Dynamic Crew Pairing Recovery

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TU Delft

Kenya Airways
The Pride of Africa

Dynamic Crew Pairing Recovery

by

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Preface

Last year was very tumultuous in which I have learned a lot. Not only knowledge about the work field but also things about myself as a person. I had my ups and downs, worked very hard, travelled many times to Kenya and gained many experiences. The project contained all aspects that I preferred, like the collaboration with a company, the tangibility of the project and besides that working close to the operation of an airline. I have learned myself in a way I did not expect. Programming for days was something new for me and in the beginning I was anxious for it. However, after a while I was confident in the programming language and even during my summer holidays I felt the urge to continue with the project. This project was not possible without the help of some people. Therefore, I would like to take a moment for all of those who supported me and helped me during the project.

First of all, I would like to thank Bruno Santos, my supervisor from Delft University of Technology. In all the meetings, he provided me with feedback and supported me with the continuation of the project. He was always a few steps ahead, what was sometimes annoying, but at the end it definitely helped me to push the project to a higher level. His input was of a great value for the project. Furthermore, I would like to thank Bruno Santos and Ricky Curran to come all the way to Kenya for important meetings with Kenya Airways.

Of course, I would really like to thank Kenya Airways to make this project possible. All the support and information the employees from Kenya Airways provided me to make this project a success. The colleagues from OCC at JKIA, with whom I had a great time during my visits to Kenya. Thank you for the hospitality and the efforts to come and pick me up every day at the crew gate. Moreover, thanks to teach me some Swahili words with which we had a lot of fun, asante sana! Special thanks to John Nalianya and Esther Wagumba for all the meetings and support during my project. Furthermore, special thanks to Thomas Omondi who made it possible to execute this project in collaboration with Kenya Airways. Many thanks for making this project an amazing experience for me and I hope to see you all again soon.

Last but not least, I would like to thank my family and friends for all their support during my project. They had to hear all my stories, picked me up and took me away to the airport many times and had to deal with the ups and downs. Especially, I would really like to thank my girlfriend who was always there for me. She supported me in good and bad times and even visited me in Kenya where we had an amazing time together. Thank you so much.

Without all these people this project would never became to what it is now. Therefore, many thanks to you all and I really appreciate what you all have done for me in the last year.

N.J.M.Hoeben
Delft, April 2017

Summary

Introduction

An aircraft breakdown, crew coming late, or bad weather conditions are examples of disruptions that airlines have to cope with on a daily basis. Even small disruptions might cause infeasibility of airline schedules. Currently, operation controllers of most airlines solve disruptions manually at the day of operation. They attempt to make the schedules feasible again and strive to return to the original schedule as soon as possible. In addition, it is of great importance to minimize the costs. However, dealing with all the rules, regulations, preferences and costs makes that the recovery process is a complex problem.

Therefore, decision support tools need to be developed to assist operation controllers during the recovery process. A decision support tool can provide several solutions to the operation controllers considering all kind of parameters. However, it is of great interest that solutions are generated in short computation times since decisions have to be made in a short amount of time.

This research project considers the crew recovery problem, since crew recovery is one of the hardest recovery tasks. Many regulations have to be considered and human factors are involved as well. In addition, after fuel costs, crew costs are one of the largest costs of an airline. Therefore, in this research project a decision support tool is developed for the crew recovery problem.

This Master Thesis research project is conducted at the University of Technology Delft (TU Delft). More specifically, at the Air Transport and Operations department from the faculty of Aerospace Engineering. Furthermore, the research is conducted in collaboration with Kenya Airways (KQ).

Literature review

The literature study was used to define the gap in knowledge about crew recovery. Since crew recovery is part of airline recovery, the literature on airline recovery is reviewed to gain a complete overview of the problem. Airline recovery consists of aircraft, crew and passenger recovery.

Since the 90's, airline recovery is an upcoming research topic. Decision support tools are developed to assist operation controllers during disruptions. The aim is to provide better and more solutions to the operation controllers. Most research investigates one part of the recovery problem. Some papers investigate the integration of the several recovery problems into one model. However, with no success, since the models cannot be used in real time operation due to the long computation times.

All papers use a selection of aircraft or crew together with a time window in which the problem must be solved. This decreases the computation times making it for most models possible to use it in real time operations albeit with many assumptions.

Papers about crew recovery use a fixed schedule as input. Some papers allow cancelling or delaying flights to obtain better results. However, in all cases the disruption or set of disruptions is known at the start of the day. It cannot be forecast which disruptions will arise during the day of operation. A dynamic decision support tool that models disruptions at the moment of notification only exists for aircraft recovery. To the knowledge of the author of this research project there is no dynamic crew recovery model present in literature. Therefore, the gap in the literature is defined as the dynamic crew recovery problem.

Project Plan

The main research question and the research objective are formulated as follows:

Main research question

How does a dynamic decision support model for crew recovery problems contribute to the recovery solutions of an airline regarding computation time and cost?

Main research objective

Develop a dynamic decision optimization model to minimize the crew recovery cost during disruptions that supports operation controllers to obtain feasible and where possible optimal solutions.

Information was gathered from the literature review as well from interviews with experts at KQ. A linear programming model was developed and together with an optimization tool the problems were solved. The model was verified by testing small test cases with obvious solutions. Data from KQ were used to set up and test the model. In addition, analysing the results of test cases together with experts at KQ resulted in the validation of the model.

The model solved the problem with a dynamic approach. Delaying, cancelling and swapping flights together with using standby crew are recovery options in the model. Furthermore, individual crew members were considered to generate more possible solutions. A selection algorithm was used to consider only a part of the crew members in the generation of new pairings. Finally, together with the new pairings the problem was solved.

Model Framework

A linear programming model was developed for the crew recovery problem in which the recovery costs are minimized. The model is programmed in Python and CPLEX is used as optimization tool. The general outline of the model is illustrated in Figure 1.

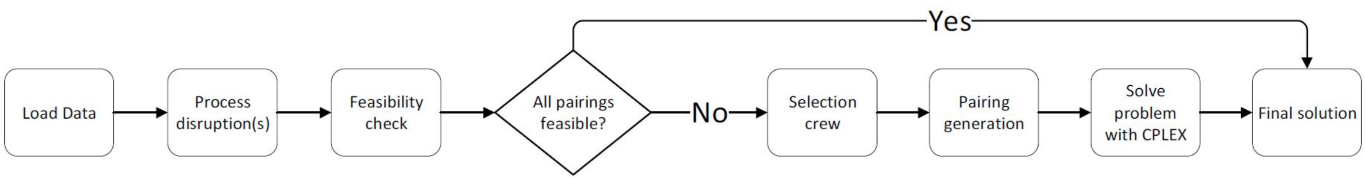

Figure 1: Flowchart of the recovery model.

Together with the disruptions, flight- and crew schedules are the input of the model. The input disruptions are processed in the schedule after which a feasibility check of the pairings was done. Some examples of the feasibility checks are rest times, duty times and transition times. In case pairings are infeasible, new pairings are generated based on a selection of crew members. In the selection algorithm, many options are available for an airline. The selection of crew members can be based on reporting times, duty times or block hours of crew members. Thereafter, new pairings are generated for the selected crew members by using a depth first search algorithm. The model solves the problem by using a dynamic approach and therefore previous recovery decisions can be revised. The quality of the solutions depends on the choices made by the airline. A trade-off can be defined between running times of the model and the quality of the solution. This implies that limited selections will negatively influence the quality of the solutions, however lower computation times will be achieved.

Verification and Validation

Small test cases were defined to verify the model. Cancellations of flights, adding delay, swapping flights, using standby crew members and testing the dynamic approach are examples of the small test cases performed. In all cases, the model provided the expected results and therefore the model is verified.

Full day scenarios were tested to validate the model. Before day scenarios were tested an initial run was performed. This was necessary to eliminate changes made by the model to the original schedule. The initial run already optimized the schedule and lower costs were generated. A set of disruptions was used as input and the results obtained by the model were analysed with experts from KQ. This is called face-validation. All computation times were less than a minute when using a selection of crew members. Even the use of the entire set of crew members resulted in solutions in less than three minutes. Using the entire set of crew members results in the best recovery solutions. Based on the computation times and recovery costs of the test cases it was concluded that the model is valid.

Sensitivity analysis

Several sensitivity test analysis were performed to analyse the performance of the model in case of different input parameters and choices made in the model. Different numbers of selected crew members, different selection options (as reporting time, duty time and block hours) and the comparison of the results with the global optimums were analysed.

In general, it can be concluded that the best option was to use the reporting time as selection option. In addition, using a maximum of eight crew members provided the best results in the shortest computation times. Although, the differences in computation times was only a matter of seconds. Furthermore, the performances of the different parameters depend on a great extent of the input disruption.

Finally, the global optimum was defined for every disruption in a day scenario and the results were compared with the results obtained from the selection of crew members. In all cases the selection of crew members provided solutions that differ to a maximum of 21% with the global optimum. Over 70% reduction in computation times was achieved with the selection of crew members. This reduction was gained with disruptions that were notified at the start of the day. The percentages became lower with increasing time of notification of disruptions at the day of operation.

Conclusion

The objective function stated that costs and computation times are the most important parameters to analyse. The validation of the model concluded that cost improvements were gained by the model with short computation times. In all cases, the computation times were below one minute. It is confirmed by experts from KQ that these computation times are valid for using the model in real time operations.

The contribution to literature of the research project was stated as the dynamic approach of the problem. An overview of the differences between the dynamic and non-dynamic approach was presented and it showed that the non-dynamic approach obtained better results, as already expected. Individual schedules were generated by the model which made it possible to change only one crew member from a flight instead of changing the entire cockpit crew. Another contribution to literature is the fact that multiple recovery options are available in the model, like cancelling, delaying, swapping flights or using standby crew members.

Many assumptions had to be made in the model and higher costs were generated by using the dynamic approach instead of the non-dynamic approach. However, a new approach of the crew recovery problem is modelled and the model is found useful to use in real time operations of KQ.

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Acronyms

AC	Aircraft
Am	After midnight
Arr	Arrival
Blh	Block Hours
CP	Captain
Canx	Cancellation
Dep	Departure
Dis	Disrupted
DV	Decision variable
Etc	Et cetera
EASA	European Aviation Safety Agency
E.g.	For example
FAA	Federal Aviation Administration
FDP	Flight Duty Period
FO	First Officer
Hrs	Hours
JKIA	Jomo Kenyatta International Airport
KES	Kenyan Shilling
KQ	Kenya Airways
OCC	Operational Control Center
Pax	Passengers
PaxJ	Business class passengers
PaxM	Economy class passengers
Pm	Pro midnight
Sel	Selection/Selected
STA	Scheduled Time of Arrival
STD	Scheduled Time of Departure
Tw	Time window
Unc	Uncovered
US	United States
UTC	Coordinated Universal Time

Contents

1
Introduction

Airlines plan their schedule months before the actual operation. The more efficient the schedules are planned the more profit the airline can obtain from the operated flights. However, maximize the profit is not the only parameter to consider during the development of airline schedules. The robustness of the schedule is important as well to deal with disruptions. A robust schedule implies that small disruptions do not affect the schedule. However, this does not solve all the disruptions. For example, severe weather conditions, mechanical failure, airport closures and crew absences may cause many problems in the airline schedules. A small disruption can have a huge impact on the rest of the operation, since schedules can become infeasible. For example, a delayed flight may result in the fact that crew members exceed the maximum working hours. Therefore, they have to be rescheduled to make the schedule feasible again. Not only the crew members of the disrupted flights are affected but also others who are used to solve the infeasibility of the schedules. Therefore, a 'snowball' effect can arise on the rest of the operation during the day. Monitoring and rescheduling these schedules close to the day of operation is called Disruption Management *(Kohl et al., 2007)*.

A part of disruption management is recovery which is solving disruptions at the day of operation. Such disruptions may cause immediate infeasibility of schedules. Furthermore, it results in delayed or even cancelled flights. The recovery process can be divided in aircraft recovery, crew recovery and passenger recovery. This is the sequential order in which recovery is usually done. In 2007, the total delay cost in the airline industry in the United States (US) was $32.9 billion from which $8.3 billion was of increased expenses for fuel, crew and maintenance *(Ball et al., 2010)*. This is to give an indication of the size of the problem and the costs involved.

At most airlines in the world, recovery of airline schedules is done manually by operation controllers. They attempt to make the schedules feasible again considering to return as soon as possible to the original schedule. In addition, it should be done with minimum costs *(Clausen et al., 2010)*. However, dealing with all rules, regulations, preferences and costs makes the recovery process a complex problem.

Therefore, decision support tools need to be developed to assist operation controllers during the recovery process. A decision support tool can provide several solutions considering all kinds of parameters. However, it is of great interest that solutions are generated in short computation times since decisions have to be made in a short amount of time. This research project considers the crew recovery problem, since this is one of the hardest recovery tasks. Many regulations have to be considered and human factors are involved as well. In addition, after fuel costs, crew costs are one of the largest costs of an airline. Therefore, in this research project a decision support tool is developed for the crew recovery problem.

This Master Thesis research project is conducted at Delft University of Technology. More specifically, at the department Air Transport and Operations from the faculty of Aerospace Engineering. In addition, the research is conducted in collaboration with Kenya Airways (KQ).

In Chapter 2 the literature review is described after which the gap in the literature is defined. In Chapter 3, the project plan is described which is based on the gap in the literature. Thereafter, in Chapter 4 the model framework is described which is developed for the specific problem. In Chapter 5, the model is verified with small test cases and in Chapter 7, test cases are performed. The results are analysed with experts from KQ to validate the model. In Chapter 8, a sensitivity analysis is performed to test the performance of the model when changes are applied to specific parameters. Finally, in Chapter 9 a conclusion is drawn and recommendations are given for future research.

2

Literature Study

Since the 90's, airline recovery is an upcoming research topic. Decision support tools are developed to assist operation controllers during disruptions. This is done to provide better and more solutions to the operation controllers. Airline recovery can be divided in three recovery areas; aircraft recovery, crew recovery and passenger recovery. The first studies were focussed on the three recovery areas separately. However, the last few years integrated recovery is an upcoming topic in the research field *(Clausen et al., 2010)*.

This chapter represents the literature review done about the recovery problem. The aim of the literature review is to define the research possibilities in the recovery problem and to gain insight into the different models and solution techniques used to solve the problems. This research is focussed on the crew recovery. However, aircraft and passenger recovery papers are examined as well to get a total overview of the recovery papers present in literature.

The thesis of *Vos (2015)* together with the paper from *Clausen et al. (2010)* are used as main references for the literature review. *Vos (2015)* provided an overview of the most important papers published on airline recovery. This overview, as illustrated in Figure 2.1, is expanded with published papers from last years. The papers indicated in red are the new papers which are added to the overview from *Vos (2015)*. All the papers in the overview will be discussed in this chapter.

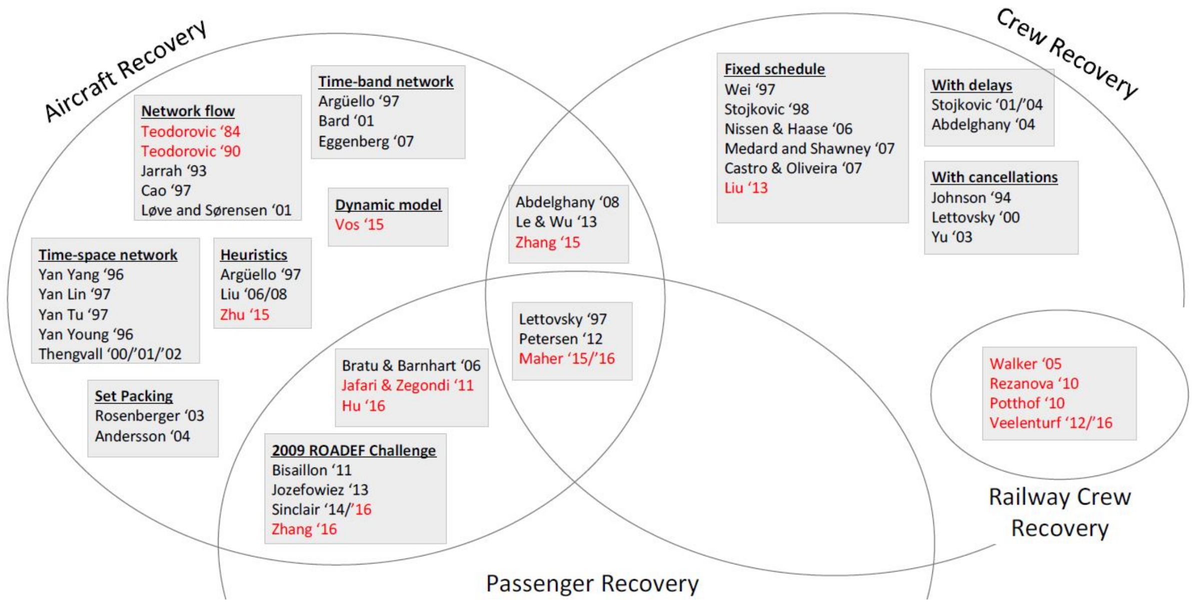


Figure 2.1: Overview of relevant papers in the field of recovery problems *(Vos, 2015)*.

In Section 2.1 the basics of the airline scheduling process are described. Thereafter, in Section 2.2 an overview of the literature about the crew recovery is presented. Within this section, a distinction is made between papers in which the model uses a fixed schedule as input and in which the model allows to delay or cancel flights, as can be seen in Figure 2.1. In addition, papers about crew recovery in the railway sector are described. After crew recovery, an overview of the literature about other recovery areas is presented in Section 2.3. A distinction is made between aircraft recovery and integrated recovery. Finally, in Section 2.4 a conclusion is drawn from the gathered information.

2.1. Airline scheduling

Airline scheduling is of great importance for an airline. The objective is to maximize the profit generated from the routes that are flown, taking operational, marketing and strategic goals into account. The airline scheduling problem is a complex problem and for that reason it is decomposed into several subproblems which are sequentially solved. First, a flight schedule with a timetable is designed. After the timetable set up, aircraft types are assigned to specific flights. For each aircraft a route path is composed, which is called the aircraft routing, taking maintenance constraints into account. Finally, crew is assigned to specific flights by minimizing crew costs. Figure 2.2 illustrates the scheduling subproblems *(Belobaba et al., 2009; Kohl et al., 2007)*.

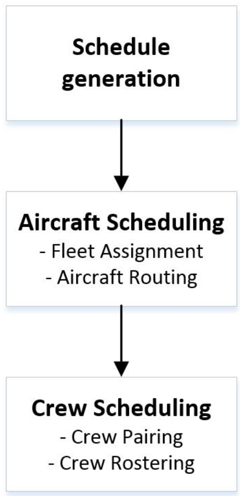


Figure 2.2: The scheduling subproblems in sequential order *(Barnhart et al., 2003)*.

This research is focussed on crew and therefore crew scheduling is described into more detail to understand the basics. The reader is referred to *Belobaba et al. (2009)* for a more detailed description of the entire airline scheduling process.

2.1.1. Crew Scheduling

After fuel costs, crew costs are the largest costs of an airline. For that reason, it is of major importance for an airline to have an efficient and robust crew schedule. The objective of crew scheduling is to minimize the crew costs while regulations, labour agreements and airline requirements are taken into account. All these rules make crew scheduling a complex problem. In addition, crew is divided in cockpit crew and cabin crew. The two crew types are scheduled separately, since cockpit crew is qualified to fly a certain fleet type or related fleet type and cabin crew are qualified for several fleet types. In addition, the number of cabin crew on a flight depends on the number of passengers. Different regulations account for both types. The reader is referred to Appendix A for more detailed information about specific crew regulations. Crew scheduling is divided into two subproblems: crew pairing and crew rostering. Both problems are solved for each fleet type and the basics of both subproblems are described in this paragraph.

Crew pairing
In the crew pairing problem all possible combinations of flights are defined. A crew pairing consists of duty periods. Usually, it consists of a sequence of duty periods separated by layovers at outstations or periods of rest times. However, a crew pairing may consist of one duty period as well. A duty period is a sequence of flight legs, typically one working day. Every flight leg consists of a start time, end time, start location and end location. It is possible that the start and end position of a duty period differ from each other. The crew must often layover and the next day they start with another duty period. Figure 2.3 illustrates a pairing of two days in which duty periods and flight legs are defined.

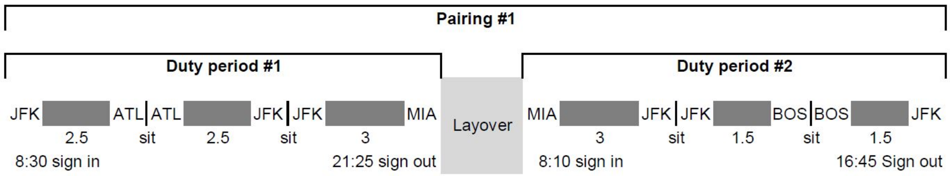


Figure 2.3: An example of a pairing consisting of two days *(Bazargan, 2004)*.

The grey bars illustrate the flight legs and as shown the start and end location of the pairing is JFK. Beneath the bars, the flight leg time is indicated. 'Sit' is the transition time between two flights varying from 30 minutes to several hours and the layover is the overnight at an outstation hotel. The duration of a crew pairing varies from one day till one week. However, a crew pairing starts and ends always at their base airport.

