. Please ascertain if you are able to perform all functions without any challenges.

1. Were you able to access the web application easily?

( ) Yes ( ) No

2. If not, kindly list the problems you encountered

____

3. The web application was appealing

( ) Strongly Agree ( ) Agree ( ) Neutral ( ) Disagree

4. If you disagree, kindly give your reason

____

5. Core functionalities were easy to find.

( ) Strongly Agree ( ) Agree ( ) Neutral ( ) Disagree

6. The application's performance was great when interacting with other systems and recovering the schedule.

( ) Strongly Agree ( ) Agree ( ) Neutral ( ) Disagree

7. On a scale of 1-5 with 5 being the highest and 1 the lowest, kindly rate the usability of the application in different browsers

( ) 5 ( ) 4 ( ) 3 ( ) 2 ( ) 1

8. Would you consider the application more effective as compared to the current system?

( ) Yes ( ) No

9. Please specify after how long the system took to come up with a solution?

( ) 2hrs ( ) 1hr 30mins ( ) 1hr ( ) 30 minutes ( ) 10 minutes

10. Do you find this time computationally feasible based on the urgency of the situation?

( ) Yes ( ) No

11. If no, please suggest ways which the system could be improved to make it better.

____

Appendix B: Interview Questions

1. How a disruption is made known to the whole airline network? Through what channels?
2. What is the first step of action in case a disruption has been reported? Say an aircraft is unavailable due to technical issues?
3. During your peak hours, in case a disruption takes place, how do you manage the large traffic?
4. How did you solve the disruption that took place last week 20th March 2017 where a passenger passed on while boarding the aircraft leading to the aircraft being grounded and cancellation of flights assigned to it?
5. At what point does tail switching seem the only left alternative to solve the disruption?
6. After how long does cancelling a flight seem the best option or the most cost effective?
7. Why are flights to Europe given a higher recovery priority that other destinations?
8. If an automated system would be proposed to generate recovery solutions, what would you require it to do?
9. What's the minimum average time required to solve a disruption?

Appendix C: Interview Questions- Validation

1. Kindly explain the process it would take you to recover a full day schedule with the disruptions in the scenarios document.

2. How long on average can you take to solve such disruptions in your line of duty?

3. Base on the duration taken by the model to generate these solutions, would you consider it a faster method than the manual way?

4. What challenges do you encounter solving these disruptions?

5. In comparison to the manual disruption recovery, would you find solutions generated by the model cost effective?

Appendix D: Two-day Schedule

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	ALC	Date	Day	DayNr	flightnr_origi	flightnr	flightnr2	tailnr	origin	destination	STD_original	STA_original	STA_day_cor	STD	STA	STD_new	STA_new	delay	cancelled	passengers	Business	Economy
2	KQA	11/21/17	21	0	101	101	21101	KQS	LHR	NBO	1900	330	2730	1900	2730	1900	2730	0	0	186	23	163
3	KQA	11/21/17	21	0	102	102	21102	KQT	NBO	LHR	2050	545	2945	2050	2945	2050	2945	0	0	118	23	95
4	KQA	11/21/17	21	0	112	112	21112	KZB	NBO	CDG	2040	520	2920	2040	2920	2040	2920	0	0	175	11	164
5	KQA	11/21/17	21	0	113	113	21113	KZB	CDG	NBO	955	1800	1800	955	1800	955	1800	0	0	175	11	164
6	KQA	11/21/17	21	0	116	116	21116	KZX	NBO	AMS	525	1420	1420	525	1420	525	1420	0	0	119	1	118
7	KQA	11/21/17	21	0	117	117	21117	KZX	AMS	NBO	1940	400	2800	1940	2800	1940	2800	0	0	161	18	143
8	KQA	11/21/17	21	0	190	190	21190	FFE	NBO	NBO	600	900	900	600	900	600	900	0	0	10	5	5
9	KQA	11/21/17	21	0	202	202	21202	KYZ	NBO	BOM	1410	2015	2015	1410	2015	1410	2015	0	0	251	8	243
10	KQA	11/21/17	22	0	203	203	21203	KYZ	BOM	NBO	2130	325	2725	2130	2725	2130	2725	0	0	157	7	150
11	KQA	11/21/17	21	0	204	204	21204	KYD	NBO	BOM	1920	125	2525	1920	2525	1920	2525	0	0	164	1	163
12	KQA	11/21/17	21	0	310	310	21310	KZD	NBO	DXB	1610	2125	2125	1610	2125	1610	2125	0	0	93	11	82
13	KQA	11/21/17	21	0	311	310	21310	KZD	DXB	NBO	2245	350	2750	2245	2750	2245	2750	0	0	220	14	206
14	KQA	11/21/17	21	0	340	340	21340	KYH	NBO	KRT	945	1235	1235	945	1235	945	1235	0	0	31	6	25
15	KQA	11/21/17	21	0	341	341	21341	KYH	KRT	NBO	1325	1625	1625	1325	1625	1325	1625	0	0	41	4	37
16	KQA	11/21/17	21	0	350	350	21350	KYH	NBO	JUB	450	630	630	450	630	450	630	0	0	40	4	36