The crew pairing problem is usually solved in two separate phases: The pairing generation, in which feasible pairings are generated, and the optimization phase, in which a subset of feasible pairings is selected with minimal cost. Figure 2.4 illustrates the separate phases of the crew pairing problem.

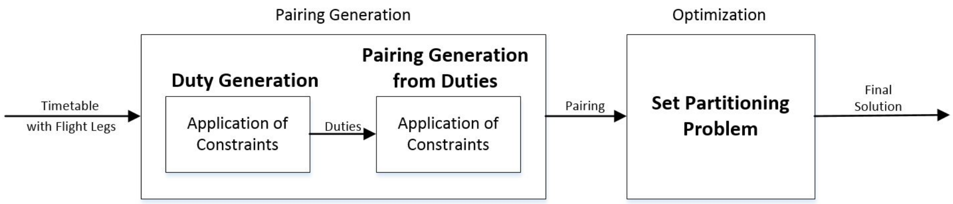


Figure 2.4: The two phases to solve the crew pairing problem *(Kornilakis & Stamatopoulos, 2002)*.

The pairing generation phase is divided into two parts. In the first part, duties are generated from the timetable with the flight legs and only the duties that satisfy the regulations are stored. In this phase, a 'depth first search' is usually used to generate a large set of duties. The depth first search is an algorithm that searches for all possible paths from a starting point to an end point. First, the algorithm searches deeper before it explores the breadth of the graph data structure *(Cormen et al., 2009)*.

In the second part, feasible pairings are generated from the set of duties. A similar process, as for the duty generation, is used to generate feasible pairings. The same as for the duty generation, only the pairings that satisfy the regulations are stored. The costs of a feasible pairing is usually equal to the salaries of the crew. However, this depends on the payment structure of an airline. In general, the costs of a pairing is a function of the flying time, duty time or the number of duties of a pairing. The feasible pairings and its cost are used as input for the optimization phase of the problem *(Kornilakis & Stamatopoulos, 2002)*.

Crew rostering
After the crew pairing problem, individual crew members are assigned to pairings. This is done in the crew rostering problem or also called crew assignment problem. In the crew rostering problem all crew pairings are merged, in order to form personnel rosters for typically one month. Usually, the same algorithm is used for the personnel rosters as for the pairing generation. A set of feasible schedules or rosters are generated from the feasible pairings and only the schedules that satisfy the regulations will be stored. For the optimization problem, the cost of a schedule for a crew member might represent how close the schedule is to the preference of the crew member *(Barnhart et al., 2003)*.

2.2. Crew Recovery

The recovery problem is usually solved sequentially as well. The first step is to recover the flight and aircraft schedule. The next step is to recover the crew schedule and the last step is to recover the passenger itineraries. Crew management is usually the bottleneck in the recovery process due to the myriad of crew rules. This makes the crew recovery problem very complex *(Belobaba et al., 2009)*. The majority of the publications on crew recovery assume that the flight schedule is recovered before crew recovery is applied.

In the following paragraphs, first the differences between crew scheduling and crew recovery are described. Thereafter, some recovery options and two general methods are described that are used by the majority of the authors to solve the recovery problem. Subsequently, papers are described which use a fixed recovered schedule as input. Thereafter, papers are described of authors that allow the model to delay flights to obtain better crew recovery solutions. Subsequently, papers are described of authors that allow the model to cancel flights as well. Thereafter, some papers are described of crew recovery in the railway sector, since these problems are similar. Finally, an overview of the used methods and solution techniques of crew recovery is presented.

2.2.1. Crew scheduling versus Crew recovery

The crew recovery problem is similar to the crew scheduling problem. However, there are some differences between the two problems. The major difference between recovery and scheduling is the time in which the task has to be performed. Recovery has to be done in a few minutes where scheduling can be done in a few months. In addition, the solution quality for the recovery problem does not have to be optimal. Feasible solutions are already acceptable where the scheduling problem strives for optimal solutions. This results in the fact that for recovery multiple solutions are preferred. As long as there is time to recover, better solutions should be found which will finally result in the optimal solution. However, there is not always time to reach this point. Table 2.1 shows a complete overview of the differences between crew recovery and crew scheduling.

Table 2.1: Differences between crew scheduling and crew recovery *(Wei et al., 1997)*.

	Scope	**Time horizon**	**Solution time requirement**	**Solution quality requirement**	**Solution quantity requirement**
Crew Scheduling	Global, all crew members	Long, usually months	Not restrictive, usually a few weeks	High, optimal solutions	One
Crew Recovery	Local, only a few crew members	Short, from a few hours to a few days	Restrictive, should not take more than a few minutes	Reasonable, good feasible solutions	Multiple

2.2.2. Crew Recovery options

Airline operation controllers have some options to cope with disruptions and recover the schedule as soon as possible. The options are applicable for the aircraft recovery and the crew recovery. The several options are *(Barnhart et al., 2003; Belobaba et al., 2009)*:

- *Delaying flights*: This recovery option can ensure that passengers and crew can make their connections to other flights.
- *Swapping aircraft or crew*: This recovery option can prevent delays, since aircraft or crew are switched from flights.
- *Reserve/Standby aircraft and crew*: This recovery option can be used at any point in time during the duty or standby time of aircraft or crew, provided that they are located where the recovery action is needed.
- *Deadheading aircraft or crew*: Deadheading of an aircraft means repositioning of the aircraft to another place without passengers on board. The same applies to crew, where crew is reposi-

tioned to another place by flying as passengers. Aircraft and crew can resume their schedule or duty from the new location.

- *Cancelling flights*. When no recovery solution is found the airline is forced to cancel the flight. Usually, this is the last choice of an airline, since cancellation costs are high.

With these recovery options, schedules have to be recovered and as already mentioned, a recovery solution must be computed in short computation time. Two general methods are used by the majority of the authors to reduce the size of the problem: the *recovery time window technique* and the *set of candidate crew members*. The idea of both techniques is to reduce the size of the problem which will result in shorter computation times. This is necessary to make the model useful for operation controllers.

With the time window technique the recovery time is limited. The starting point of the time window is the time at which the disruption occurs. The end point in time of the time window varies per problem. Typical end points in time are a couple of hours later or at the end of the day of operation.

The second technique that is used to reduce the size of the problem is to use a set of candidate crew members. A limited number of crew members are used to recover the schedule to decrease the size of the problem. The set of crew members consists of the disturbed crew members and a number of selected crew members. The more selected crew members are used, the better the solution will be. However, this will result in larger computation times as well. Figure 2.5 shows an example of a schedule in which both techniques are used.

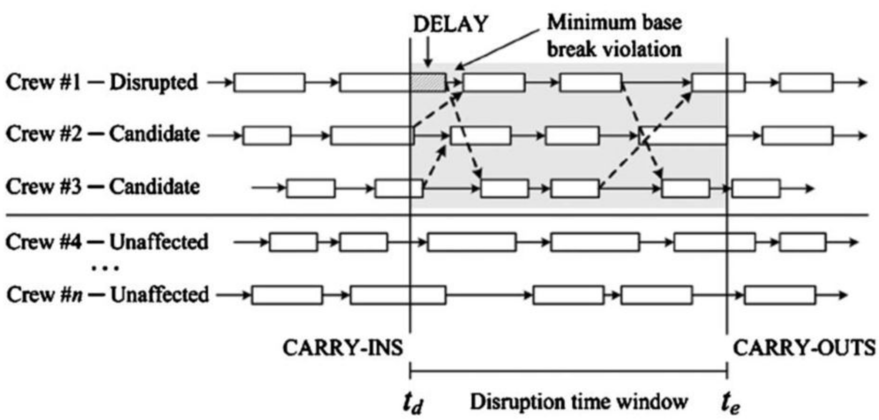


Figure 2.5: An example of the time window technique and the set of candidate crew members *(Clausen et al., 2010)*.

The figure shows that the time window spans from t_d till t_e. It shows the selection of limited candidate crew members, crew #1, #2 and #3, as well. Pre-processing is required to set up a time window and to select the candidate crew members.

2.2.3. Fixed schedule

The first research that investigated crew recovery assumed a recovered schedule as input. Crew members have to be assigned to flights from which the crew pairing became infeasible. Adapting the flight schedule by delaying and/or cancelling flights is not considered in these papers. This subsection describes papers that used a fixed schedule as input to recover the crew schedule.

Wei et al. (1997) were the first who developed an optimization algorithm for crew management during irregular operations. They developed an integer multi-commodity network flow model for the crew pairing recovery problem. The problem is formulated as a set covering problem and a Branch-and-Bound method together with a depth-first search is used to solve the problem. The objective is to return to the original schedule as soon as possible with minimal costs. The model was tested with a simple problem of 6 airports, 51 flights and 18 pairings. The model provided solutions within a few seconds for the small problem considered.

Wei et al. (1997) only recovered the pairing problem and did not consider the crew rostering problem.

Stojković et al. (1998) were the first that developed a model that considers both problems. They developed an integer nonlinear multi-commodity network flow model and a Dantzig-Wolfe decomposition implemented in a Branch-and-Bound search tree is used as solution technique. The master problem is described as a set partitioning problem and the subproblems are described as shortest path problems with resource constraints. The objective is to cover all flights at minimum cost and minimize the deviation from the original schedule. Data from a US carrier was used to test the model and only cockpit crews were considered. The results were obtained within an acceptable computation time ranging from a few seconds for a one day scenario to 20 minutes for seven days scenario.

Stojković et al. (1998) sequentially solved the pairing and rostering problem. *Medard and Sawhney (2007)* integrated both problems into one model in which the problems are solved simultaneously. They described the model as a set covering problem and the objective is to cover all flights with minimal costs and to minimize the deviation from the original schedule. The problem is solved using the column generation technique and the shortest path algorithm. Two different solution techniques are applied for the column generation which are a depth-first search and a reduced cost column generator. The depth-first search enumerates all feasible pairings where the reduced cost column generator generates negative reduced cost rosters. The latter option reduces the size of the problem that has to be solved. The depth-first search performed better than the column generator based on the computation times. However, the authors indicated that the model used all crew members for recovery. Improvements can be made by using a subset of crew members.

Nissen and Haase (2006) used a different approach for the crew recovery problem. The model is based on European airlines which use fixed crew salaries and therefore they developed a duty-period-based network model for the crew recovery problem. This implies that every disruption is solved in each duty period. It reduces the size of the problem and therefore decreases the computation times. The model is solved with a Branch-and-Price algorithm and the objective is to minimize the costs. These costs are formulated as the costs for changing each crew's original schedule. The master problem is formulated as a set covering problem and the subproblem is described as a shortest path problem with resource constraints. The model was tested with several scenarios based on data from a European carrier. The model provided solutions within the short period of time available and therefore it can be used as a decision support tool in real-time operation.

Previous papers only considered cabin crew or did not make distinctions between crew types in their models. *Q. Liu et al. (2013)* developed two different models, intrafleet and interfleet, to make a distinction between cockpit crew and cabin crew. In the intrafleet model pilots, first officers and second officers are assigned to flights of the same fleet type and the model is formulated as a 0-1 set covering problem. In the interfleet model flight attendants are assigned to flights of different fleet types and the model is formulated as a set covering problem. The models are solved with a simulated annealing algorithm and the solutions are compared with the solutions from the Branch-and-Bound method. The objective is to minimize the uncovered flights which simplifies the problem. Data from a major airline was used to test the model and several scenarios were tested. In most cases, the simulated annealing algorithm provided better solutions than the Branch-and-Bound method. In addition, the computation times were much shorter for the simulated annealing algorithm.

Castro and Oliveira (2006, 2007) developed a complete different model than previous papers. They developed a distributed Multi-Agent System (MAS) which represents several roles of the Operational Control Center (OCC). Specialized agents, like crew, aircraft and passenger recovery agents, are used in MAS to minimize the impact to the schedule, minimize the cost and meeting the required rules during a disruption in the operation. Every agent uses its own Operations Research mathematical model. The paper is focused on the crew recovery agent however, the algorithms used are not described. The results of MAS were compared with the results of the human operators. Even a simple example showed that MAS provided better solutions in less time.

In 2010, *Castro and Oliveira (2010)* continued on the work and considered all agents (crew, aircraft and passenger) in the outcome. The outcomes showed that the model improved passenger satisfaction and reduced the flight delays compared with models that only considered operational cost.

2.2.4. Delay opportunities in the model

The previous subsection describes models that use a fixed schedule as input. Cancelling and delaying flights was not considered. In this section some papers are described where delaying flights is allowed to obtain better recovery results. A recovered schedule is used as input as well.

Stojković and Soumis (2001) continued on the work of *Stojković et al. (1998)* and implemented the allowance to delay flights. The model solves the pilot-scheduling problem and the flight-scheduling problem simultaneously. The problem is described as a multi-commodity network flow model that is solved using a Dantzig-Wolfe decomposition combined with the Branch-and-Bound method. The master problem is described as a set covering problem and the subproblem per pilot is described as a shortest path problem with resource constraints The model only considers the pilot-scheduling problem and the objective is to maximize the number of covered flights and minimize the deviation from the original schedule. The largest problem considered consists of 59 pilots and 190 flights. The solutions were promising regarding computation time (few seconds) and quality.

In 2004, the authors have extended the crew recovery model from *Stojković and Soumis (2001)* to consider individual crew members. The computation time was low for small and medium sized problems. However, the computation time was high for larger problems *(Stojković & Soumis, 2004)*.

Abdelghany et al. (2004) developed a tool that proactively recovers the cockpit crew schedule. Flights are recovered in chronological order of the departure time and the objective is to maximize the number of covered flights while minimizing the total cost. A pre-processing phase decreases the size of the problem and the time horizon is divided into stages. Each stage consists of resource independent flights which means that these flights are infeasible to exchange resources. Figure 2.6 shows an example of a few stages within each stage a set of independent flights.

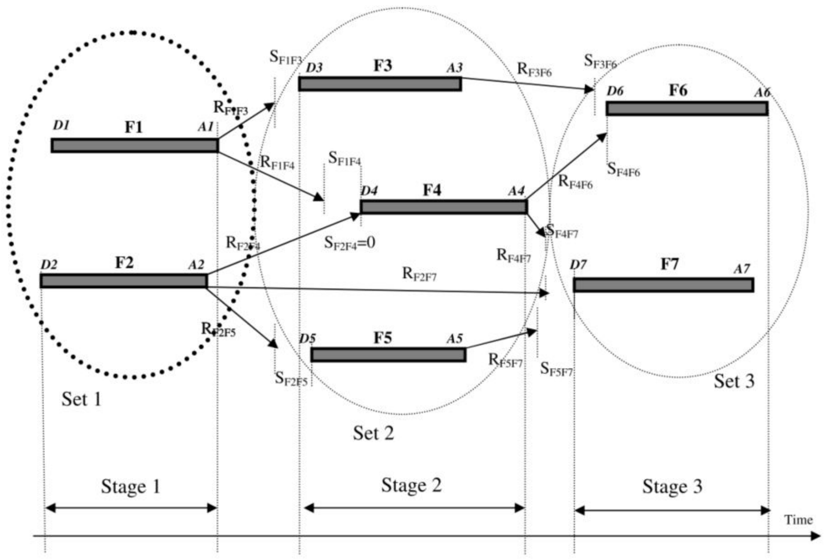


Figure 2.6: An example of the stages *(Abdelghany et al., 2008)*.

The problem is formulated as a mixed integer program and each stage is solved sequentially. Data from a major US carrier was used to test the model and a scenario with 18 disrupted crew members and 121 candidate crew members was set up. The model generated solutions in less than 2 minutes computation time; however, it should be expanded by including cabin crew.

2.2.5. Cancellation opportunities in the model

In this subsection some papers are described where cancelling flights is allowed to obtain better results. A recovered schedule is used as input as well.

Johnson et al. (1994)[1] published the first paper in which flight cancellation was considered as well. The work done by *Johnson et al. (1994)* is the groundwork for *Lettovsky et al. (2000)*. The objective is to minimize the cost and the deviation from the initial schedule, since the assumption is made that the initial schedule is optimal. In the pre-processing phase a heuristic is used to reduce the size of the problem by considering a selection of candidate crew. The crew recovery model is formulated as a set covering problem and is solved with a Branch-and-Bound method using LP relaxation. The model provided acceptable computation times (few seconds till one minute) and solutions for medium sized problems (3-10 involved crews). However, for larger problems further research is required.

Another paper which allows cancellation is the paper of *Yu et al. (2003)*. They implemented a decision support system called CrewSolver in Continental Airlines. The CrewSolver describes the problem as a set covering problem that uses the depth-first Branch-and-Bound method from *Wei et al. (1997)* to solve it. The model provided solutions which return to the original schedule as soon as possible at minimal cost. Multiple solutions were generated by the model from which the operator can choose the most suitable one. The model generated solutions in a low computation time and the authors claimed that Continental Airlines saved millions of dollars by using the CrewSolver.

2.2.6. Crew Recovery in the Railway sector

Crew scheduling of airlines can be compared with the crew scheduling of railway operators. For that reason, crew recovery can be compared in both sectors as well. Literature about crew recovery in the railway sector is scarce; however, the last few years more and more papers are published about this topic in the railway sector. This subsection describes some papers about railway crew recovery.

Walker et al. (2005) were the first who developed a model that described the railway crew recovery problem. The paper describes schedule recovery and crew recovery simultaneously. The crew recovery problem is described as a set partitioning problem. The problem is solved with LP relaxation, column generation and the Branch-and-Bound method. The objective is to minimize the deviation from the original schedule and to minimize the crew cost. The model provided solutions in less than 2 minutes. However, it was tested on a relatively small network, namely the Wellington Metro Line in New Zealand.

Rezanova and Ryan (2010) developed a model that uses a fixed schedule as input. They developed a set partitioning model with side constraints to solve the railway crew recovery problem. The model is finished when all affected train drivers are assigned to a task and when all tasks are covered. When no feasible solution is found, the problem is expanded by increasing the time period or adding train drivers. Column generation and LP relaxation is used to obtain solutions. When non integer solutions are obtained a depth-first search of the Branch-and-Bound tree is used to obtain integer solutions. The objective is to minimize the crew cost and the deviation from the original schedule. The model uses a rolling time horizon approach in which the disruptions become known at a certain point in time. The model was tested with real-life data from a Danish railway operator. The results showed that the model can be used in real-time operations.

Another paper about railway crew recovery is the paper from *Potthoff et al. (2010)*. Their model is formulated as a set covering model and it is solved with column generation and Lagrangian relaxation. When the outcome provides uncovered flights, a neighborhood exploration is used to improve the solution. The objective is to minimize crew cost for rescheduling. The model was tested with real-life data and it provided acceptable solutions in terms of quality and computation time.

Veelenturf et al. (2012) extended the model from *Potthoff et al. (2010)* by implementing the allowance of retiming. *Veelenturf et al. (2012)* present two approaches to deal with the problem and retiming of trains is allowed when better solutions are obtained for the crew recovery problem. The first approach is the neighborhood exploration from *Potthoff et al. (2010)* only extended with the possibility to retime trains (INER). The second approach is to extend the main problem by adding the possibility to retime trains (ECPR) and not to apply a neighborhood exploration afterwards. The objective of

[1]The paper of *Johnson et al. (1994)* was not available to the author. The information is gained from *Lettovsky et al. (2000)*

both models is to minimize the deviation from the original schedule and to minimize the crew cost for rescheduling. The model was tested with real-life data as well and the solutions showed that the computation times for the ECPR model were much larger than for the INER model. For this reason, only the INER model can be used in real-life operation.

Another extension of the model of *Potthoff et al. (2010)* is the model of *Veelenturf et al. (2016)*. They developed a quasi-robust optimization approach in which the duration of the disruption is not known where the duration was known in previous described models. *Veelenturf et al. (2016)* describe the problem as a mixed integer problem which is an adapted version of the set covering problem. A two stage optimization approach is used in which the first stage considers the shortest possible duration of the disruption and the second stage the real duration of the disruption. In the first stage an optimistic time (t_1) and a pessimistic time (t_2) is estimated. In the second stage the real-time (t_3) is estimated for which counts $t_1 < t_3 < t_2$. This makes the solutions robust, since all possible scenarios are considered and the solutions can be realized. The model is solved with the same solution technique as used by *Potthoff et al. (2010)*, namely column generation with Lagrangian relaxation. The objective of both stages is to minimize the total cost for rescheduling the crew. The model was tested with real-life data and it obtained good solutions in a few minutes of computation time. This showed that the model can be used for real-time operation.

2.2.7. Overview of models and methods

Table 2.2 shows an overview of the models and solution techniques used in the papers of the crew recovery problem.

Table 2.2: Overview of the used models and solution techniques in crew recovery.

Authors	*Year*	*Model*	*Solution Technique*	*Additional information*
		Fixed schedule		
Wei	1997	Integer multi-commodity network flow (set covering)	Branch-and-Bound	Depth-first search
Stojkovic	1998	Integer nonlinear multi-commodity network flow	Dantzig-Wolfe decomposition & Branch-and-Bound	Master: Set partitioning Sub: Shortest path problem
Nissen	2006	Duty-period-based network flow	Branch-and-Price	Master: Set covering Sub: Shortest path problem
Medard	2007	Set covering	Column generation	(1) Depth-first search, (2) Cost column generator
Liu	2013	Set covering	Simulated annealing	-
		With delays		
Stojkovic	2001	Integer nonlinear multi-commodity network flow	Dantzig-Wolfe decomposition & Branch-and-Bound	Master: Set covering Sub: Shortest path problem
Stojkovic	2004	Integer nonlinear multi-commodity network flow	Dantzig-Wolfe decomposition & Branch-and-Bound	Master: Set covering Sub: Shortest path problem
Abdelghany	2004	Mixed integer program	-	-
		With cancellations		
Lettovsky	2000	Set covering	Branch-and-Bound	LP relaxation
Yu	2003	Set covering	Branch-and-Bound	Depth-first search
		Railway crew recovery		
Walker	2005	Set partitioning	Column generation & Branch-and-Bound	LP relaxation
Rezanova	2010	Set partitioning	Column generation & Branch-and-Bound	LP relaxation & Depth-first search
Potthof	2010	Set covering	Column generation	Lagrangian relaxation
Veelenturf	2012	Set covering	Column generation	Lagrangian relaxation
Veelenturf	2016	Mixed integer program	Column generation	Lagrangian relaxation

The model type that is mostly used in the literature is the set covering model which is used for crew scheduling as well *(Barnhart et al., 2003)*. This model describes a set of tasks (flights) and every task has to be covered by at least one crew. In addition, it allows deadheading on flights by considering multiple crew on a flight.

Another model that is sometimes used is the set partitioning model. This model describes a set of tasks and every task has to be covered by one crew member only. In this model deadheading crew is not possible. The difference between the two models is the way of formulating the constraints.

As solution technique, a Dantzig-Wolfe decomposition is sometimes used in the papers. However, a Dantzig-Wolf decomposition is based on column generation. Column generation is by far the most used solution technique for the crew recovery problem. In addition, column generation is used for crew scheduling as well *(Barnhart et al., 2003)*. Column generation considers only a subset of decision variables that can improve the objective function. This is based on the fact that not all decision variables of a large linear problem are used in the solution. The complexity of the problem decreases by considering a subset of decision variables.

Most of the papers consider the cockpit crew, since these costs are higher compared with the costs of cabin crew. In addition, cockpit crew members stay together in a pairing where cabin crew members do not. This makes it easier to solve the problem. In addition, the crew recovery papers use a recovered aircraft and flight schedule as input. Therefore, no delays and cancellations are allowed. However, this limits the model in generating solutions. Considering delays and cancellations makes it harder to generate solutions in a short computation time but the quality of the solutions increase due to more options. The same applies for considering deadheading crew on flights.

Currently, the paper from *Q. Liu et al. (2013)* is the only one that considers cabin crew as well. However, this model is simplified and has the objective to minimize the uncovered flights. Costs are not considered in the model.

The gap in the literature, that can be defined by considering the papers is the dynamic crew recovery in which disruptions become known at the time of occurrence. In addition, the possibility to delay and cancel flights will make the model more flexible in generating solutions. The last opportunity is considering individual crew members in the problem in order that the model can be used for cabin crew as well.

2.3. Remaining Recovery

Despite the fact that this research project is focussed on the crew recovery problem, research has been done to other recovery problems as well. This chapter contains information about published papers that describe the aircraft recovery problem or the integrated recovery problem. This research is done to gain knowledge about the methods and solution techniques that are used for recovery problems. Some of these methods can probably be used for crew recovery as well. First, some published papers about the aircraft recovery problem are described. Thereafter, some papers about integrated recovery are described.

2.3.1. Aircraft Recovery

Within disruption management many research has been done to the aircraft recovery problem. The same as the scheduling problem, the flight schedule and aircraft schedule are the first schedules that are recovered during disruptions. In addition, there are fewer rules for aircraft recovery than for crew recovery and therefore the problem is less complex. As illustrated in figure 2.1, the papers about aircraft recovery can be subdivided in some groups as well. This subsection describes the most important papers about aircraft recovery.

Network flow

Teodorović and Guberinić (1984) are the first researchers that came up with a model for the aircraft recovery problem from an Operations Research perspective. In 1984, they introduced a model that minimizes the total passenger delays by swapping and delaying flights. They considered a situation where one or more aircraft are taken out of service and solved the problem with the Branch-and-Bound method. The paper describes a simple example (3 aircraft and 8 flights) to present some results of the model. The model did not consider maintenance constraints and it used a single fleet type.

In 1990, *Teodorović and Stojković (1990)* continued with the model of *Teodorović and Guberinić (1984)*. They included flight cancellations and station curfews. The objective is to minimize the total number of cancelled flights. In case of multiple solutions a second objective is used to generate an optimal solution. The second objective is to minimize the total passenger delays. They considered a situation where one or more aircraft are taken out of service as well and solved the problem with a heuristic algorithm. The authors use a single fleet type and preflights are not allowed in the model. The model is tested with 14 aircraft and 80 flights and one aircraft is out of service at the beginning of the day. The solutions of the computation times showed that the model can be used in real-time operations.

After *Teodorović and Stojković (1990)*, *Jarrah et al. (1993)* continued on the topic of aircraft recovery. They presented two network flow models. The first model is only based on delaying flights, where the second model is only based on the cancellation of flights. The objective of both models is to minimize the costs by delaying flights, cancelling flights, swapping flights, or using spare aircraft. The problem is solved with the shortest path method and was tested with data from United Airlines. The results showed that the model can be used for real-time operations. A single fleet type is used in the model and a drawback is that it cannot consider cancellations and delays simultaneously.

The model of *Cao and Kanafani (1997)* is based on the model of *Jarrah et al. (1993)*. A quadratic 0-1 programming model is used and the objective is to maximize profit minus delay and swapping costs. Different cost penalties of delay and flight cancellation are considered. A trade-off is made between delaying or cancelling flights which was a shortcoming of the model of *Jarrah et al. (1993)*. Aircraft swapping and ferrying are considered as well. However, *Løve and Sørensen (2001)* suggest that the model is not completely described, since reproduction of the results was not possible.

Time-space network

Cao and Kanafani (1997); Jarrah et al. (1993); Teodorović and Guberinić (1984); Teodorović and Stojković (1990) used network flow models to solve the recovery problem. *Yan and Yang (1996)* introduced another approach which is based on time-space networks. They developed a time-space network model in which flight cancellation, delays and ferry flights are included. This was the first model that had all these parameters included in a single model and the objective of the model is to minimize the total cost. They developed four models in which the first two models are pure network flow problems which are solved with the simplex method. The latter two are network flow problems with side constraints which are solved with the Lagrangian relaxation. *Yan and Yang (1996)* considered a situation in which one aircraft is taken out of service in a single fleet type. The model considers aircraft that perform only non-stop flights. The model is tested with data from a major Taiwan airline (15 airports, 12 aircraft and 319 flights). The results showed that the model is efficient and effective for real-time operations.

Yan and Lin (1997) improved the model by including airport closures and *Yan and Tu (1997)* improved the model by including multiple fleet types. Finally, *Yan and Young (1996)* added multi-stop flights to the model. All papers used the same solution technique and the results were satisfactory. *Thengvall et al. (2000)* extended the models of *Yan and Lin (1997); Yan and Tu (1997); Yan and Yang (1996); Yan and Young (1996)* by minimizing the deviation from the original schedule. LP relaxation is used to solve the problem and when it did not provide integer solutions a heuristic is used to provide near-optimal solutions. The objective is to minimize the costs for delaying or cancelling flights and consider the deviation from the original schedule as well. The model does not take crew and maintenance issues into account. The model is tested with data from Continental Airlines. Two fleets (16 aircraft, 13 airports and 27 aircraft, 30 airports) are solved with the model and the results showed that the model generates different solutions depending on the priorities between delay, cancellation and deviation from the original schedule. The results showed that the model can be used in real-time operations.

Thengvall et al. (2001, 2003) continued on their work done in 2000 by including airport closures and multiple fleet types. Three mixed integer programming models are introduced. Two models describe the problem with a time-space network and the other model describes the problem with a time-band network which is based on the model introduced by *Argüello (1997)*[2].

Time-band network

Argüello (1997) introduced this new network representation in his PhD Thesis. In a time-band network, which is based on the time-line network, the time horizon is discretized. Only arcs that correspond to a flight of the schedule are used in the model. *Bard et al. (2001)* developed a time-band network model as well. The objective is to minimize the flight cancellations and delay costs and LP relaxation is used to solve the problem. The model is tested with data from Continental Airlines. The results are compared with the lower bound solution and it showed that the obtained results did not differ much from the lower

[2]The paper from *Argüello (1997)* was not available to the author. The information is gained from *Argüello et al. (1997); Clausen et al. (2010)*

bound solution. The quality of the solution depends on the used time-band resolution. Increasing the time-band resolution will result in a decrease in the quality of the solution.

Eggenberg et al. (2007) used a time-band network as well and used column generation to solve the aircraft recovery problem. The objective is to minimize the costs and the recovery time period. The model considers maintenance as well and it is tested with data from Thomas Cook Airlines. Different solutions are obtained to make a trade-off between the two objectives. Results showed that the model obtains efficient solutions and that it can be used for medium sized airlines.

Set packing

Andersson and Värbrand (2004); Rosenberger et al. (2003) used both a different method to describe the aircraft recovery problem than previous ones. They formulated the problem as a set packing problem and used a connection network. The set packing problem ensures that every flight is assigned to at most one aircraft (constraint ≤ 1). *Rosenberger et al. (2003)* used an aircraft selection heuristic and *Andersson and Värbrand (2004)* used a Dantzig-Wolfe decomposition to decrease the size of the problem. *Rosenberger et al. (2003)* used column generation to obtain solutions where *Andersson and Värbrand (2004)* used two different methods to solve the problem. The first method is LP relaxation and the second method is Lagrangian relaxation. Both models are tested and the results showed that both models can be used in real-time operation.

Heuristics

Argüello et al. (1997) developed a time-band network model that uses a greedy randomized adaptive search procedure (GRASP) to solve the problem. The GRASP contains of a solution phase and a local search phase. Neighboring solutions are determined and the best ones are stored in a candidate list. A random one from the list is chosen as new solution and this is repeated until the stopping criterion are reached. *Argüello et al. (1997)* is one of the first that used heuristics to solve the problem and after this publication it became a popular solution technique for the recovery problem. He considers that one or more aircraft are taken out of service and the objective is to minimize the flight cancellation and delay costs. The model is tested with data from Continental Airlines and only contains the 757 fleet. Maintenance is not considered as well and the model provided good solutions within 15 seconds.

T.-K. Liu et al. (2006) use heuristics as well in their model. They use a Multi-objective Evolutionary Algorithm (MOEA) with the objective to minimize the total delay and number of aircraft swaps. Ferrying or cancelling flights is not permitted. The model is tested with data from a Taiwan airline (7 aircraft and 70 flights). It is stated that the model can generate optimal solutions; however, no computation times are presented. *T.-K. Liu et al. (2008)* extended the model by implementing multiple fleet types.

Zhu et al. (2015) used a heuristic as well and the same method as *Veelenturf et al. (2016)*, in which the restoration time of the aircraft is unknown. They developed a two stage stochastic aircraft recovery model which is solved with a Greedy Simulated Annealing algorithm. The first stage uses a fixed disruption time and minimizes the delay and cancellation costs. The second stage evaluates the outcomes of the first stage and determines costs that reflect the possible changes of the recovery plans. The model is tested with 23 flights operated by 6 aircraft from which one aircraft obtains a failure at a certain point in time. The results showed that the stochastic model decreases operational cost of an airline.

Dynamic model

Previous papers describe models that recovered the schedule of aircraft when one disruption becomes known. However, previous recovery decisions are not taken into account. Another method that is used in previous papers is that the set of disruptions is known at the beginning of the day. *Vos et al. (2015)* introduce a model which is much more realistic, since it solves the problem at a certain point in time when the disruption becomes known. For every disruption that occurs the model recovers the schedule taken previous recovery decisions into account. These decisions may be not optimal anymore or may have become infeasible. This way of modelling is much more realistic and contains the dynamic approach of the problem. The objective is to return to the original schedule as soon as possible by minimizing cost.

Vos et al. (2015) introduced a Dynamic Recovery Model (DReM) which uses a Disruption Set Solver (DSS). The DSS contains of a search algorithm and a Selected Aircraft Linear Solver (SALS). The algorithm finds a best selection of aircraft to solve the disruption and the SALS solves the linear problem with the use of a parallel time-space network representation. The model is always solved within 15 minutes and in most of the times it generates solutions within 10 minutes. The model is tested in a dynamic and a static case. The static case performed better than the dynamic case in terms of costs. However, the dynamic case is much more realistic.

2.3.2. Integrated Recovery

Some researchers developed models for the recovery problem in which aircraft, crew and passenger recovery are integrated. This is a very complex problem which explains why there is not much research done in the integrated recovery problem in the past. However, the last few years increasing research has been done to the integrated recovery problem due to the improvements in solution techniques and the capacities of computers.

First, some papers are described that integrated aircraft and passenger recovery into one model. Thereafter, some papers are described that integrate aircraft and crew recovery into one model. Finally, some papers are described in which an integrated aircraft, crew and passenger recovery model is developed.

Integrated Aircraft and Passenger Recovery

The most recovery models do not take passenger itineraries into account in the objective. During a disruption some passenger itineraries have become infeasible as well. The costs involved by rescheduling passengers depend on the amount of passengers. When the amount of passengers that miss their connection is big, it can be more favourable to delay flights instead of rescheduling passengers. Passengers are not modelled explicitly and hence, passenger delay cost are only approximated. This subsection describes some papers that consider passenger itineraries in the objective.

The first authors who developed a model that is more focused on passenger recovery are *Bratu and Barnhart (2006)*. They described two different models which are focussed on passenger recovery. The models use the approximation of reserve crews to deal with the crew recovery; however, the model does not consider crew recovery. The first model is the so called DPM model (Disruption Passenger Metric), in which the sum of operating and disrupted passenger cost is minimized. This model uses an approximation of the passenger cost. The second model is the so called PDM (Passenger Delay Metric), in which the sum of passenger delay cost and operating cost are minimized. The objective of both models is to minimize airline operating cost and passenger cost. The DPM model uses an approximation of disruption cost for the passenger cost. The PDM model uses passenger cost which are computed by modelling passenger disruptions, recovery options and delay cost. The model is tested with data from a major US airline (302 aircraft, 77 airports, 83869 passengers on 9925 different passenger itineraries). The results showed that the PDM model cannot be solved in real-time, whereas the DPM model is fast enough for real-time use.

The model from *Jafari and Zegordi (2011)* is based on the model from *Bratu and Barnhart (2006)* and *Abdelghany et al. (2008)* (described in section 2.2.4). However, *Jafari and Zegordi (2011)* consider aircraft rotations and passenger itineraries instead of flights. They are the first who consider aircraft recovery and passenger recovery simultaneously. The objective is to minimize the cancellation and delay cost as well as the disrupted passengers. The model is tested with a scenario of two disruptions and the input data is obtained from *Andersson and Värbrand (2004)* (13 aircraft, 19 airports, 2236 passengers on 8 itineraries). The results are compared with the results of *Andersson and Värbrand (2004)* and it showed that the model of *Jafari and Zegordi (2011)* reduces the total cost by considering aircraft recovery and passenger itineraries simultaneously.

In 2009 a competition, named 2009 ROADEF Challenge, about disruption management in the airline industry was organized by the French Operational Research and Decision Analysis Society and the company Amadeus S.A.S. A tool had to be designed that recovers the aircraft schedule and passenger itineraries.

Bisaillon et al. (2011) won the first price in this challenge. They developed a large neighborhood search heuristic to solve the problem. The heuristic contains three phases which are construction, repair and improvement. The construction and repair phase produce a feasible solution and the improvement phase improves the feasible solution obtained. The objective is to minimize the operating costs and impacts on passenger itineraries. The input of the model is an initial schedule, list of disruptions and a recovery period. It can cancel flights, delay flights or create new flights and it produced feasible solutions of a large problem (45 airports, 256 aircraft and 1423 flights) in 10 minutes. This indicates that the model can be used in real-time operations.

Jozefowiez et al. (2013) participated in the 2009 ROADEF Challenge as well. They developed a heuristic method which is divided in three phases, called the new connection flight heuristic method (NCF). The first phase of the heuristic integrates the disruptions into the initial schedule. This is done sequentially where each step has its own algorithm. The second phase reassigns as many passenger groups as possible to the existing set of rotations. This is done with the shortest path method. The third phase tries to assign the remaining passenger groups to a new set of aircraft rotations. For a detailed description of all the algorithms and results the reader is referred to *Jozefowiez et al. (2013)*. The inputs of the model are the same as the ones from *Bisaillon et al. (2011)*. The model obtains good solutions; however, not as good as *Bisaillon et al. (2011)* An advantage of the model is the computation time. In most cases the model finishes within 1 minute and the remaining runs do never pass the 4 minutes which is below the 10 minutes time limit stated in the challenge.

In 2014, *Sinclair et al. (2014)* presented a research which suggests improvements to the model developed by *Bisaillon et al. (2011)* They introduce a number of improvements in each phase in order to obtain better results. For a detailed description of the improvements made in each phase the reader is referred to *Sinclair et al. (2014)* The model is tested on the same scenarios as used for the model of *Bisaillon et al. (2011)* The improved model showed that the modifications significantly improved the solution costs. In 17 out of 22 instances the model obtained the best known solution within five minutes of computing time and in 21 out of 22 instances it obtained a solution within 10 minutes of computation time. A computation time longer than 10 minutes is advantageous in case of high numbers of cancelled itineraries.

Sinclair et al. (2016) continued on their work done in *Sinclair et al. (2014)*. They modelled the aircraft and passenger recovery as a mixed integer programming problem. First, the large neighborhood search heuristic developed by *Bisaillon et al. (2011)* and improved by *Sinclair et al. (2014)* is used to solve the problem. Thereafter, a column generation post-optimization heuristic is used to obtain better solutions. The same test models are used as in *Bisaillon et al. (2011); Sinclair et al. (2014)*. The solutions obtained by the model are better than the best known solutions from the 2009 ROADEF challenge. However, the computation times were higher than 10 minutes which is a disadvantage regarding real-time use.

Zhang et al. (2016) used the input data from the 2009 ROADEF challenge as well. However, they used a different approach to the problem. A three stage math heuristic framework is developed to solve the integrated aircraft and passenger recovery problem with the objective to minimize the aircraft and passenger cancellation and delay cost. *Zhang et al. (2016)* use a time-space network, mixed integer programming formulation and greedy heuristics in their model. In the first stage the aircraft recovery problem is solved. In the second stage the flight schedule is recovered taken passenger connections into account and in the third stage passenger itineraries are recovered. The last two stages are swapped compared with previous papers which makes this approach different than previous ones. The results showed that the model from *Zhang et al. (2016)* generated better solutions, since *Zhang et al. (2016)* stated that their algorithm generated the best solution in 72% of the test cases compared with other models that participated in the 2009 ROADEF challenge.

Hu et al. (2016) were focussed on the costs of passenger reassignments and considered the passenger itineraries at the same time as the aircraft recovery. They developed an integer programming model for the integrated recovery of aircraft and passengers. The model is formulated as a set partitioning problem with side constraints and a heuristic based on a GRASP algorithm is used to solve the problem. The objective is to minimize the passenger delay, reassignment and refunding tickets cost. The model is tested with data from a major Chinese airline and a set of disruptions is used as input. It provided a feasible solution in less than one minute. The results are compared with the original solution, the airline heuristic and the SRM model in which the SRM model sequentially solved the aircraft problem and passenger reassignment. The model developed by *Hu et al. (2016)* provided better results than the other models that considered the aircraft recovery and passenger itineraries separately.

Integrated Aircraft and Crew Recovery
In the previous subsection some papers are described that integrated aircraft recovery and passenger recovery into one model. In addition, some published papers describe an integrated recovery model of aircraft and crew. However, integrated models of aircraft and crew are complex. Sometimes the constraints are contradictory with each other which makes it hard to find the optimal solution. This subsection describes some papers that integrate aircraft and crew into a recovery model.

One of the first papers that describe an integrated recovery model of aircraft and crew is the paper of *Abdelghany et al. (2008)*. The model developed by *Abdelghany et al. (2008)* is an extension of the model of *Abdelghany et al. (2004)*. The recovery problem is formulated as a mixed integer problem which uses a rolling horizon framework. *Abdelghany et al. (2008)* integrated a decision support tool for airline schedule recovery, called DSTAR. The input for the model is a Ground Delay Program (GDP) after which a flight simulation model predicts the disrupted flights for each stage. The stages are sequentially recovered with the objective to minimize the total system costs which consists of reassignment, flight delay and cancellation cost. Data from a major US airline is used to test the model (522 aircraft, 1360 pilots, 2040 flight attendants, 1100 flights, 112 airports). The results showed that the model generated efficient recovery solutions in computation times of less than one minute.

Another paper that described an integrated recovery model of aircraft and crew is the paper of *Le and Wu (2013)*. They used an iterative tree growing with a node combination heuristic to solve the problem. Two preprocessing phases, node aggregation and island isolation, are used to decrease the number of nodes and ground arcs in the time-space network. Node aggregation combines arrival and departure nodes and island isolation eliminates unused ground arcs. This reduces the size and therefore the computation time of the problem. Figure 2.7 illustrates the original schedule and the schedule after node aggregation and island isolation.