17	KQA	11/21/17	21	0	351	351	21351	KYH	JUB	NBO	720	900	900	720	900	720	900	0	0	36	1	35
18	KQA	11/21/17	21	0	352	352	21352	KYP	NBO	JUB	955	1135	1135	955	1135	955	1135	0	0	60	4	56
19	KQA	11/21/17	21	0	353	353	21353	KYP	JUB	NBO	1225	1405	1405	1225	1405	1225	1405	0	0	14	0	14
20	KQA	11/21/17	21	0	354	354	21354	KYR	NBO	JUB	1205	1350	1350	1205	1350	1205	1350	0	0	40	2	38
21	KQA	11/21/17	21	0	355	355	21355	KYR	JUB	NBO	1440	1625	1625	1440	1625	1440	1625	0	0	25	2	23
22	KQA	11/21/17	21	0	402	402	21402	FFJ	NBO	ADD	650	900	900	650	900	650	900	0	0	62	3	59
23	KQA	11/21/17	21	0	402	402	21402	FFJ	ADD	JIB	950	1110	1110	950	1110	950	1110	0	0	38	5	33
24	KQA	11/21/17	21	0	403	403	21403	FFJ	JIB	ADD	1200	1315	1315	1200	1315	1200	1315	0	0	21	3	18
25	KQA	11/21/17	21	0	403	403	21403	FFJ	ADD	NBO	1405	1615	1615	1405	1615	1405	1615	0	0	50	4	46
26	KQA	11/21/17	21	0	408	408	21408	FFC	NBO	JIB	1930	2205	2205	1930	2205	1930	2205	0	0	21	3	18
27	KQA	11/21/17	21	0	408	408	21408	FFC	JIB	ADD	2255	10	2410	2255	2410	2255	2410	0	0	28	3	25
28	KQA	11/21/17	21	0	408	408	21408	FFC	ADD	NBO	2510	2715	2715	2510	2715	2510	2715	0	0	44	4	40
29	KQA	11/21/17	21	0	410	410	21410	FFG	NBO	EBB	500	615	615	500	615	500	615	0	0	96	13	83
30	KQA	11/21/17	21	0	411	411	21411	FFG	EBB	NBO	705	815	815	705	815	705	815	0	0	130	6	124
31	KQA	11/21/17	21	0	412	412	21412	KYT	NBO	EBB	945	1100	1100	945	1100	945	1100	0	0	60	2	58
32	KQA	11/21/17	21	0	413	413	21413	KYT	EBB	NBO	1150	1300	1300	1150	1300	1150	1300	0	0	74	5	69
33	KQA	11/21/17	21	0	414	414	21414	KYT	NBO	EBB	1425	1540	1540	1425	1540	1425	1540	0	0	43	2	41
34	KQA	11/21/17	21	0	415	415	21415	KYT	EBB	NBO	1630	1740	1740	1630	1740	1630	1740	0	0	86	7	79
35	KQA	11/21/17	21	0	416	416	21416	KYT	NBO	EBB	2005	2115	2115	2005	2115	2005	2115	0	0	43	5	38
36	KQA	11/21/17	21	0	417	417	21417	KYR	EBB	NBO	205	315	315	205	315	205	315	0	0	117	4	113
37	KQA	11/21/17	21	0	418	418	21418	KYP	NBO	EBB	1600	1715	1715	1600	1715	1600	1715	0	0	47	2	45