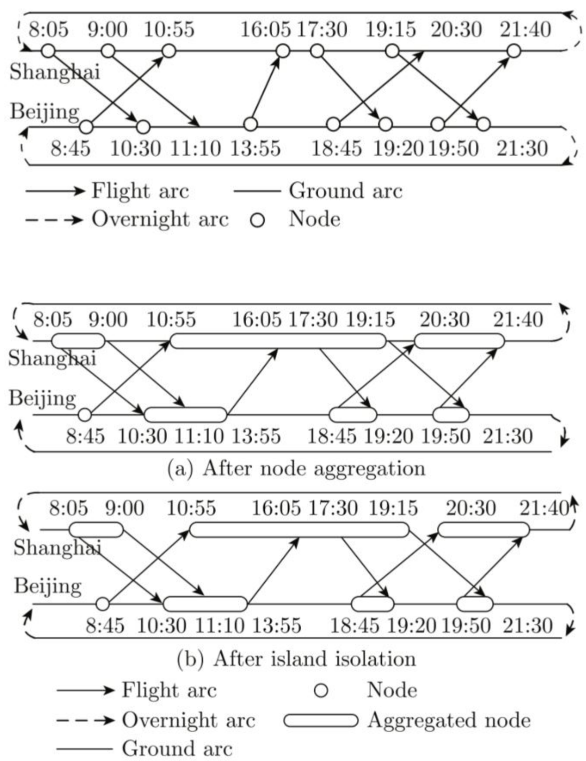


Figure 2.7: An example of the node aggregation and island isolation *(Le & Wu, 2013)*.

The objective is to minimize the total system costs which consist of reassignments, flight delays and cancellation cost. The model is tested with data from a medium sized Chinese Airline (170 flights, 35 aircraft and 51 airports). The examples use a single disruption that must be solved. The authors did not compare the obtained results with the current operation and no computation times are presented.

The quality cannot be assessed and it is not known if the model is applicable in real-time operation. However, in the paper is stated that the results showed that the model can be used in real-time operation.

Zhang et al. (2015) used a different approach of modelling the integrated aircraft and crew recovery problem. They are the first that model the crew recovery problem in a multi-commodity time-space network. Figure 2.8 illustrates an example of one crew.

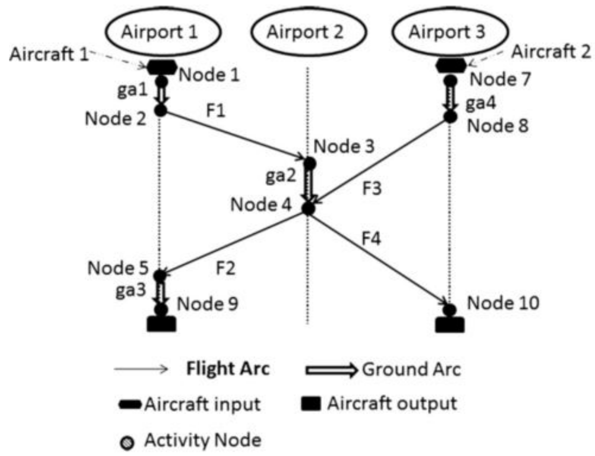


Figure 2.8: An example of the integrated aircraft and crew time-space network *(Zhang et al., 2015)*.

Zhang et al. (2015) developed a two stage heuristic algorithm to solve the problem. In the first stage aircraft recovery is considered with partial crew considerations and in the second stage crew recovery is considered with partial aircraft considerations. The second stage uses the solution from the first stage. Both stages are modelled as a multi-commodity network model. The objective of the first model is to minimize the total costs that consists of cancellation, delay and crew connection disruption penalties. The objective of the second model is to minimize crew cost. The model is tested with data from a regional US carrier (351 flights, 70 aircraft and 134 crews) and it provided high quality solutions in computation times of less than 2 minutes.

Integrated Aircraft, Crew and Passenger Recovery

Integrate all three recovery problems into one model is an enormous difficult task. The problem becomes extremely complex and the size increases that much that it is impossible to find the optimal solution within a low computation time. Nevertheless, some papers are published about the fully integrated recovery problems. This subsection describes published papers that consider the integrated recovery model of aircraft, crew and passengers.

Lettovsky (1997)[3] is the first who developed a fully integrated recovery model. A combination of aircraft, crew and passenger recovery is formulated as a linear mixed-integer problem. The objective is to maximize the total profit and a Bender´s decomposition algorithm is used to solve the problem. A Bender's decomposition is the same as column generation only now instead of columns, rows are generated. *Lettovsky (1997)* developed a master problem called the Schedule Recovery Model (SRM). First the SRM solves the aircraft recovery model after which the crew recovery model is solved. At the end the passenger flow is evaluated with the passenger flow model. The master problem represents the sequential solving strategy which is used by the airline OCC's.

Petersen et al. (2012) are the first who developed and obtained results of a complete integrated recovery model. Schedule recovery, aircraft recovery, crew recovery and passenger recovery are the four problems that have to be solved. Since, the problem is too large and complex, Bender decomposition is used to decompose the problem in a master problem and three subproblems. The master

[3]The paper from *Lettovsky (1997)* was not available to the author. The information is gained from *Clausen et al. (2010); Lettovsky et al. (2000)*

problem is the schedule recovery and the remaining problems are the aircraft, crew and passenger recovery. The integrated recovery model is tested with data from a major US-carrier (800 flights) and the results are compared with the sequential recovery model. Results showed that the sequential method sometimes provided infeasible solutions in contrary to the integrated model. However, the model is not applicable for real-time operations due to the long computation time.

The Bender's decomposition method used by *Petersen et al. (2012)* does not guarantee integer solutions. For that reason, *Maher (2015)* used an alternative solution approach to obtain integer solutions, namely column-and-row generation. This method decreases the size of the master problem by eliminating constraints. For that reason, the method provided near integer optimal solutions and achieved faster run times than Bender's decomposition. The model is tested with two different schedules: point-to-point schedule with 262 flights, 48 aircraft of a single fleet and 79 crew groups and hub-and-spoke schedule with 441 flights, 123 aircraft of a single fleet type and 182 crew groups. The model solved both schedules with a set of 16 disruptions as input. The objective of the model is to minimize the recovery costs that consist of flight delay, flight cancellation and crew cost. The computation times differed per scenario and vary between 3 minutes and 30 minutes which is the maximum run time. In the majority of the scenarios column-and-row generation performs better than column generation regarding computation time and quality of the solution.

The integrated recovery model of *Maher (2016)* considered the schedule, aircraft and crew and did not explicitly consider passenger itineraries. *Maher (2015)* extended the work done by *Maher (2016)* and described a passenger recovery approach for the integrated recovery model.

2.4. Conclusion

The aim of this literature review was to define the gap in the literature about crew recovery. Crew recovery is similar to crew scheduling however, both processes differ in some aspects. For example, time is of main importance during recovery where it may take months before crew scheduling is finished. Operation controllers have some recovery resources to deal with disruptions, like standby crew, swapping flights, delaying and cancelling.

The last few years, airline recovery has been an upcoming topic for operation researchers. Most of the models that are described, investigate one part of the recovery problem. Some papers investigate the integration of the several recovery problems into one model. However, with no success, since the models cannot be used in real time operation due to the long computation times.

The majority of the researchers decrease the size of the problem to obtain solutions in acceptable computation times. Two methods are used to decrease the size of the problem; the time window technique and the identification of the set of candidate crew members for the recovery solution. In addition, all the papers about crew recovery use a fixed schedule as input. Some papers allow cancelling or delaying flights to obtain better results. However, in all cases the disruption or set of disruptions is known. In the aircraft recovery, *Vos (2015)* developed a model that dynamically solves the recovery problem by modelling the disruption at the time of notification. In the railway recovery, *Rezanova and Ryan (2010)* used a dynamic approach of the disruptions as well. However, to the knowledge of the author of this report such a dynamic approach is not applied to the crew recovery problem.

For that reason, the gap in the literature is defined as the dynamic crew recovery problem. Disruptions are modelled at the time of notification. The dynamic approach considers previous recovery decisions as well, since these decisions may not be optimal any more or have become infeasible. The model defines if the recovery actions can still be revised at the time of the occurrence of the new disruption.

None of the papers in the literature combine the options to cancel and delay flights into one model. Considering these options in one model will result in more recovery possibilities.

Furthermore, considering individual crew members will increase the possibilities of the model to generate feasible solutions. The model will be able to only change a captain (CP) or a first officer (FO) from a specific flight instead of changing the entire cockpit crew. In the literature, only *Q. Liu et al. (2013)* considers individual crew members. However, this model uses the objective to minimize uncovered flights and costs are not considered. Using individual crew members will result in more recovery possibilities and therefore it will be more useful during the recovery of airline crew schedules.

3

Project Plan

This chapter represents the project plan that is outlined for this research project. Based on the literature review, described in Chapter 2, the topic of this research is defined as dynamic crew recovery. First the research question and objective are formulated in Section 3.1. Then, in Section 3.2 the research framework is presented together with the hypotheses. Thereafter, in Section 3.3 the experimental set-up and the assumptions made are described. Finally, the expected results and the relevance of the research are given in Section 3.4.

3.1. Research question and objective

Based on the literature review, the topic of this research project is set to the development of a dynamic decision support tool for operation controllers. The following main research question is formulated:

Main research question

How does a dynamic decision support model for crew recovery problems contribute to the recovery solutions of an airline regarding computation time and cost?

An important parameter for answering the research question are the costs. Therefore, the research aim is to minimize crew recovery costs and the research objective is formulated as follows:

Main research objective

Develop a dynamic decision optimization model to minimize the crew recovery cost during disruptions that supports operation controllers to obtain feasible and where possible optimal solutions.

The research question is subdivided into subquestions which will help by structuring the approach of the problem. The answers to these questions will contribute to the clarification of the problem, design of the model and an answer to the research question. The subquestions are formulated as follows:

1. How do operation controllers cope with the crew recovery problem nowadays?
    a. What kind of disruptions do operation controllers cope with?
    b. What is the effect of the disruptions to the schedules?
    c. What are the driving factors to make decisions regarding the crew recovery problem?
    c. What are the rules-of thumbs during recovery problems?
    d. What kind of recovery resources are applied nowadays?
2. What are the constraints regarding crew scheduling and recovering?
    a. What are the crew regulations?
    b. What are the labor agreements?

3. Which models and solution techniques can be used for the dynamic crew recovery problem?

    a. What modelling techniques are present for crew recovery?
    b. Which solution techniques are present for crew recovery?

4. How should the data be implemented in order to test the model?

    a. Where can the data be obtained?
    b. What is the structure of the data?
    c. What is the required output from the model?

5. What is the quality of the solutions obtained by the model?

    a. What are the computation times?
    b. What are the recovery costs?
    c. Does the model provide valid solutions?

6. How can the model be implemented at an airline?

3.2. Research Framework and Methodology

The research question, subquestions and the research objective can be summarized in a research framework. This represents the several steps to be taken to achieve the desired result (objective). The research framework for the crew recovery problem is illustrated in Figure 3.1.

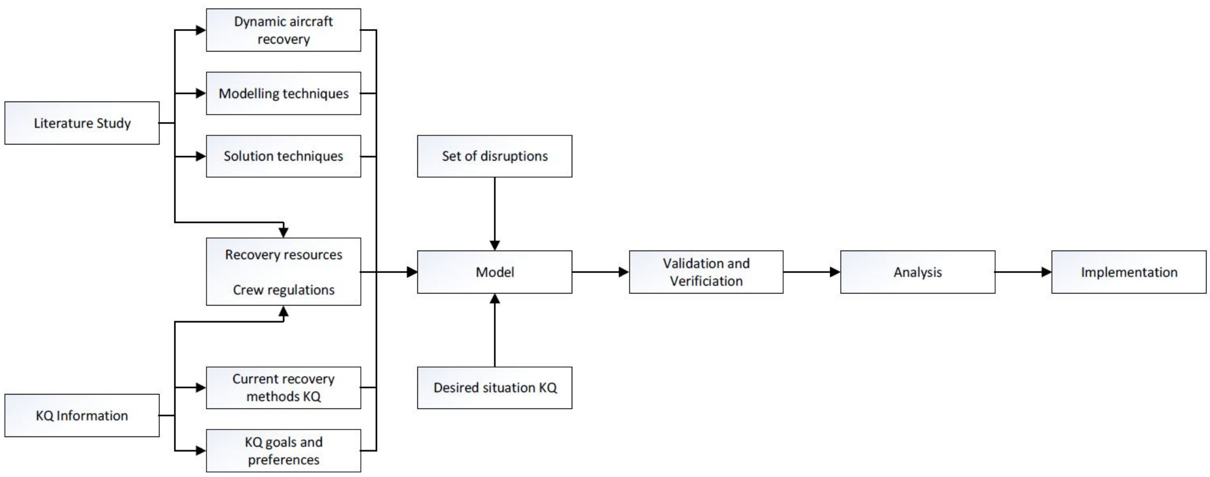


Figure 3.1: Research framework of the crew recovery problem

The research will be done in collaboration with Kenya Airways (KQ). Information will be gathered from interviews with experts from KQ. This will provide insight in the current recovery options, crew regulations and goals of KQ in the recovery process. In addition, the literature study provided insights in modelling and solution techniques used in previous research projects. Information about crew regulations and recovery resources are gathered in the literature study as well. All this information will be used for the development of the dynamic model. Finally, the model will be tested and analysed.

Based on the methodology and the research question two hypotheses are formulated:

Hypotheses

The dynamic crew recovery model will generate lower costs than the solutions obtained by operation controllers of an airline.

The dynamic crew recovery model will generate higher costs than the non-dynamic model.

3.3. Experimental Set-up

The hypotheses, formulated in Section 3.2, need to be tested by an experimental set-up. In this section the experimental set-up is described.

Based on the literature study, a linear programming recovery model will be developed. The problem will be programmed in Python and CPLEX will be used as optimization tool. Different optimization tools can be used for the problem, like CPLEX, Gurobi and Xpress. However, KQ is already familiar with both Python and CPLEX which will be an advantage in the implementation process. The model developed for this research project is described in more detail in Chapter 4.

3.3.1. Test cases

Small test cases will be performed to verify the developed model. Thereafter, data from KQ will be used as input to simulate a realistic scenario. Together with experts from KQ, results will be evaluated taking into account the quality of performance and feasibility. This is called face-validation. By the time the model is valid, the model will be implemented at KQ.

Another test case that will be done is the comparison with a non-dynamic model. The difference between both models will be the time the disruptions are notified. In the non-dynamic case, all times are the same and therefore all disruptions are notified and solved at the same time (one iteration). In the dynamic case, every disruption is notified and solved at a different time (several iterations).

Solving the complete recovery problem will not be feasible within the time period of the project. Furthermore, the size, complexity and the capabilities of computers will cause that delimitation of the problem will be necessary. During the project the delimitations can be revised if necessary. In consultation with experts from KQ and the literature study, the delimitations are formulated as follows:

- **Individual cockpit crew**:
  In the model, only individual cockpit crew members will be considered. Cockpit crew are the most important ones for an airline to solve, since they have less options due to the regulations. Cabin crew have other regulations and are able to operate multiple aircraft types which makes it easier to recover their schedules. Therefore, the model will only consider cockpit crew.
- **Three days of operation**:
  Most of the pairings of KQ can be covered in three days of operation. Considering more days will increase the computation time and therefore the model will consider a maximum of three days of operation.
- **Partly crew rostering**:
  Individual crew members will be assigned to pairings. However, considering individual monthly rosters and the balancing in pairings between crew members is beyond the scope of this project.

3.3.2. Input and output data

It is of great importance to know the outlook of the input and output data. In addition, it is important which data will be available to the author. The input data for the model will be provided by KQ and will be as follows:

- **Flight schedule**
  The original flight schedule will be used as input file. The original schedule will be assumed as the optimal schedule and the model will strive to keep the recovered schedule as closely as possible to the original one.
- **Crew data**
  - All crew regulations that have to be met during the operation.
  - The original crew schedules will be combined with the original flight schedule.
  - Duty hours and block hours of all crew members in the past 28 days. These parameters should not exceed the maximum allowed hours.
- **Disruption information**
  All the information concerning the disruption will be used to process the disruption into the schedule.

- **Cost data**
  - Salaries of crew members to determine the pairing costs
  - Layover costs of crew members at outstations
  - Cancellation costs that should be applied for flights
  - Delay costs that should be applied per minute or set of minutes
- **Booking details**
  It is important to know what the number of passengers is on board of a flight. This number will determine the cancellation or delay costs of a flight.

The output data that will be provided by the model will be as follows:

- **Recovered flight and crew schedule**
  New generated and chosen pairings will be processed in the schedule and given as an output file
- **Recovery cost**
  The recovery costs associated with the recovery actions taken (objective value).
- **Computation time**
  The computation time of the model to solve the problem.
- **Cancellations and delays**
  The flights that are cancelled and the flights that are delayed.

The input and output data will be made anonymous due to privacy reasons. The output data will contribute to confirm or disprove the hypotheses defined in Section 3.2.

Since data will be used from KQ the project will be done partly in Nairobi and partly at the University of Technology Delft. At the University, every two weeks a meeting will be planned with the supervisor to discuss the progress of the project. Most of the time at Nairobi, time will be spent at the Operation Control Center (OCC) of KQ at the crew scheduling department. Therefore, it will be possible to work closely with crew schedulers and crew controllers from KQ.

3.4. Results and Relevance

The model will generate numerical solutions in the form of costs, number of cancellations and the pairings to be operated by crew members, whether or not with delayed flights. The recovery model should generate feasible solutions in acceptable computation times. Based on the size, complexity and the short amount of time in which solutions have to be obtained, it is not required to obtain optimal solutions. A trade-off will be made between computation time and the quality of the outcomes. This will be done in consultation with experts from KQ. The outcomes of all test cases will conclude if the model is suitable to use as a decision support model for airline crew recovery problems.

The relevance of the work will be to have a decision support tool for crew recovery that minimizes the costs and generates feasible solutions. The model can be used by operation controllers to obtain several solutions and even the optimal solution during a recovery process. This will improve the recovery efficiency, since a better overview will be gained of possible solutions. Even better solutions will be obtained compared with manual recovery. Therefore, there will be focussed on an operational tool that can be used in real-time operations. This implies that short computation times of the model are of great importance.

The research will contribute to the body of knowledge regarding the crew recovery problem by the development of a dynamic decision support model. The novelty of the research will be the dynamic approach of the model. This implies that the model recovers the crew schedule at the time disruptions are notified and previous taken recovery decisions are reconsidered. Previous models solved the problem for an entire set of disruptions or a single disruption without considering previous recovery decisions.

Another contribution of the research will be the consideration of individual crew members. The model will consider the cockpit crew individually, respectively captains (CP) and first officers (FO). This is also done by *Q. Liu et al. (2013)* however, in their research costs are not involved. In addition, a selection of crew members will be used to solve the problem and to keep the computation times low.

4

Model Framework

This chapter describes the dynamic model in more detail. A linear programming model is designed to reach the goal of the project, described in Chapter 3. First, a brief introduction of the model is given in Section 4.1. Thereafter, in Section 4.2 the processing of the disruptions is described after which an overview of the feasibility checks, that are performed in the model, is presented in Section 4.3. Subsequently, in Section 4.4 a description is given about the selection of crew members and thereafter in Section 4.5 the pairing generation of new feasible pairings is explained. The mathematical formulation of the model is described in Section 4.6. Within this section, the decision variables, parameters and indices are described and thereafter the objective function with the constraints are presented. In Section 4.7 the dynamic part of the model is described and finally in Section 4.8 the conclusion is given about the model framework.

4.1. Introduction of the model

This section briefly introduces the developed model to get a general idea of the model framework. It provides insight in the options available and the assumptions made in the model.

Several steps are taken within the model to come to the solution. The several steps are illustrated in the flowchart presented in Figure 4.1.

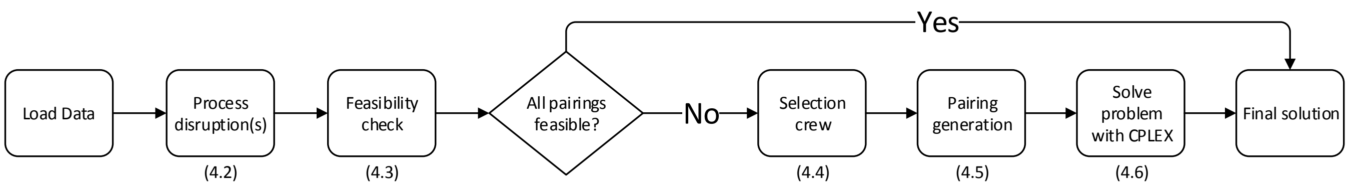


Figure 4.1: Flowchart of the recovery model

Based on the literature review and the project plan the most important aspect of the model is the dynamic approach. This implies that disruptions are solved the moment of notification and previous recovery decisions are reconsidered. The operational goal is to have a decision support tool that provides recovery solutions within short computation times. A selection algorithm will be used to consider only a set of crew members to solve the problem. This will decrease the computation times as well. In addition, only three days of operation are considered. These two methods are used in literature as well to obtain solutions in short computation times.

Crew members are considered individually and therefore new pairings are generated per crew member. Several recovery options are available in the model. E.g. to cancel, delay or swap flights and to use standby crew members.

Most of the blocks, in Figure 4.1 are indicated with a section number. In these sections, the specific blocks are described in more detail.

4.2. Disruptions

Disruptions are input for the model and it may cause infeasibility of the schedule. When the disruptions are given as input, the model processes the disruptions into the schedule. There are some input disruptions available, however not all disruptions are captured in this model. This section gives an overview of the kind of disruptions possible in the model and how the disruptions are processed.

Cancel flight

If a flight is cancelled, the specific flight is removed from the schedule and it is not considered in the generation of new pairings. Before the model is solved, the cancelled flights are added to the list of flights to ensure that there is only one possibility for the specific flight: cancelling. The mathematical formulation of a cancelled flight is given in Equation 4.1.

$$\delta_{Canx_i} = 1 \tag{4.1}$$

After every iteration in which the problem is solved, the model defines if the flight can be left uncovered instead of cancelling. Cancelling a flight implies that it cannot be reversed. Leaving the flight uncovered implies that the flight can still be operated if other crew members are found in time for operating the flight. A flight is left uncovered if Equation 4.2 is valid, otherwise the flight is cancelled.

$$\text{STD} - \text{changing flights time} > Tw_{start} \tag{4.2}$$

In this equation, STD is indicated as the scheduled time of departure of a specific flight. The scheduled time of arrival of a specific flight is indicated with STA. The changing flights time is stated as:

Changing flights time:

The minimum time before STD of flight i to cancel flight i

Delay flight

If a flight is delayed, the STD and STA are adapted for the specific flight. The input of the disruption defines a time until the flight is delayed. This time is used as new STD and adding the old flight time to STD results in the new STA of that specific flight. In case of an input delay, it is assumed that the aircraft will not fly faster to undo the delay.

Sick crew

If a crew member calls in sick, the specific crew member is removed from the schedule. The flights that the crew member would operate become uncovered. It depends on the aircraft type of the crew member for what time period the crew member will be scheduled sick.

Change aircraft type

It occurs that flights are upgraded or downgraded. This means an aircraft type change for a specific flight. Multiple reasons can cause the aircraft type change, like overbooked flights, aircraft breakdown or cancelled previous flights which increased the number of passengers to a specific destination.

In the model, the aircraft type of the specific flight is adapted and the crew is removed from the flight. This ensures that the flight will not be operated by crew who are not licensed for the aircraft type. The flight becomes uncovered and is considered in the pairing generation with the new aircraft type.

Airport unavailable

If an airport is unavailable within a certain time period, all flights to and from that specific airport are removed from the schedule. However, it is checked if the flight can be delayed up to a maximum allowed delay time. The maximum allowed delay time is an input value to the model.

First, all arriving flights at the disrupted airport are considered within the time period. If the STA is within the time period the airport is closed, the delay time is determined of the specific flight. In case the delay time is above the maximum allowed delay time, it is assumed that the flight has to be cancelled. Otherwise, the flight is delayed with the determined delay time.

After the arrival flights, the departing flights are checked which depart within the time period the airport is closed. Again the delay time is determined after which it is checked if the delay time is above the maximum allowed delay time. When this is true it is assumed that the flight has to be cancelled, otherwise the flight is delayed with the determined delay time.

Diverted flights

The last input disruption possible for the model is a diverted flight. This implies that a flight flies to another destination than planned. In the input disruption is stated what the new arrival time (STA_{new}) and the new destination airport is of the flight. In addition, if there is chosen to add a new flight ($flight_d$) to the schedule, the flight time of $flight_d$ is input as well. $flight_d$ is indicated as: D + number of $flight_d$ + day index (e.g. D0A, D1B, etc).

In addition, $flight_d$ flies from the new destination to the old destination. The departure time (STD_d) of $flight_d$ is defined as:

$$STD_d = STA_{new} + \text{ground hours}$$

In which ground hours is an input value to the model. However, if the flight is diverted because of an airport closure STD_d of $flight_d$ is the ending time of the airport closure.

4.3. Feasibility checks

After the disruptions are processed into the schedule, the feasibility checks are performed. This is done for the pairings of crew members who are affected by the disruptions. The reason why the feasibility checks are done, is because of the possibility that the pairings are still feasible despite the disruption(s). If one of the pairings is infeasible, the specific pairing is placed in a list with all infeasible pairings. At the end of the feasibility checks, a list of feasible and infeasible pairings is defined together with a list of uncovered flights. The definition of a pairing is given in Section 2.1. The feasibility checks performed in the model are described in this section. The parameters and indices used in this section, are described in more detail in Section 4.6.

(1) Pairing start and pairing end airport

The first feasibility check verifies if the start airport of the pairing, mostly the home base of the crew member, equals the end airport of the pairing. This is essential, otherwise crew members will end up at an outstation and not at their home base. The algorithm used for this feasibility check is presented in Algorithm 1.

(2) Arrival and departing airports

The second feasibility check verifies if the arrival airport of flight i equals the departure airport of flight $i + 1$. This is essential, otherwise crew members have to depart from an airport which is not equal to the airport where they arrived. The algorithm used for this feasibility check is presented in Algorithm 1 as well.

Algorithm 1 Feasibility Checks 1 and 2

```
procedure Check airports
    Loop:
    for each disrupted crew member k ∈ K  do
        Pairing P_k of disrupted crew member k with flights i
        for each flight i ∈ P_k  do
            if flight i = first flight of pairing P_k then
                Pairing start airport = Departing airport flight i
            else if flight i = last flight of pairing P_k then
                Pairing end airport = Arrival airport flight i
                Go to Feasibility check 1
            else
                Go to Feasibility check 2

        Feasibility check 1:
        if Pairing start airport = Pairing end airport then
            Continue check
        else
            Add pairing to list of infeasible pairings and continue check

        Feasibility check 2:
        if Arrival airport flight i = Departure airport flight i + 1 (next flight in pairing) then
            Continue check
        else
            Add pairing to list of infeasible pairings and Go to Loop
    return list of infeasible pairings
```

(3) Transition time crew

The third feasibility check verifies if crew members have sufficient transition time between flights. If the transition time is lower than the minimum needed transition time for crew, the crew members cannot operate the pairing. Since the model considers three days of operation the transition times are checked between flights within a duty. In the pre-processing phase the pairing of a crew member is divided in duties per day. The definition of a duty is given in Section 2.1. The algorithm used for this feasibility check is presented in Algorithm 2.

Algorithm 2 Feasibility Check 3

```
procedure Check transition times
    Loop:
    for each disrupted crew member k ∈ K do
        Pairing P_k of disrupted crew member k with duties D_{d,k}
        for each duty D_{d,k} ∈ P_k do
            for each flight i ∈ D_{d,k} do
                t_1 = STD flight i
                t_2 = STA flight i − 1 (previous flight)
                transition time = t_1 - t_2
                Go to Feasibility check 3

                Feasibility check 3:
                if transition time < minimum needed transition time then
                    Add pairing to list of infeasible pairings and Go to Loop
                else
                    Continue check for crew member k
    return list of infeasible pairings
```

(4) Duty hours day

The fourth feasibility check verifies if crew members do not exceed the maximum allowed duty time per day. The maximum allowed duty time per day depends on the number of flights the crew members are assigned to for that day and the time at which the duty starts. Every duty in the pairing is checked if the maximum hours are exceeded or not. The algorithm used for this feasibility check is presented in Algorithm 3.

Algorithm 3 Feasibility Check 4

```
procedure Check duty times day
    Loop:
    for each disrupted crew member k ∈ K do
        Pairing P_k of disrupted crew member k with duties D_{d,k}

        for each duty D_{d,k} ∈ P_k do
            Determine duty time day:
            Duty start time = STD first flight duty D_k - reporting minutes
            Duty end time = STA last flight duty D_k + signing out minutes
            Duty time day = Duty end time - Duty start time
            Go to Feasibility check 4

            Feasibility check 4:
            if Duty time > maximum duty hours then
                Add pairing to list of infeasible pairings
            else
                Pairing is still feasible for crew member k
    return list of infeasible pairings
```

(5) Duty hours 28 days

The fifth feasibility check verifies if crew members do not exceed the maximum allowed duty hours in 28 days. The duty hours in the past 28 days per crew member is input of the model. First, the original duty hours at the considered day are determined and subtracted from the duty hours in 28 days to get the duty hours in 27 days per crew member. Thereafter, the disrupted duty hours at the considered day, in which the disruptions are considered, are added to the duty hours in 27 days to get the disrupted duty hours in 28 days per crew member. Finally, the disrupted duty hours in 28 days are checked with the maximum allowed duty hours in 28 days. This is done for every duty in the pairing of a crew member. The algorithm used for this feasibility check is presented in Algorithm 4.

Algorithm 4 Feasibility Check 5

procedure Check duty times 28 days
    Loop:
    for each disrupted crew member $k \in K$ **do**
        Original pairing $P_{k,old}$ of disrupted crew member k with duties $D_{d,k,old}$
        Disrupted pairing P_k of disrupted crew member k with duties $D_{d,k}$

        for each duty $D_{d,k,old} \in P_{k,old}$ **do**
            Determine original duty hours:
            Duty start time old = STD first flight duty $D_{d,k,old}$ - reporting minutes
            Duty end time old = STA last flight duty $D_{d,k,old}$ + signing out minutes
            Duty time day original = Duty end time - Duty start time
            Duty time 27 days at day d = Duty time 28 days of crew k - Duty time day original

        for each duty $D_{d,k} \in P_k$ **do**
            Determine disrupted duty hours:
            Duty start time dis = STD first flight duty $D_{d,k}$ - reporting minutes
            Duty end time dis = STA last flight duty $D_{d,k}$ + signing out minutes
            Duty time day dis = Duty end time dis - Duty start time dis
            Duty time 28 days disrupted at day d = Duty time 27 days at day d + Duty time day dis
        Go to *Feasibility check 5*

        Feasibility check 5:
        for each duty $D_{d,k} \in P_k$ **do**
            if Duty time 28 days disrupted at day d > maximum duty hours 28 days **then**
                Add pairing to list of infeasible pairings
            else
                Pairing is still feasible for crew k
    return list of infeasible pairings

Subtracting the reporting minutes from the STD results in the reporting time of the crew member. Adding the signing out minutes to the STA results in the time the crew member is finished with their duty.

(6) Block hours 28 days

The fifth feasibility check verifies if crew members do not exceed the maximum allowed block hours (Blh) in 28 days. The same strategy is used as in feasibility check 5. However, in this case the Blh have to be determined per duty instead of the duty times. The algorithm used for this feasibility check is presented in Algorithm 5.

Algorithm 5 Feasibility Check 6

procedure Check Block hours 28 days
  Loop:
  for each disrupted crew member $k \in K$ **do**
    Original pairing $P_{k,old}$ of disrupted crew member k with duties $D_{d,k,old}$
    Disrupted pairing P_k of disrupted crew member k with duties $D_{d,k}$

    for each duty $D_{d,k,old} \in P_{k,old}$ **do**
      Determine original BLH:
      BLH day old = summation of all flight times in duty $D_{d,k,old}$
      BLH 27 days at day d = BLH 28 days of crew k - BLH day old

    for each duty $D_{d,k} \in P_k$ **do**
      Determine disrupted BLH:
      BLH day dis = summation of all flight times in duty $D_{d,k}$
      BLH 28 days disrupted at day d = BLH 27 days at day d + BLH day dis
    Go to *Feasibility check 6*

    Feasibility check 6:
    for each duty $D_{d,k} \in P_k$ **do**
      if BLH 28 days disrupted at day d > maximum BLH 28 days **then**
        Add pairing to list of infeasible pairings
      else
        Pairing is still feasible for crew k
  return list of infeasible pairings

(7) Arrivals after night limit
The seventh feasibility check verifies if crew members arrive after the night limit. When crew members arrive after the night limit it is not allowed to operate a duty on the next day. The use of this limit is necessary since duties during the night (in the dark) are more intensive due to the human biological clock[1]. Therefore, it is checked if the specific crew members are scheduled for duty after a night limit arrival. The night limit may differ per airline. The algorithm used for this feasibility check is presented in Algorithm 6.

Algorithm 6 Feasibility Check 7

procedure Check arrivals after midnight
  Loop:
  for each disrupted crew member $k \in K$ **do**
    Pairing P_k of disrupted crew member k with duties $D_{d,k}$

    for each duty $D_{d,k} \in P_k$ **do**
      if STA last flight in duty $D_{d,k}$ + signing out minutes > 12:00am **then**
        if $D_{d+1,k}$ is not empty **then**
          Arrival after midnight and next duty is not empty
          Add pairing to list of infeasible pairings
        else
          Continue check for crew member k
  return list of infeasible pairings

[1]The biological clock is the internal clock of a human or animal that controls the psychological activities (like sleep, hunger and other activities) which change on a daily, weekly, yearly, or other regular cycle

(8) Rest times
The eight feasibility check verifies if crew members have sufficient rest time after a duty. It depends on the duty hours what the minimum rest time for a crew member is. These minimum rest times should be met, otherwise a crew member is not allowed to operate their next duty. The algorithm used for this feasibility check is presented in Algorithm 7.

Algorithm 7 Feasibility Check 8

procedure Check rest times
  Loop:
  for each disrupted crew member $k \in K$ **do**
    Pairing P_k of disrupted crew member k with duties $D_{d,k}$

    for each duty $D_{d,k} \in P_k$ **do**
      Duty end time = STA last flight duty $D_{d,k}$ + signing out minutes
      Duty start time next day = STD first flight duty $D_{d+1,k}$ - reporting minutes
      Rest time = Duty end time - Duty start time next day
      if Rest time < minimum allowed rest time **then**
        Add pairing to list of infeasible pairings
      else
        Continue check for crew member k
  return list of infeasible pairings

(9) Covered flights
The last feasibility check verifies if all the flights are covered. In case, a crew member called in sick it is possible that flights are not fully covered. Every flight should have a CP and a FO. It is allowed to have two CPs on a flight as well. When this is not the case, the flight is stated as uncovered. The algorithm used for this feasibility check is presented in Algorithm 8.

Algorithm 8 Feasibility Check 9

procedure Check if flights are covered
  Loop:
  for each flight $i \in F$ **do**
    if flight i has a captain AND a first officer or a second captain **then**
      Flight is covered
    else
      Add flight i to list of uncovered flights
  return list of infeasible pairings

After the feasibility check, an entire list of infeasible pairings, with the concerned crew members, is returned by the model. Due to disruptions, pairings became infeasible. However, it is also possible that flights became uncovered due to sick crew. The model generates a new list of all uncovered flights and all the flights of the infeasible pairings. This list is called the *recovery flights* list. All crew members involved are stored in the *recovery crew* list.

4.4. Selection crew

A list of infeasible pairings with the concerned crew members is defined from the feasibility check. Before new pairings are generated, a selection of crew members is defined to recover the schedule. Using only the disrupted crew members will make it very hard to recover the schedule. However, considering all crew members will make the model very slow. In addition, the goal is to change the initial schedule as least as possible. Therefore, a trade-off has to be made between those parameters. The user can change the parameters if they have other interests. Hence, an important part of the model is the selection algorithm. Several options are available for the user and the model uses clusters of crew members. This section describes the selection algorithm of crew members together with the different options the user can choose from.

Clustering of crew members

As mentioned in Chapter 2, crew members are certified to operate certain aircraft types. Therefore, the first and standard selection the model executes is based on the aircraft type that is disrupted. The decision has to be made if all crew members will be considered or only a selection of the crew members. In case of the last decision, a maximum number of selected crew members to consider is defined by the user.

In case a selection of crew members has to be defined, clusters are used. The first clusters defined are based on the aircraft type for which crew members are certified. It is assumed that crew members are only certified for one aircraft type. Within the aircraft type clusters, the crew members are sorted into smaller clusters. Algorithm 9 represents the algorithm used to store the crew members into smaller clusters.

Algorithm 9 Clustering crew members

procedure Cluster all crew members
    Loop crew:
    for each crew member $k \in K$ **do**
        if Crew member k is not already in a cluster **then**
            Start new cluster
            Define list of flights (F_k) crew member k is assigned to within the considered time period
            Loop flights:
            for each flight $i \in F_k$ **do**
                Define colleague crew member (k_c) on flight i
                if Crew k_c is not already in cluster **then**
                    Store crew k_c in cluster
                    Define list of flights crew k_c is assigned to within the considered time period
                    Go to *Loop flights* to store colleague crew members in same cluster
    return list of all clusters

Crew members that operate flights together are stored in the same cluster. Therefore, all crew members that are connected to each other by flights are stored in the same cluster. The algorithm shows that crew members are stored in only one cluster. Using these clusters is necessary to apply changes to all crew members that are connected to each other and to prevent infeasible pairings. Figure 4.2 illustrates an example of the clusters based on the aircraft type and based on the same flights to be operated.

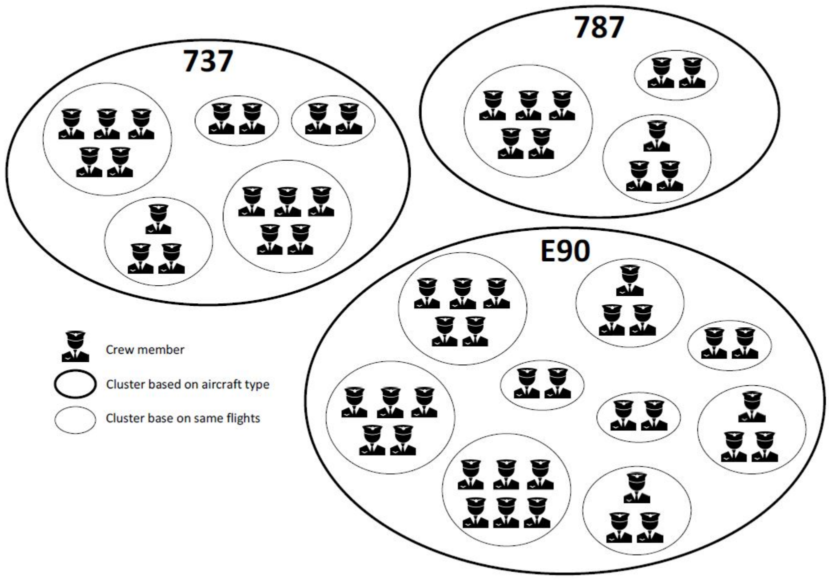


Figure 4.2: An example of aircraft type clusters and clusters based on the same flights to be operated.

Decrease number of crew members to consider
In case the number of selected crew members is above the maximum number of selected crew members, the selection has to be decreased. Several options are available and the user can decide what their preference is in selecting crew members. However, it is only possible to choose one of the options for the entire problem.

The selection of crew members is made per disrupted AC type and per crew function. Hence, a selection for CPs and a selection for FOs are defined. For example, two AC types are disrupted and the number of selected crew members is set to five. A selection of five CPs and five FOs is defined for one AC type and the same for the other.

The first selected crew members are the ones that are stored in the same cluster as the disrupted crew member. Based on the size of the cluster and the maximum number of selected crew members, the model selects more crew members if necessary. In the model, there are five options available to sort the remaining list of crew members:

1. **Reporting time** Crew members are ranked based on the reporting time at the considered day. The reporting time is stated as the time the crew member has to report for duty. First, crew members with the reporting time close to Tw_{start} are chosen.

2. **Duty time day** Crew members are ranked based on the duty time at the considered day. First, crew members with low duty times are chosen.

3. **Duty time in 28 days** Crew members are ranked based on the duty time in 28 days. First, crew members with low duty times in 28 days are chosen.

4. **Blh in 28 days** Crew members are ranked based on the Blh in 28 days. First, crew members with low Blh in 28 days are chosen.

Based on the option, the remaining crew list is sorted. The first crew member of the list together with the entire cluster of the selected crew member is added to the list of selected crew members. When the maximum number of selected crew members is still not reached, the model adds the entire cluster of the second best crew member to the selected crew members list. This process continues till the maximum number of selected crew members is reached or exceeded.

The model continues with the pairing generation with the selection of crew members as input to the algorithm. In the pairing generation, only the flights from the selected crew members are used to generate new pairings.

Additional options
There are some additional options that can be used in the selection algorithm. One of those options is whether to use uncovered flights or not. At the start of the day it is possible that some flights are uncovered. This may have several reasons. However, there is an option to consider uncovered flights in the recovery phase or not.

The other option available is whether to use day-off crew or not. Using day-off crew increases the possibility to recover the schedule in the most efficient way. However, the model will definitely assign duties to those crew members. In reality, it is still possible that those crew members will refuse to operate the flights. Therefore, a maximum number of using day-off crew is implemented in the model.

4.5. Pairing Generation

The list of considered crew members together with the involved flights are used to define new feasible pairings. Before the pairing generation, per crew member is defined if there are any fixed flights and if the reporting time is fixed.

Fixed flights
Based on the start time of the time window (Tw_{start}) some flights have already been operated or are in operation. It is not possible to change those flights and therefore these flights are fixed for the specific crew members. When $STD - transition\ time$ of a flight is before Tw_{start}, that flight is fixed for crew members as well. The crew member is already heading to the aircraft or preparing for the flight. However, in this case it is still possible to cancel the flight. In the duty generation this flight is only available for the original crew members.