1	ALC	Date	Day	DayNr	flightnr_origi	flightnr	flightnr2	tailnr	origin	destination	STD_original	STA_original	STA_day_cor	STD	STA	STD_new	STA_new	delay	cancelled	passengers	Business	Economy
243	KQA	11/22/17	22	1	650	1650	22650	KYR	NBO	KIS	400	450	450	2800	2850	2800	2850	0	0	66	4	62
244	KQA	11/22/17	22	1	651	1651	22651	KYR	KIS	NBO	535	625	625	2935	3025	2935	3025	0	0	48	0	48
245	KQA	11/22/17	22	1	654	1654	22654	KYR	NBO	KIS	720	810	810	3120	3210	3120	3210	0	0	55	0	55
246	KQA	11/22/17	22	1	655	1655	22655	KYR	KIS	NBO	855	945	945	3255	3345	3255	3345	0	0	38	3	35
247	KQA	11/22/17	22	1	656	1656	22656	KYR	NBO	KIS	1030	1120	1120	3430	3520	3430	3520	0	0	35	1	34
248	KQA	11/22/17	22	1	657	1657	22657	KYR	KIS	NBO	1205	1255	1255	3605	3655	3605	3655	0	0	53	5	48
249	KQA	11/22/17	22	1	670	1670	22670	KYQ	NBO	KIS	1430	1520	1520	3830	3920	3830	3920	0	0	70	3	67
250	KQA	11/22/17	22	1	671	1671	22671	KYQ	KIS	NBO	1610	1655	1655	4010	4055	4010	4055	0	0	79	11	68
251	KQA	11/22/17	22	1	702	1702	22702	KQU	NBO	HRE	450	750	750	2850	3150	2850	3150	0	0	79	11	68
252	KQA	11/22/17	22	1	702	1702	22702	KQU	HRE	LUN	840	945	945	3240	3345	3240	3345	0	0	79	11	68
253	KQA	11/22/17	22	1	702	1702	22702	KQU	LUN	NBO	1035	1315	1315	3435	3715	3435	3715	0	0	79	11	68
254	KQA	11/22/17	22	1	704	1704	22704	FFD	NBO	HRE	1000	1300	1300	3400	3700	3400	3700	0	0	79	11	68
255	KQA	11/22/17	22	1	704	1704	22704	FFD	HRE	LUN	1350	1455	1455	3750	3855	3750	3855	0	0	79	11	68
256	KQA	11/22/17	22	1	704	1704	22704	FFD	LUN	NBO	1545	1825	1825	3945	4225	3945	4225	0	0	79	11	68
257	KQA	11/22/17	22	1	732	1732	22732	FFC	NBO	LLW	1840	2105	2105	4240	4505	4240	4505	0	0	25	2	23
258	KQA	11/22/17	22	1	732	1732	22732	FFC	LLW	LUN	2205	2315	2315	4605	4715	4605	4715	0	0	25	2	23
259	KQA	11/22/17	22	1	732	1732	22732	FFC	LUN	NBO	2415	2655	2655	4815	5055	4815	5055	0	0	25	2	23
260	KQA	11/22/17	22	1	748	1748	22748	FFK	NBO	APL	720	950	950	3120	3350	3120	3350	0	0	27	5	22
261	KQA	11/22/17	22	1	749	1749	22749	FFK	APL	NBO	1040	1310	1310	3440	3710	3440	3710	0	0	27	5	22
262	KQA	11/22/17	22	1	752	1752	22752	FFJ	NBO	LLW	600	810	810	3000	3210	3000	3210	0	0	27	5	22
263	KQA	11/22/17	22	1	752	1752	22752	FFJ	LLW	BLZ	855	945	945	3255	3345	3255	3345	0	0	27	5	22
264	KQA	11/22/17	22	1	752	1752	22752	FFJ	BLZ	NBO	1035	1305	1305	3435	3705	3435	3705	0	0	27	5	22
265	KQA	11/22/17	22	1	756	1756	22756	KYQ	NBO	TNR	540	900	900	2940	3300	2940	3300	0	0	27	5	22
266	KQA	11/22/17	22	1	757	1757	22757	KYQ	TNR	NBO	950	1310	1310	3350	3710	3350	3710	0	0	27	5	22
267	KQA	11/22/17	22	1	760	1760	22760	KYS	NBO	JNB	335	750	750	2735	3150	2735	3150	0	0	34	4	30
268	KQA	11/22/17	22	1	761	1761	22761	KYS	JNB	NBO	855	1305	1305	3255	3705	3255	3705	0	0	57	9	48
269	KQA	11/22/17	22	1	762	1762	22762	KYF	NBO	JNB	545	1000	1000	2945	3400	2945	3400	0	0	113	12	101
270	KQA	11/22/17	22	1	763	1763	22763	KYF	JNB	NBO	1120	1530	1530	3520	3930	3520	3930	0	0	120	16	104
271	KQA	11/22/17	22	1	764	1764	22764	CYA	NBO	JNB	1735	2150	2150	4135	4550	4135	4550	0	0	94	14	80
272	KQA	11/22/17	22	1	861	1861	22861	KZC	HKG	BKK	1340	1620	1620	3740	4020	3740	4020	0	0	214	10	204
273	KQA	11/22/17	22	1	861	1861	22861	KZC	BKK	NBO	1735	215	2615	4135	5015	4135	5015	0	0	214	10	204
274	KQA	11/22/17	22	1	882	1882	22882	KZF	NBO	CAN	2155	825	3225	4555	5625	4555	5625	0	0	170	11	159
275	KQA	11/22/17	22	1	883	1883	22883	KZF	CAN	NBO	3740	2500	4900	6140	7300	6140	7300	0	0	170	11	159
276	KQA	11/22/17	22	1	886	1886	22886	KZA	NBO	BKK	2045	615	3015	4445	5415	4445	5415	0	0	175	23	152
277	KQA	11/22/17	22	1	886	1886	22886	KZA	BKK	CAN	3150	3505	3505	5550	5905	5550	5905	0	0	175	23	152

Appendix E: Results

	A	B	C	D	E	F	G	H	I
1	runs	hauls	solution_values	COST_no_delays	COST_with_delay	runtimes	# of airports	# of ACused	# of AC selection
2	primary filter	short-haul ['E70' 'E90']	435080	430473	4607	01:30.1	20	7	9
3	primary filter	short-haul ['E70' 'E90']	378904	373806	5098	00:52.2	17	6	9
4	greedy0	short-haul ['E70' 'E90']	406286	401760	4526	01:12.9	17	8	9
5	greedy0	short-haul ['E70' 'E90']	424639	420032	4607	01:33.9	20	7	9
6	greedy0	short-haul ['E70' 'E90']	403090	398547	4543	01:25.5	18	7	9
7	greedy0	short-haul ['E70' 'E90']	390811	387607	3204	01:10.2	18	7	9
8	greedy1	short-haul ['E70' 'E90']	384907	381684	3223	00:59.6	17	8	9
9	greedy1	short-haul ['E70' 'E90']	422738	419534	3204	01:07.5	19	7	9
10	greedy1	short-haul ['E70' 'E90']	396384	393180	3204	01:08.1	18	7	9
11	greedy1	short-haul ['E70' 'E90']	383935	380731	3204	00:59.4	16	7	9
12	primary filter	short-haul ['other' 'B738' 'B73L' 'B73W']	430404	424603	5801	01:14.7	19	6	9
13	primary filter	short-haul ['other' 'B738' 'B73L' 'B73W']	389295	384846	4449	00:53.3	16	6	9
14	greedy0	short-haul ['other' 'B738' 'B73L' 'B73W']	360823	358067	2756	00:52.2	14	7	9
15	greedy0	short-haul ['other' 'B738' 'B73L' 'B73W']	423745	419296	4449	00:58.1	17	6	9
16	greedy0	short-haul ['other' 'B738' 'B73L' 'B73W']	398689	395619	3070	01:00.0	18	6	9
17	greedy1	short-haul ['other' 'B738' 'B73L' 'B73W']	472577	469611	2966	01:32.7	17	8	10
18	greedy1	short-haul ['other' 'B738' 'B73L' 'B73W']	412778	410022	2756	01:30.7	17	7	10
19	greedy1	short-haul ['other' 'B738' 'B73L' 'B73W']	385951	383195	2756	01:19.1	15	7	10
20	primary filter	short-haul ['E70' 'E90']	524186	521948	2238	04:11.5	23	4	13
21	primary filter	short-haul ['E70' 'E90']	519137	516880	2257	03:55.9	24	5	13
22	greedy0	short-haul ['E70' 'E90']	435963	433706	2257	02:04.9	20	5	11
23	greedy0	short-haul ['E70' 'E90']	404768	402511	2257	01:47.4	19	5	11
24	primary filter	short-haul ['other' 'B738' 'B73L' 'B73W']	459449	464719	-5270	01:51.3	16	6	11
25	primary filter	short-haul ['other' 'B738' 'B73L' 'B73W']	457496	462766	-5270	02:05.0	18	6	11
26	greedy0	short-haul ['other' 'B738' 'B73L' 'B73W']	367593	372863	-5270	00:52.2	14	6	9
27	greedy0	short-haul ['other' 'B738' 'B73L' 'B73W']	375135	380405	-5270	00:57.8	16	6	9
28	greedy0	short-haul ['other' 'B738' 'B73L' 'B73W']	334780	340050	-5270	00:43.7	13	6	9
29	primary filter	long-haul ['B767' 'B772' 'B773' 'B788']	2083156	2082131	1025	01:51.4	13	1	9
30	primary filter	long-haul ['B767' 'B772' 'B773' 'B788']	2066062	2065037	1025	01:12.9	10	1	9
31	greedy0	long-haul ['B767' 'B772' 'B773' 'B788']	2214850	2213825	1025	01:58.4	13	1	9
32	greedy0	long-haul ['B767' 'B772' 'B773' 'B788']	2055553	2054528	1025	01:47.9	13	1	9
33	primary filter	short-haul ['B738' 'B73W' 'B73L']	319535	318799	736	00:13.8	11	1	8
34	primary filter	short-haul ['other' 'E70' 'E90']	530775	529939	836	09:13.4	24	3	15
35	primary filter	short-haul ['other' 'E70' 'E90']	522481	521745	736	10:01.5	25	1	15
36	greedy0	short-haul ['other' 'E70' 'E90']	522481	521745	736	08:49.1	25	1	15
37	greedy0	short-haul ['other' 'E70' 'E90']	542156	541320	836	08:58.0	25	3	15
38	primary filter	long-haul ['B767' 'B772' 'B773' 'B788']	1930783	1929758	1025	01:07.8	12	1	9
39	primary filter	long-haul ['B767' 'B772' 'B773' 'B788']	1913689	1912664	1025	00:41.1	9	1	9
40	greedy0	long-haul ['B767' 'B772' 'B773' 'B788']	1946778	1945753	1025	01:11.8	12	1	9
41	greedy0	long-haul ['B767' 'B772' 'B773' 'B788']	1930783	1929758	1025	01:05.9	12	1	9