Fixed reporting times
Not only flights can be fixed, the reporting time of crew members can be fixed as well. If Tw_{start} is after reporting time of crew members, they are already at the airport and the reporting time has passed. However, changing the reporting time five minutes before the actual reporting time is not possible as well. In this case, a crew member is already heading to the airport or preparing for a flight. A parameter is introduced which can be set by the user:

Changing reporting time:

The minimum time before the old reporting time to inform the crew member of the changed reporting time

Duty generation
The fixed flights and reporting times are used as input for the duty generation algorithm. Together with the recovery flight list, new feasible duties are generated per selected crew member. The flowchart of generating new duties is illustrated in Figure 4.3.

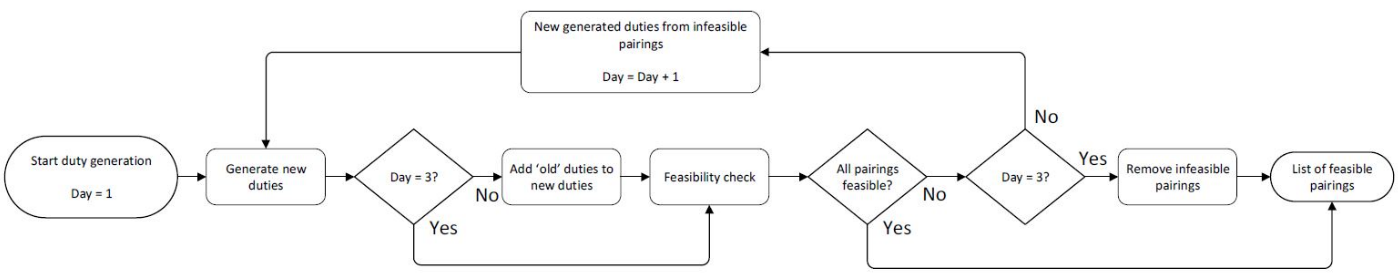


Figure 4.3: Flowchart of the generation of new duties and pairings.

It is preferred to stay close to the original schedule and therefore first duties are generated for only the first day of operation. There are a few options available for the generation of new pairings. It is possible to generate duties for only the first day, or the second day as well, or all three days. A depth

Algorithm 10 Duty Generation

```
procedure Generate new duties

    Loop crew:
    for each crew member k ∈ recovery crew list do
        Define start flight(s)
        Flight_fix = last flight of fixed start flights
        Dest_fix = destination of Flight_fix

        Loop flights:
        for each flight i ∈ recovery flights list do
            if Dest_fix = departure airport flight i then
                if flight i not already in the new duty then
                    if lenght of new duty < allowed number of flight legs then
                        if There is enough transition time between Flight_fix and flight i then
                            if duty time day ≤ maximum duty time day then
                                if duty time in 28 days ≤ maximum duty time in 28 days then
                                    if Blh in 28 days leq maximum Blh in 28 days then
                                        Store flight i in the new duty
                                        Flight_fix = flight i
                                        Dest_fix = destination of flight i
                                        Save duty for crew member k
                                        Go to Loop flights to check possible flights behind last flight of duty
                        else
                            Delay:
                            delay = minimum transition time - real transition time between flights
                            if delay ≤ maximum delay then
                                STA_i = STA_i + delay
                                if duty time day ≤ maximum duty time day then
                                    if duty time in 28 days leq maximum duty time in 28 days then
                                        if Blh in 28 days leq maximum Blh in 28 days then
                                            Store flight i in the new pairing
                                            Flight_fix = flight i
                                            Dest_fix = destination of flight i
                                            Save duty for crew member k
                                            Go to Loop flights to check possible flights behind last flight of duty
    return list of new generated duties
```

first search (see Section 2.1) is used to generate new duties. The algorithm used for the duty generation is presented in Algorithm 10.

New duties are generated for the first day and the 'old' duties of day 2 and 3 are added to the duties to get the new pairings. However, it is possible that some new generated pairings are still infeasible. This is checked with a smaller part of the feasibility check presented in Section 4.3. The other feasibility checks are already verified in the duty generation algorithm. The feasibility checks performed in the pairing generation are:

- **Feasibility check 2: Arrival and departing airports**
  Only the airports between the duty days have to be checked.

- **Feasibility check 5: Duty times in 28 days**
  With the new generated duty it is possible that the maximum duty times in 28 days are exceeded for the other days.

- **Feasibility check 6: Blh in 28 days**
  With the new generated duty it is possible that the maximum Blh in 28 days are exceeded for the other days. In that situation, the pairing is infeasible.
- **Feasibility check 7: Late arrivals**
  When the new generated duty has a late arrival, it should be checked if the next day contains no flights. In that situation, the pairing is infeasible.
- **Feasibility check 8: Rest times**
  With the new generated duty the rest time might be changed. Therefore, it should be checked again between the duties.

The feasibility check returns again a list with infeasible pairings if there are any. Feasible pairings are saved in the new generated pairing list and the new generated duties from the infeasible pairings are used as fixed flights to start a new duty generation at the next day. The process of generating new duties starts again and is repeated till all pairings are feasible or when duties are generated for day 3. At the end of the pairing generation a list of all new feasible generated pairings is returned. The reader is referred to Appendix B for an example of the pairing generation algorithm.

4.6. Mathematical formulation

This section describes the mathematical formulation of the linear programming problem. The mathematical formulation exists of an objective function and some constraints. However, to set up the objective function and constraints first the decision variables and some other parameters have to be defined for a better understanding of the mathematical formulation of the problem. This section describes these elements and thereafter the objective function with the constraints is described.

4.6.1. Decision variables, parameters and indices

The decision variables used in this model are boolean variables which means that the value is 0 or 1. The explanation per decision variable is given below:

Decision variables:

$\delta_{CF_{k,p}}$ = 1 if pairing p is used for crew member k, 0 otherwise
δ_{Canx_i} = 1 if flight i is cancelled, 0 otherwise
$\delta_{C_{slack}}$ = 1 if the slack variable is used for crew member k, 0 otherwise

Using the slack variable for crew member k indicates that there are no feasible solutions present for the specific crew member. The operation controller should look for a solution of the considered crew member.
The parameters used in the model are defined below:

Parameters:

K = set of crew members
P = set of feasible pairings
F = set of flights
D = set of duties
$c_{k,p}$ = cost of operating pairing p by crew member k
c_{c_i} = cost of cancelling flight i
$c_{slack,k}$ = cost of using the slack variable for crew member k
a_{ip} = 1 if pairing p contains flight i, 0 otherwise
b_{kp} = 1 if pairing p can be flown by crew member k, 0 otherwise
fo_{ipk} = 1 if pairing p contains flight i and crew k is a first officer, 0 otherwise

The determination of the cost parameters differ per airline. The costs determined in this research project are described in Chapter 6.

Indices are used to define specific flights, crew members, pairings or days. The indices used in the model are defined below:

Indices:

k = crew member index
p = pairing index
i = flight index
d = day index

4.6.2. Objective function and constraints

In this research the objective function is a minimization function. The aim is to minimize the recovery costs and these costs are defined in the objective function. This results in Equation 4.3 which represents the objective function as it is determined for this research project. Respectively, the cost of operating pairing p by crew member k, the cost of cancelling flight i and the cost of the slack variable for crew member k.

$$Minimize \sum_{k \in K} \sum_{p \in P} c_{k,p} \cdot \delta_{CF_{k,p}} + \sum_{i \in F} c_{c_i} \cdot \delta_{Canx_i} + \sum_{k \in K} c_{slack,k} \cdot \delta_{C_{slack}} \tag{4.3}$$

The decision variables have some boundaries which are described as constraints. The first constraint defined for this research project is presented in Equation 4.4. This constraint ensures that every flight has to be covered. In this case the flight can be flown or be cancelled. The summation of the decision variables should be equal to 2, since two cockpit crew members should be assigned to a flight. When a flight will be cancelled, the multiplier 2 will ensure that the constraint is valid for the specific flight.

$$\sum_{p \in P} a_{ip} \cdot \delta_{CF_{k,p}} + 2\delta_{Canx_i} = 2 \qquad \forall i \in F \tag{4.4}$$

Equation 4.5 represents the constraint that every crew member has to be assigned to only one pairing. In this case the crew member should be assigned to a pairing or the slack variable should be used for crew member k. The slack variable will be used to prevent that the model will become infeasible. The costs for the slack variable are extremely high, therefore it will only be chosen when there is no other solution possible.

$$\sum_{p \in P} b_{kp} \cdot \delta_{CF_{k,p}} + \delta_{C_{slack}} = 1 \qquad \forall k \in K \tag{4.5}$$

Equation 4.6 represents the constraint that every flight should contain 0 or 1 FO. In general, a flight will be operated by a CP and a FO. However, sometimes it is possible that two CPs operate a flight. It is not allowed to have only two FOs on a flight. This constraint ensures that in all circumstances the flights are covered in a proper way.

$$\sum_{p \in P} fo_{ipk} \cdot \delta_{CF_{k,p}} \leq 1 \qquad \forall i \in F, \forall k \in K \tag{4.6}$$

4.7. Dynamic recovery

The contribution to the literature of this research project is the dynamic approach that is used in recovering the crew schedule. The schedule at the start of the day is used as original schedule and it is assumed that this schedule is the optimal one. During the day the model will strive to stay close to the original schedule. Disruptions are processed in the model at the moment of notification. Due to a new disruption it is possible that some recovery decisions are no longer optimal or can be revised. The dynamic approach ensures that previous recovery decisions are reconsidered. It defines if it is still possible to revise certain decisions.

It is possible that a disruption is updated. Therefore, the model checks if the occurrence of a flight or airport is more than once in the disruption overview. In case the occurrence of a flight is more than once, it is checked if one of the occurrences is a cancellation. In that case, the cancellation disruption is used, otherwise the disruption with the highest input time is chosen. All remaining disruptions of that specific flight are removed from the disruption overview.

In case, the occurrences of an airport is more than once, the disruption with the highest input time is chosen by the model. All the remaining disruptions of that specific airport are removed from the disruption overview. This is necessary to prevent multiple disruptions of the same flight or airport.

4.8. Conclusion Model Framework

This chapter has described how the entire model is built. The most important elements are described in detail. Feasibility checks are performed and from the list with infeasible pairings, new pairings are generated. In the part of the selection of crew members, many options are available for the user. By using the clusters of crew members it is prevented that the model will become infeasible. New pairings are generated by using a depth first search algorithm. A dynamic approach is used in the model and therefore previous recovery decisions are reconsidered. All the different aspects mentioned in Chapter 2 and 3 are covered in the model. The development of the model is finished and the test cases are described in the following chapters.

5 Verification

This chapter describes the verification of the model. Verification of the model is important to confirm if the model generates the expected solutions. Small test cases are defined to verify the model. First an introduction of the used network is given together with an explanation of how the figures should be read. The test cases are divided in cancelling flights, delaying flights, using standby crew and swapping flights. Thereafter, a dynamic test case is performed as well after which a conclusion is defined about the verification of the model.

5.1. Test network and figure explanation

A small network is used for the test cases performed in this chapter. By using a small network, it is possible to understand the choices made by the model and to compare those results with the expected results. An overview of the used network is given in Table 5.1[1]. In some cases only a part of the network is used.

Table 5.1: Small network that is used for the verification. An overview of the airport codes can be found in Appendix D.

Flight	Origin	Destination	STD	STA
KQ100	NBO	MBA	8:00	9:00
KQ200	MBA	NBO	9:40	10:40
KQ300	NBO	MBA	11:20	12:20
KQ400	MBA	NBO	13:00	14:00
KQ500	NBO	KIS	8:00	9:00
KQ600	KIS	NBO	9:40	10:40
KQ700	NBO	DAR	11:40	13:10
KQ800	DAR	NBO	14:00	15:30

Before the verification is described, an explanation is given about the figures presented in this chapter. Figure 5.1 illustrates the general outlook of the figures which are direct outputs of the model. Figure 5.2 illustrates the different arcs and lines used in the figures. It illustrates that a flight is indicated with a colour bar. In the original and recovered situation a flight is indicated with the same colour.

[1]The flights are fictitious and not based on reality

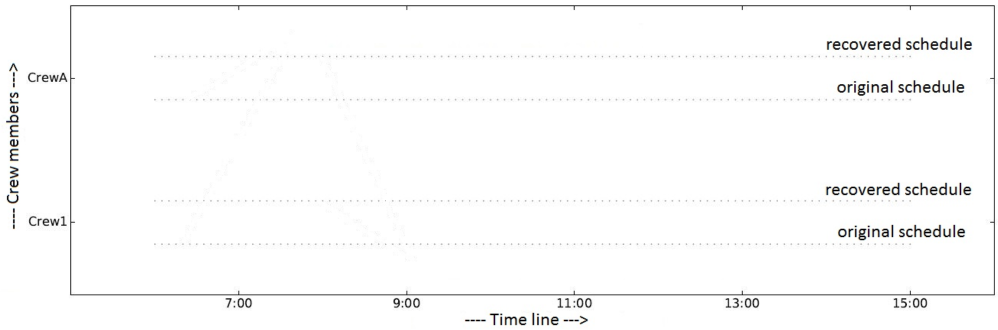


Figure 5.1: General outlook of the figures produced by the model.

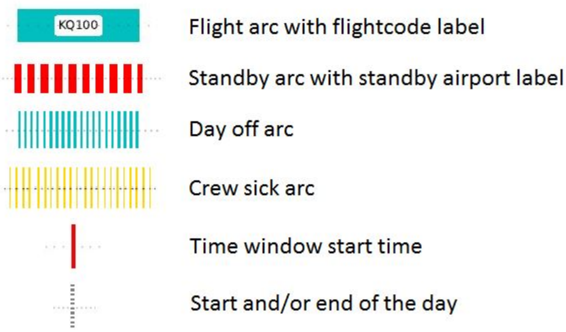


Figure 5.2: Legend of the figure arcs and lines.

5.2. Cancellations

In this section cancellations of flights are tested. The model is forced to cancel flights, since there are no other options available. All test cases consider one CP (Crew1) and one FO (CrewA) with the same duty which contains the first four flights of the network in Table 5.1.

The first test done is a test where the input disruption is the cancellation of flight KQ300 known at 7:00am. Operating the three remaining flights of the duty is not possible since the arrival airport and departure airport of the upcoming flight are not the same (NBO and MBA). Either KQ200 or KQ400 has to be cancelled to make the duty feasible again. The number of passengers are the same for all flights which means that the shortest duty has the lowest costs. Figure 5.3 illustrates that KQ400 is cancelled.

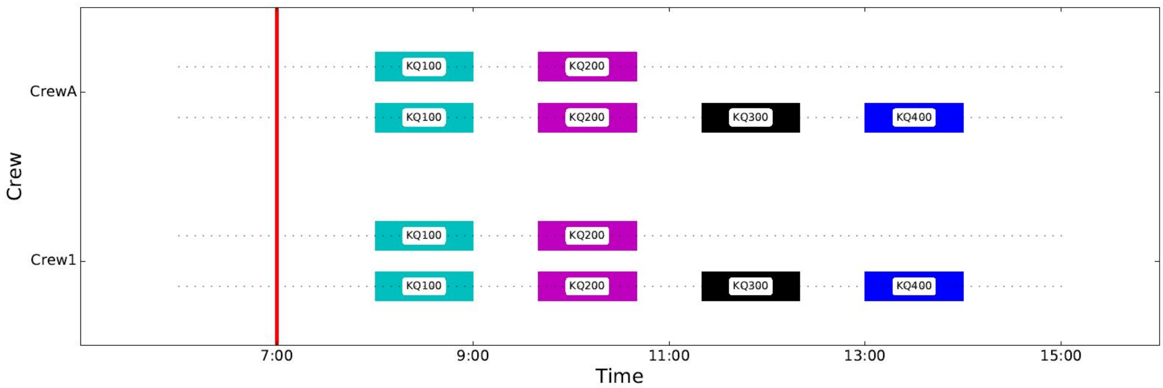


Figure 5.3: Cancellation of KQ300 results in cancellation of KQ400 as well.

The next test done has the same input disruption, however, KQ200 has less passengers. This implies that KQ200 has lower cancellation costs compared with other flights. The cancellation costs of KQ200 cannot compete with a longer duty time of the crew members. KQ200 is cancelled in this case and this is illustrated in Figure 5.4.

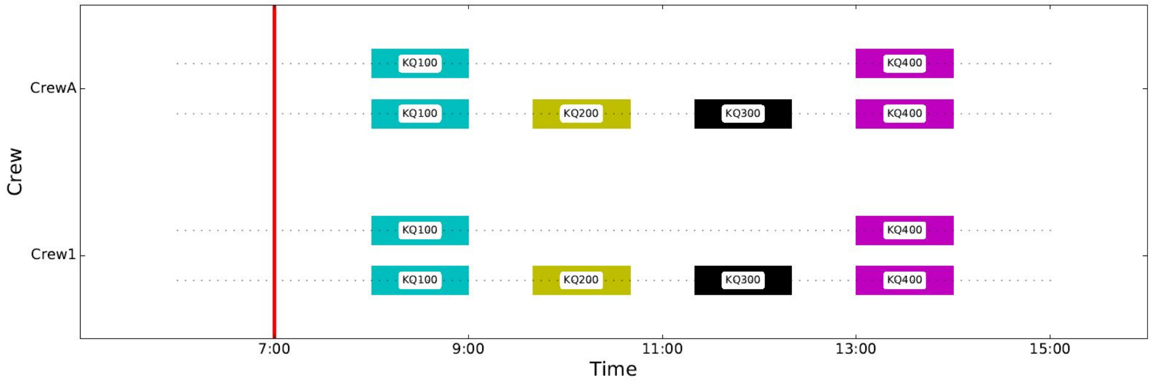


Figure 5.4: Cancellation of KQ300 results in cancellation of KQ200 with less passengers.

In both cases, the time of notification is before the duty start time. The situation changes when the time of notification is later in time, for example at STA of KQ200. KQ100 and KQ200 cannot be cancelled, since both flights are already operated. For the next test the time of notification is 10:40am and therefore KQ400 is cancelled as illustrated in Figure 5.5

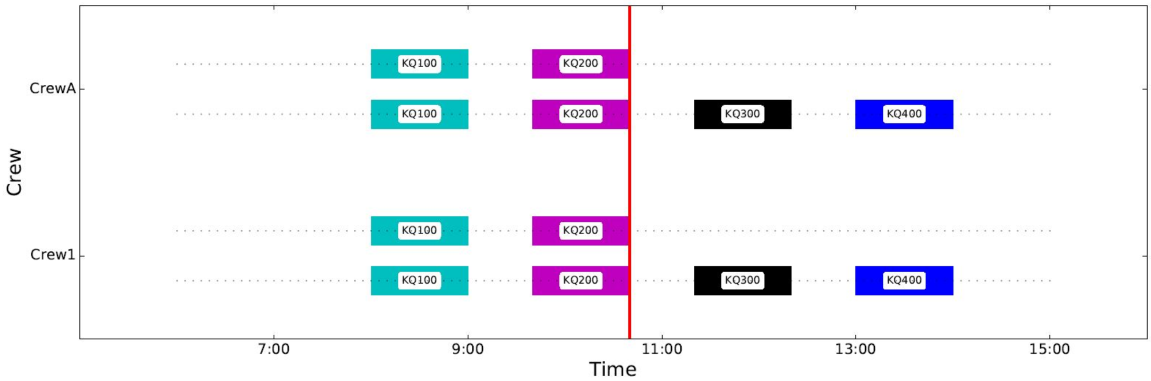


Figure 5.5: Cancellation of KQ300 results in cancellation of KQ400, since the time of notification is at STA of KQ200.

The next test done is to test if the model is able to add a layover for crew members. The same duty has to be performed at day 2 as at day 1 by Crew1 and CrewA. In this case KQ400 is cancelled and known at 12:20pm. A layover at airport MBA and cancelling KQ100 at day 2 is necessary to make the pairing feasible again. This is illustrated in Figure 5.6.

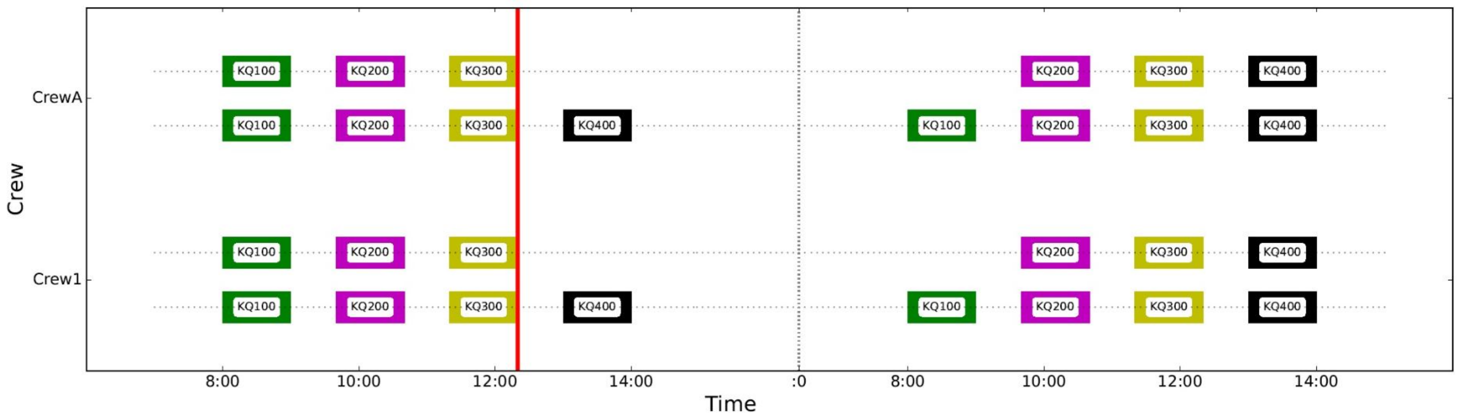


Figure 5.6: Cancellation of KQ400 results in cancellation of KQ100, since time of notification is at STA of KQ300. Crew has to layover at airport MBA.