Figure E.1 Results

Appendix F: Turnitin Report

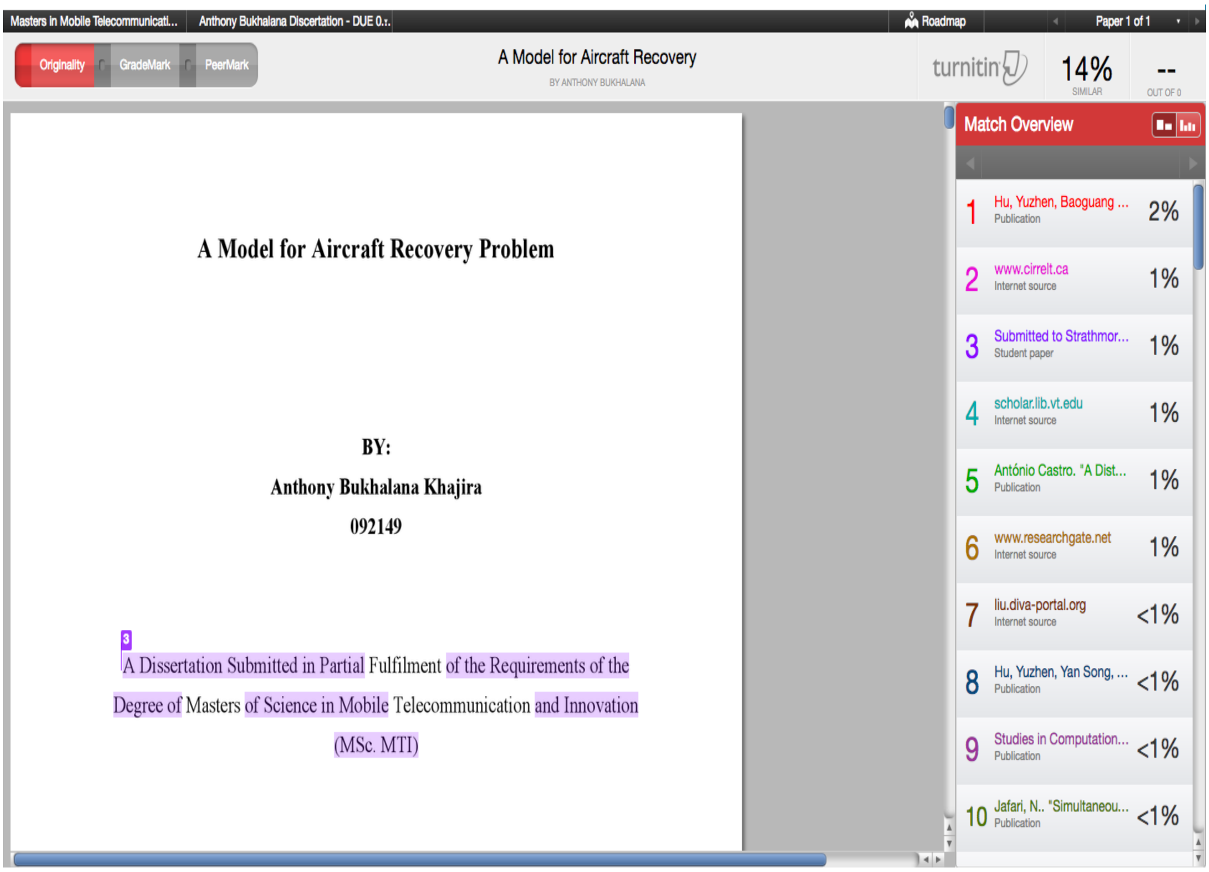

Figure F. 1 Turnitin Report