5.3. Delays

The model is not only able to cancel flights but is also able to delay flights. In this section, the possibility to delay flights is tested. The model is forced to delay flights, since there are no other options available. The same crew members and duties are considered as in Section 5.2.

The first test done is a test where the input disruption is a delay of 15 minutes of KQ100 known at 7:00am. As a result of the delay there is not sufficient transition time between KQ100 and KQ200. KQ200 has to be delayed to maintain the transition time. However, this causes problems for the transition time between the upcoming flights. The solution is to delay all upcoming flights with 15 minutes to maintain the transition time between the flights. Figure 5.7 illustrates the solution of delaying all flights.

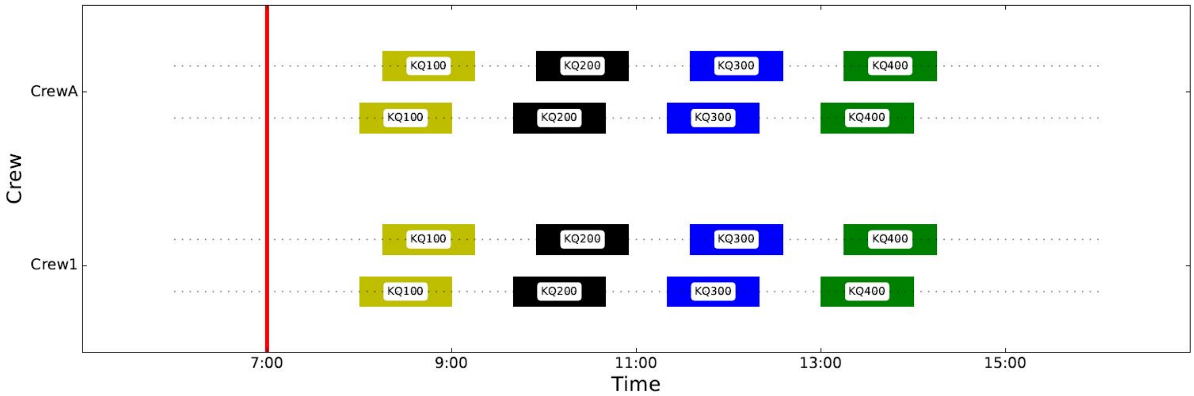


Figure 5.7: A delay of 15 minutes of KQ100 results in the same delay for all upcoming flights.

The model is restricted to a maximum delay time which is an input value of the user. The model is not allowed to delay flights above the maximum delay time. The next test verifies if the model cancels flights when the delay time is higher than the maximum delay time. The input disruption is a delay of 5 minutes above the maximum delay time of KQ100 known at 07:00am. Since the model is not allowed to delay the upcoming flights with a value beyond the maximum delay time, flights have to be cancelled. In this case the KQ100 and KQ200 are cancelled which is illustrated in Figure 5.8.

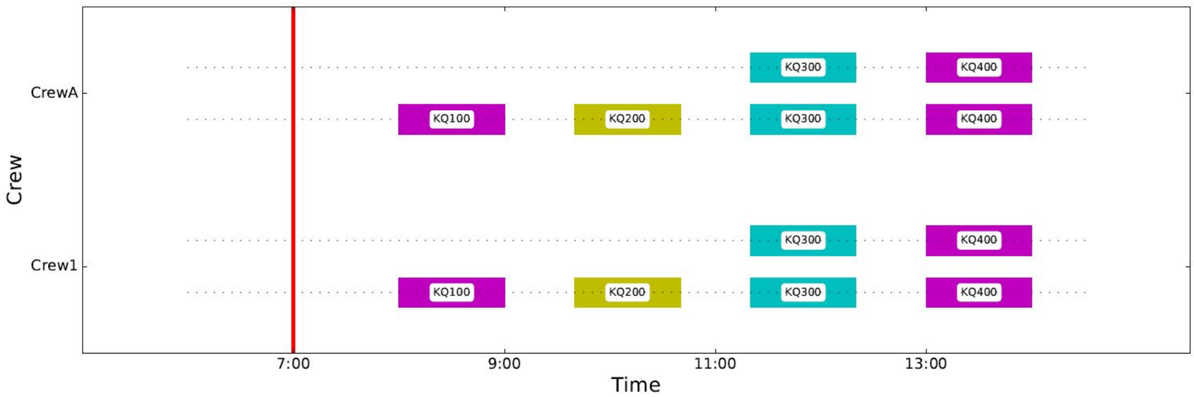


Figure 5.8: A delay of 5 minutes above the maximum delay time results in the cancellation of KQ100 and KQ200.

5.4. Standby crew

In Section 5.3 is tested if the model adds delay to flights to maintain the transition time. However, there was no other option available. In this section a test is done by using standby crew. The same network is considered as in Section 5.3, however, in this case one CP (CrewS1) and one FO (CrewSA) are standby at airport NBO as well. The input disruption is again a delay of 15 minutes of KQ100 known at 7:00am. Since, there is a standby crew available it is only necessary to delay KQ200 with 15 minutes. KQ300 and KQ400 can be operated at the scheduled times by the standby crew and adding a delay to the flights is not necessary. There is assumed that there are no additional costs for using standby crew. The solution is illustrated in Figure 5.9.

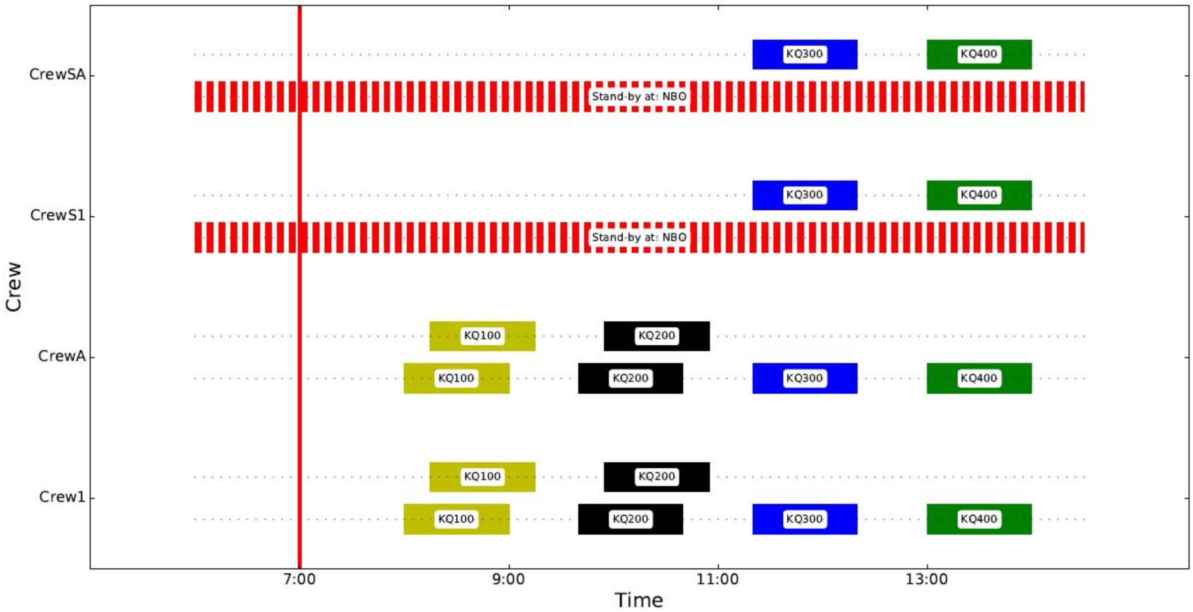


Figure 5.9: A delay of 15 minutes of KQ100 results in the same delay for KQ200. KQ300 and KQ400 are operated by the standby crew at the scheduled times.

5.5. Swap flights

So far, the model delayed flights (Section 5.3) or used standby crew (Section 5.4) to recover the schedule after a delay disruption. However, The best recovery option is to swap flights with other crew members. In this section the option to swap flights between crew members is tested.

This test case considers two CPs (Crew1 and Crew2) and two FOs (CrewA and CrewB) with a duty of four flights at day 1. Crew1 and CrewA perform the same duty (first four flights in Table 5.1) and Crew2 and CrewB perform the same duty (remaining four flights in Table 5.1).

Again, the input disruption is a delay of 15 minutes of KQ100 known at 7:00am. In this case the transition time is not valid any more for Crew1 and CrewA because of the delay. However, Crew2 and CrewB have more time between KQ700 and KQ800 than the minimum transition time. It is possible to swap KQ300 and KQ400 with KQ700 and KQ800. Only, KQ200 is delayed with 15 minutes as well and the rest of the flights are operated as planned. The solution is illustrated in Figure 5.10.

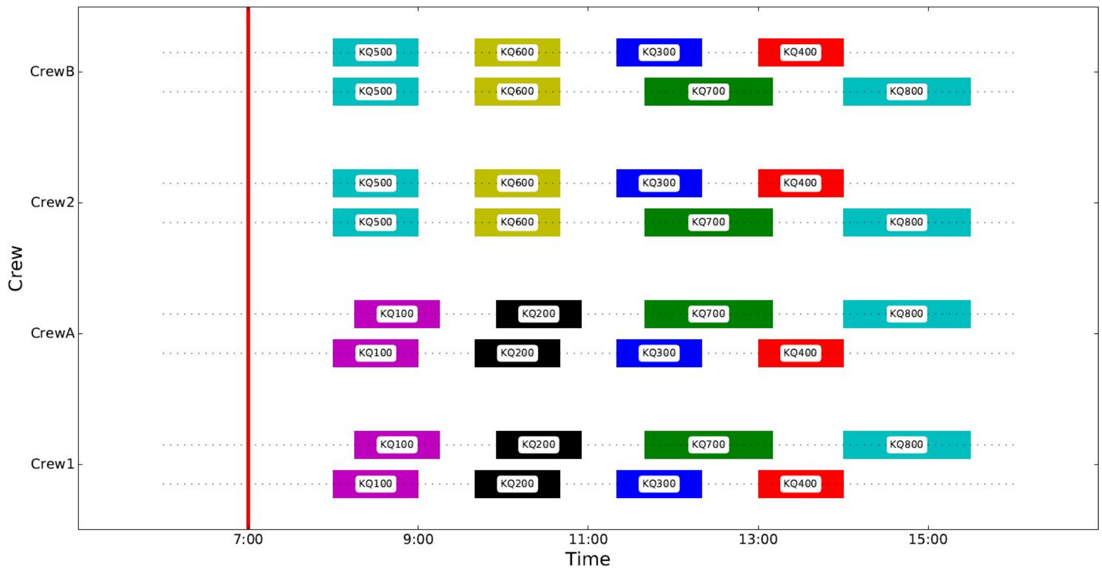


Figure 5.10: A delay of 15 minutes of KQ100 results in the same delay for KQ200. KQ300 and KQ400 are swapped with KQ700 and KQ800.

5.6. Dynamic situation

An important part of the model is the dynamic approach and therefore a dynamic test is performed as well. The same network is used as in Section 5.5 with four crew members. However, this test case considers two disruptions. The first input disruption is the same as in Section 5.5, a delay of 15 minutes for flight KQ100 known at 7:00am. The second input disruption is a delay of 15 minutes for flight KQ300 known at 10:00am.

The recovery solution after the first disruption is equal to the solution presented in Section 5.5. The moment the second disruption is notified, Crew1 and CrewA are operating flight KQ200 and Crew2 and CrewB are operating flight KQ600. Therefore, it is still possible to swap the remaining two flights of both duties, since the transition time between flight KQ200 and flight KQ300 has become valid. The model strives to return to the original schedule and therefore the recovery action after the first disruption is revised. The solution of this dynamic example is illustrated in Figure 5.11.

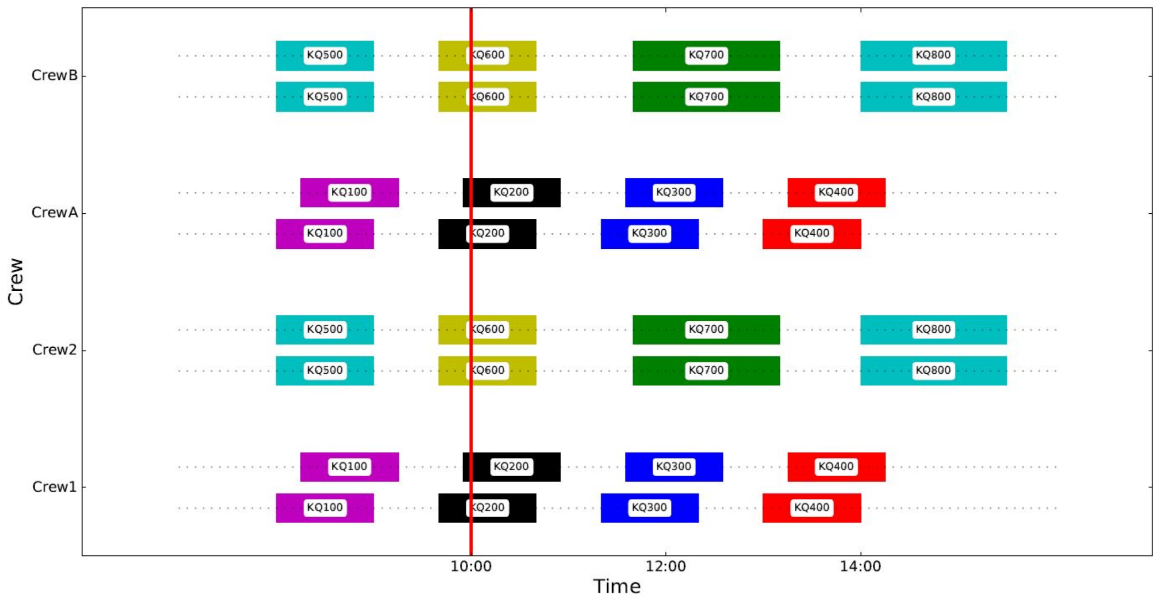


Figure 5.11: The recovery action after the first disruption is revised after notification of the second disruption.

5.7. Conclusion of the verification

In this chapter the verification of the model is done by testing several small test cases, including cancellations, delays, swapping flights and using standby crew members. At the end, the dynamic approach is tested as well which is the most important part of the model. The model revised previous recovery actions, since better recovery solutions were available after another disruption arises. Still, the model should define if previous recovery actions can be revised or not. This concludes that the dynamic approach is working correctly. After the verification tests it can be concluded that the model is working correctly. It provided the same solutions as expected and therefore it confirms that the model can be used for the scope that has been defined for this research project.

6

Case Study Kenya Airways

This chapter describes the case study of KQ with their regulations and input values to the model. The input values are used for the KQ Test Case described in Chapter 7.

In Section 6.1, general information about KQ is given after which information about the crew scheduling department is given in Section 6.2. Thereafter, in Section 6.3 the crew regulations of KQ are described with the duty hours, flight times, rest times and some additional regulations. Finally, in Section 6.4 the determination of the costs are described.

6.1. General information

Kenya Airways is one of the largest airlines in Africa and the flag carrier of Kenya. It was founded in 1977 and is a member of Skyteam, since 2010. KQ flies to destinations in Africa, Asia, Middle-East and Europe. It uses Jomo Kenyatta International Airport (JKIA) Nairobi as a Hub for their operations. In addition, it is the home base where most offices are located as well. Table 6.1 presents some general information about KQ and Table 6.2 presents the fleet composition of KQ.

Headquarter	Nairobi
Employees	3,349
Pilots	489
Fleet size	43
Destinations	53
Passengers	4,230,137
Nett income	-KShs 26,225 million

Figure 6.1: General information Kenya Airways *(Kenya Airways I. R., 2016)*

Aircraft type	Number in service
Boeing 787-800	9
Boeing 777-300	3
Boeing 737-800	8
Boeing 737-700	2
Boeing 737-300	2
Embraer 190	15
Boeing 737-300 Freighter	2
Bombardier Dash 8-400	2

Figure 6.2: Fleet composition of Kenya Airways *(Kenya Airways I. R., 2016)*

6.2. Crew Scheduling department

The Crew Scheduling department of KQ can be found at OCC which is located at JKIA Nairobi. The Crew Scheduling department is divided in Crew planning and Crew tracking.

Crew Planning is a section of Crew Scheduling where crew schedules for a period of 28 days are developed. Around eight persons develop the schedules, each for a specific aircraft type.

Crew tracking is located at the Operational Center room at OCC from where the entire operation is tracked. The crew trackers monitor the crew schedule at the day of operation. In case of disruptions crew trackers recover the schedule. Therefore, crew trackers are 24/7 present at OCC to monitor the operation. At the handover (start of duty crew tracker, end of duty previous crew tracker) a list of uncovered flights is printed for the next crew tracker together with important information about the operation. Every duty shift has at least two trackers present at OCC. One crew tracker monitors cockpit crew and one monitors cabin crew.

The Crew Scheduling department is responsible for the crew schedules and monitors it during the operation. With all the regulations involved and the low number of crew members available it is a complicated task which ensures daily challenges for the Crew Scheduling department.

6.3. Crew Regulations

Crew regulations make the recovery process very complex. As described in Chapter 2, there are many crew regulations an airline has to adhere to. In Appendix A, crew regulations of EASA and FAA are described. However, KQ has their own regulations which are described in this section.

Duty period and Block hours

The duty period is an important parameter for KQ. Every day, the duty times in 28 days are checked of crew members that are close to the maximum allowed duty time in 28 days. The block hours in 28 days are checked as well. Crew members that are close to the maximum hours can be removed from their original duty to prevent any problems in case of disruptions. The maximum duty hours and block hours are presented in Table 6.1.

Table 6.1: Maximum duty hours and block hours for KQ crew members *(Kenya Airways Limited and Kenya Airline Pilots Association, 2011)*.

Duty period		Total flight time	
Consecutive	**Maximum hours**	**Consecutive**	**Maximum hours**
28 days	160	28 days	105
-	-	12 months	850

Flight Duty Period (FDP)

The FDP is the time a crew member is on duty for operating flights. Based on the number of flight legs in the duty and the start time of the duty, crew members may operate a maximum number of hours (hrs). In special cases, it is allowed to exceed these FDPs. However in that case, strict regulations have to be complied. In this research project is chosen not to exceed the FDPs and therefore exceptions are not considered. The allowed FDP in the KQ case is presented in Table 6.2.

Table 6.2: Maximum FDP hours based on start time and number of flight legs in duty *(Kenya Airways Limited and Kenya Airline Pilots Association, 2011)*.

Scheduled time	Number of flight legs			
of start	**1**	**2**	**3**	**4**
0:00 - 05:59	12 hrs	12 hrs	11.5 hrs	11 hrs
06:00 - 15:59	12 hrs	12 hrs	12 hrs	11.5 hrs
16:00 - 23:59	12 hrs	12 hrs	11.5 hrs	11 hrs

Crew members have to report a certain amount of minutes before STD of the first duty flight (reporting time). The moment the crew member reports for duty, the duty time starts. The duty time ends the moment the crew member signs out. This is a certain amount of minutes after STA of the last duty flight (signing out time). The reporting time and the signing out time for cockpit crew members in the KQ case are:

reporting time = 75 minutes
signing out time = 30 minutes

Rest time

The last important regulation described in this section is the rest time of the crew members. It depends on the duty time what the minimum rest time of the crew members will be after their duty. Crew members are not allowed to operate a duty when there minimum rest time is not complied. An overview of the minimum rest times of KQ is presented in Table 6.3.

Table 6.3: Minimum rest times of crew members after duty based on the duty hours *(Kenya Airways Limited and Kenya Airline Pilots Association, 2011)*.

Duty time (hours)	**Minimum rest time before next duty (hours)**
Not exceeding 10 hours	11
Exceeding 10 - Not exceeding 11	12
Exceeding 11 - Not exceeding 12	13
Exceeding 12 - Not exceeding 13	14

Standby duty

A standby duty is scheduled as a period of 24 hours starting at 5:00am to 5:00am the next day. In case standby crew is assigned to a flight, the standby duty has finished and the duty hours are determined till STD of the first duty flight. Four hours of standby duty is equal to one duty hour. This implies that when a standby duty has finished after 24 hours, the crew member worked for six hours.

The rest time for standby crew members after their standby period is set to six hours. In case their standby duty is interrupted, the rest time is based on the total operated duty hours in which the standby hours are considered as well.

Additional regulations and settings

An important regulation is the definition of a *day-off*. A day-off is scheduled as a period of 24 hours rest starting at noon. When the period is less than 24 hours, it is stated as rest time and not as a day-off.

Crew members can call in *sick*. Therefore, a crew member that calls in sick is planned for five days off. All duties within those five days are removed from the schedule. When the crew member calls in fit, they are used as standby crew or to operate uncovered flights. In the model, the specific crew member is planned sick for the next three days of operation if it operates the aircraft type 737 or 787. The specific crew member is planned sick for one day when it operates the aircraft type E90.

The t*ransition time* of crew members is the minimum time needed after STA to depart gain. The minimum transition time between flights for crew members is set to 40 minutes. In this research project no difference is defined in aircraft type.

The *night limit* is set to midnight in the KQ case. This implies that arrivals after midnight will result in a day-off after the arrival.

In the pairing algorithm, an additional option is implemented to only generate new duties for day 1 for the Embraer fleet. This option is implemented in the model, since it decreases the computation time to a great extend. Besides, the Embraer fleet does not have layovers at outstations in general in the KQ case. This is also the reason why an E90 crew member is planned sick for one day in case of sickness.

6.4. Costs

The costs are an important part in developing an optimization problem. It depends on the determination of the costs how the model will solve the problem. Changing the costs may have an impact on the results of the model. In Chapter 4 some cost parameters are already mentioned. In this section these cost parameters are described in more detail.

6.4.1. Pairing Costs

The model generates new pairings for every selected crew member. Every pairing is a decision variable and the cost of a pairing is a combination of the crew costs and delay costs. Equation 6.1 represents the determination of the pairing costs.

$$\text{Pairing cost} = \text{Crew member cost} + \text{Delay costs} \tag{6.1}$$

Crew costs

The first cost element in the pairing cost are the crew costs. This cost element considers the salary of the crew member and layover allowance in case of a layover at an outstation. The crew costs are determined as described in Equation 6.2.

$$\text{Crew cost} = (\text{Duty hours} \cdot \text{Salary crew member}) + \text{Layover costs} \tag{6.2}$$

The total duty hours in a pairing are defined and multiplied with the salary per hour of the crew member. In this research project an average salary is determined per aircraft type per function. A table of the average salaries and the determination of the values can be found in Appendix C.

In case of a layover at an outstation, additional costs are involved. Crew members receive an allowance per layover. KQ has a standard layover allowance which is independent of the layover station. These are stated in Table 6.4.

Table 6.4: Layover allowance per crew member of KQ *(Kenya Airways Limited and Kenya Airline Pilots Association, 2011)*.

The layover allowances exclude accommodation costs. KQ provides first class accommodation to crew at outstations based on bed and breakfast *(Kenya Airways Limited and Kenya Airline Pilots Association, 2011)*. These costs are not available to the author of this research project and therefore only the layover allowances are considered.

Delay costs

The second cost element of the pairing costs are the delay costs. In this research project, the same delay cost structure is used as described in the report of *Vos (2015)*. For more detailed information of the determination of the delay cost factors used in this research project, the reader is referred to *Vos (2015)* and *Cook et al. (2012)*.

Since aircraft and passenger recovery are not considered, it is assumed that a small delay will not influence aircraft schedules and passengers itineraries. Therefore, the maximum allowed delay time is set to 45 minutes. However, the maximum allowed delay time is an input value to the model and can be set to the needs of the user. Additional costs are considered when flights are delayed. The delay costs consist of hard costs and soft costs.

Hard costs are the actual costs in case of a delay, e.g. extra fuel costs, passengers compensation and additional crew costs. In this research project, extra fuel costs are not considered, since delays do not result in extra flight time. Passengers compensation can be in the form of vouchers, accommodation at a hotel or access to lounges. Based on the passengers compensation in the research of *Vos (2015)*, these costs can be neglected in this research project. The additional crew costs are covered in the pairing costs, since the duty hours increase in case of delay. Therefore, it can be assumed that there is no need to implement hard delay costs in the model.

Soft costs are stated as the dissatisfaction of passengers due to delay. A research done by *Cook et al. (2012)* defined the dissatisfaction costs per passenger per delay minute. The costs are defined

Table 6.5: Delay factors used in the model that are determined in the research of *Vos (2015)*.

Delay	**0-5**	**6-10**	**11-15**	**16-20**	**21-25**	**26-30**	**31-35**	**36-40**	**41-45**	**46-50**
Delay cost	\$0.23	\$0.45	\$1.49	\$1.99	\$4.28	\$5.13	\$9.10	\$10.40	\$16.29	\$18.10
Delay	**51-55**	**56-60**	**61-65**	**66-70**	**71-75**	**76-80**	**81-85**	**86-90**	**90+**	
Delay cost	\$34.83	\$38.00	\$46.34	\$49.90	\$59.06	\$63.00	\$72.82	\$77.10	\$87.31	

for different time-bands. *Vos (2015)* distributed the cost function in smaller time-bands. Table 6.5 represents the costs per delay minute per time-band ($delay_{fac}$) used in this research project.

The delay costs are determined per flight. All delay costs of the flights in the pairing summed together are the total delay costs of the pairing. Business passengers are multiplied with a factor β, since these disruption costs are higher than for economy passengers. This factor is an input value of the user and is stated as the number of economy passengers equal to one business passenger. In the KQ case $\beta = 3$, which indicates that one business passenger is equal to three economy passengers. Equation 6.3 represents the determination of the delay costs per flight.

$$\text{Delay cost per flight} = delay_{fac} \cdot (\text{paxJ} \cdot \beta + \text{paxM}) \tag{6.3}$$

6.4.2. Cancellation costs

In some cases it is more beneficial to cancel one flight than to delay a few flights. The cancellation costs are determined per flight, based on the number of passengers on the flight. The same as in the determination of the delay costs, business passengers are multiplied with β.

Per flight is verified if there is an equal flight with available seats at the same day . When this is the case, the number of available seat per class is defined. The number of passengers that can be rebooked on another flight are multiplied with the delay factor $delay_{fac}$ determined in Paragraph 6.4.1. Equation 6.4 represents the determination of these costs.

$$Delay_{canx} = delay_{fac} \cdot (paxJ_{rebooked} \cdot \beta + paxM_{rebooked}) \tag{6.4}$$

The number of passengers that cannot be rebooked on other flights are assumed as cancelled passengers and therefore multiplied with the cancellation factor ($canx_{fac}$). This is the highest delay factor (10 hours delay) determined in Paragraph 6.4.1. In addition, per aircraft type a ticket refund is determined that every passenger receives in case of a cancellation. Actually, the ticket refund is based on the distance as well. However, in this research project only a difference in aircraft type is defined. The values are stated in Table 6.6 for the KQ case.

Table 6.6: Ticket refund and basic salary cockpit crew per aircraft type in case of a cancellation (KQ case).

Aircraft type	**Ticket refund**
787	\$400
737	\$300
E90	\$200

Equation 6.5 represents the determination of the passengers whom cannot be rebooked.

$$Canx_{canx} = (canx_{fac} + \text{ticket refund}) \cdot (paxJ_{canx} \cdot \beta + paxM_{canx}) \tag{6.5}$$

In a recovery process it is important to solve the problems for today. Problems for tomorrow are less important, since these can be recovered at another point in time. Therefore, the cancellation costs per flight are multiplied with a day factor ($canx_{day}$) in order that the model will prefer to cancel flights at day 2 or 3. These day factors are only used for the cancellation costs. Table 6.7 illustrates the factors for the KQ case.

Table 6.7: Cancellation factors per day in the KQ case

Day factors	
Day 1	1.0
Day 2	0.75
Day 3	0.5

The costs of the cancellation of flights are used in the objective function, however before a flight is stated as cancelled the model verifies if the flight can be left uncovered. The flight can be considered at a later stage where the cancellation of a flight cannot be revised. The mathematical formulation of the total cancellation costs per flight is stated in Equation 6.6.

$$c_{c_i} = canx_{day} \cdot (Canx_{canx} + Delay_{canx} + \text{basic salary} \cdot \text{flight time i}) \qquad \forall i \in F \tag{6.6}$$

An additional cost is added to the cancellation costs per flight to define a difference in short haul flights and long haul flights. When flights have to be cancelled, an airline will first choose to cancel short flights. The basic salary multiplied with the flight time is added to the total costs to define the differences in flights. The basic salaries per aircraft type are the average salaries of a CP and a FO together. The average salaries can be found in Appendix C.

7

Validation and Results

In this chapter the validation of the model is described. Test cases are performed and the results are analysed with experts from KQ to validate the model. First, in Section 7.1 an explanation is given about adaptations made to the KQ schedule before it is implemented in the model. Thereafter, in Section 7.2 the initial test run is described. Subsequently, in Section 7.3 test cases are described together with the solutions provided by the model. The results of the test cases are analysed with experts from KQ and therefore face-validation is used. Finally, in Section 7.4 a conclusion is defined about the validation of the model.

7.1. Original schedule adaptations

A pre-processing algorithm is used to combine the flight schedule, crew schedule and booking numbers into one schedule. However, the algorithm is not able to combine the right passenger numbers with night flights. Therefore, warnings are given to the user to manually adapt the numbers of the specific flights. Adaptations made to the schedule by the model itself are described in this section.

The model uses a time horizon of three days. Some flights are scheduled every day with the same flight code. A capital letter is added to the flight codes to make a difference between those flights. 'A' is for day 1, 'B' is for day 2 and 'C' is for day 3.

Triangle flights have the same flight codes and therefore a difference is made between these flights as well. A small letter is added to the flight codes to distinguish flights at the same day. Table 7.1 represents an example of adapted flight codes.

Table 7.1: Adaptations made to the schedule before it is used in the model.

Date	Flight code	Flight code (Adapted)	Arrival	Destination	STD (hours)	STA (hours)	STD adapted (hours)	STA adapted (hours)
29-1-2017	252	252Aa	NBO	DAZ	08:10	10:40	08:10	10:40
29-1-2017	252	252Ab	DAZ	HAH	11:25	12:10	11:25	12:10
29-1-2017	252	252Ac	HAH	NBO	12:55	15:05	12:55	15:05
29-1-2017	612	612A	NBO	MBA	08:25	09:25	08:25	09:25
30-1-2017	612	612B	NBO	MBA	08:25	09:25	32:25	33:25
31-1-2017	612	612C	NBO	MBA	08:25	09:25	56:25	57:25

The model is not able to define different days. Therefore, adaptations are applied to the times used in the schedule. The start date is an input value and for every upcoming day, 24 hours are added to the times. In addition, the model works with minutes instead of hours. Moreover, a time step of 5 minutes is used in the model. The model rounds up times to the nearest 5 minutes. An example of the dates converted in times is represented in Table 7.1 as well.

Regarding the flight schedule of KQ, time zones have to be considered. UTC times are used in the model to eliminate time zones. However, for outstations with a time difference, the model considers the regulations based on the local time at Nairobi (UTC+3hours). All times mentioned in the model and in this chapter are UTC times.

The adaptations described are processed by the model before the problem is solved.

7.2. Initial run

An initial run is done before the start of the test cases. This is necessary to compare results, since the model applies changes to the original schedule even when there are no disruptions. This implies that the model optimizes the original schedule and better solutions are found. Therefore, it is of great importance to eliminate initial changes made by the model. For this case study, the initial run is only performed for the considered day of operation, since simulating the three days of operation with all crew members is time consuming.

A test case is built for the initial run. A delay disruption is used as input in which one of the flights has a delay of 0 minutes. When there is no input disruption given to the model it stops running, since there are no disruptions to solve. The input time is at the start of the day. For every aircraft type a delay disruption of 0 minutes is applied to consider all aircraft types and therefore the entire schedule. In addition, the model uses all crew members in the selection algorithm and uncovered flights are considered as well.

The solutions provided by the model are compared with the original schedule. Both schedules are compared based on the delay and cancellation costs, number of cancelled flights and number of crew members on duty. The costs are determined as described in Chapter 6 and illustrated in Table 7.2.

Table 7.2: An overview of the differences between the start case and the solutions of the initial run.

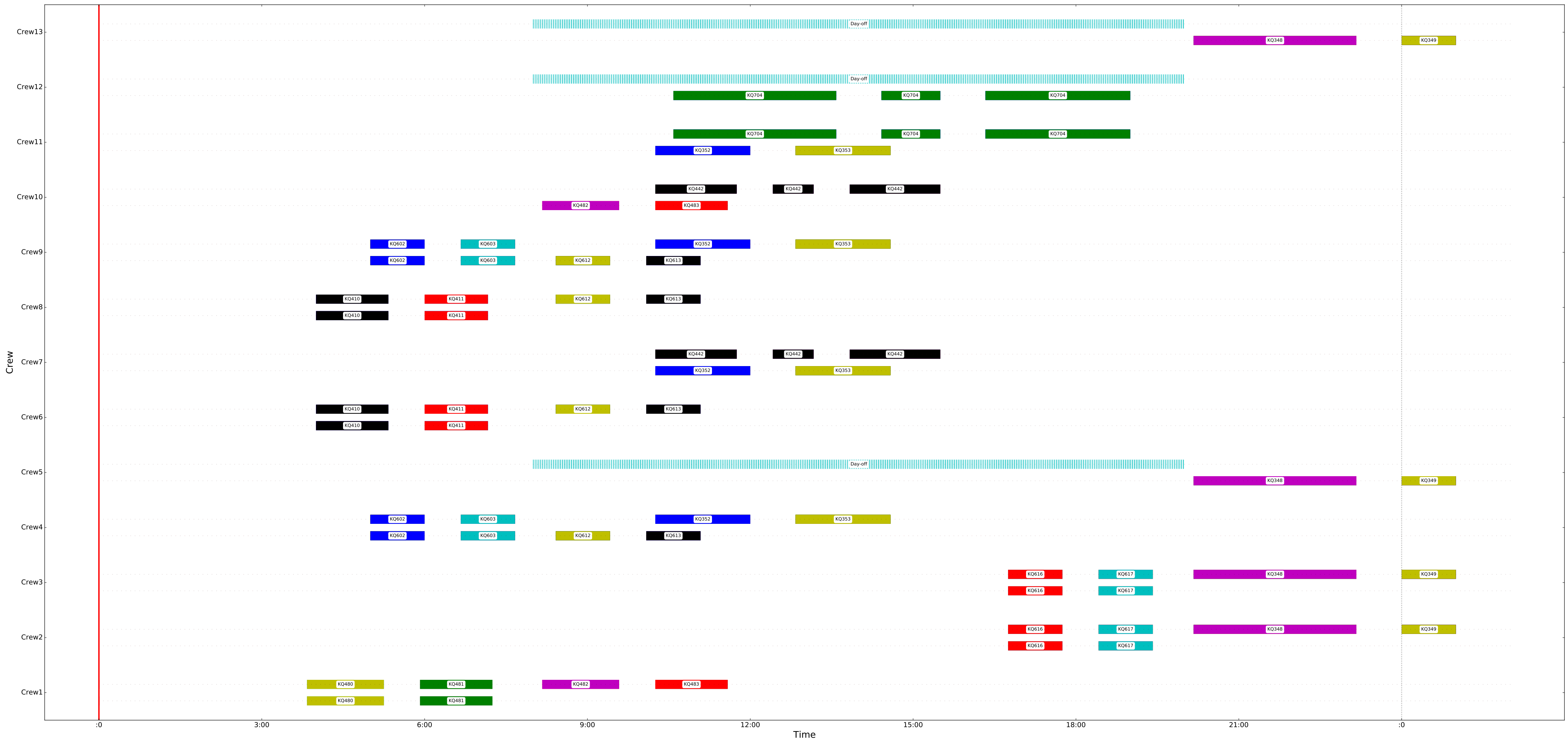
	Original Schedule (old)	Original Schedule (new)
Uncovered flights	3	0
Crew on duty	117	114
Cancellation cost	$67,448	$0
Delay cost	$0	$244
Additional duty cost	$0	$385
Total cost	$67,448	$629

The new schedule covers the three uncovered flights in the old situation. However, the three uncovered flights are delayed with 25 minutes and some flights are swapped between crew members. Still, the delay costs are lower than the cancellation costs of the three flights. Some additional swaps are applied which resulted in three crew members with a day-off instead of a duty. However, it resulted in longer duties for eight other crew members. The time at the airport between the flights KQ603 and KQ352 is around 1.5 hours. Experts at KQ mentioned that this is not preferred, since valuable duty hours are spilled. Spilling duty hours may cause problems in future regarding the maximum duty hours in 28 days. Figure 7.1 illustrates the optimized schedule in which only the changed pairings are shown.

The reason the schedule can still be optimized may have different reasons. Passenger itineraries as well as aircraft schedules are not considered. In addition, human factors cannot be modelled and therefore the model is a simplified version of reality. However, the initial run can be used as reference to optimize the schedule at the start of the day or even the day before.

Based on the costs, it can be concluded that the initial run optimizes the model, since it provides lower costs than the original schedule. In this example, the costs can be reduced with around $60,000 based on the cost determination used in the model. The results of the initial run are set as the new original schedule in order that the model only applies changes in case of a disruption. The computation time of the initial run takes around 2 to 3 minutes.

Figure 7.1: Schedule after the initial run.



7.3. Test cases

In this section, the test cases with the results are described. Four different full day cases are tested, every case with a different set of disruptions and input times. However, for every case the maximum number of selected crew members is set to eight. The selection option is based on the reporting times of crew members. These settings are the preference from KQ. Since there are six different input times for every day scenario the model performs six iterations. The names of all crew members are changed by a number due to privacy reasons. Finally, the four cases are tested in with a dynamic and non-dynamic approach to define the differences between both approaches.

7.3.1. Day scenario 1

The start case for this day scenario is described in Section 7.2 and includes 114 crew members on duty at the considered day of operation. There is no standby crew available and there are five uncovered flights at day 3 in the original schedule. The first test case considers the next set of disruptions as input:

- Flight KQ605 cancelled at 04:00am
- Crew1 (CP E90) called in sick at 05:00.
- Flight KQ412 delayed with 15 minutes at 07:00.
- Aircraft change for KQ762 and KQ763 to E90 at 09:00.
- Flight KQ414 cancelled at 12:00.
- Flight KQ330 delayed with 10 minutes at 16:00.

Table 7.3 illustrates the solutions obtained by the model per iteration.

Table 7.3: Recovery solutions per iteration of Day scenario 1.

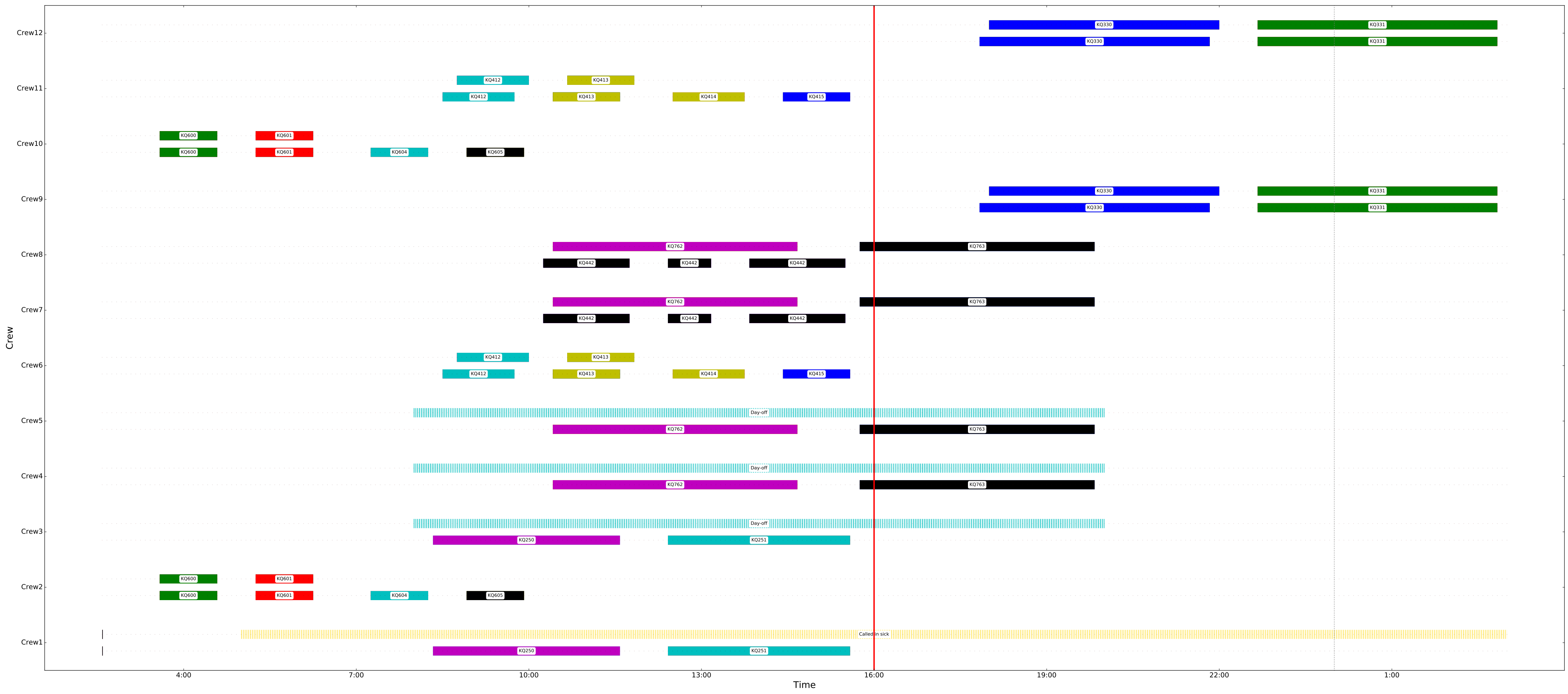
Iteration	Total cost	Iteration time	Number of canx/unc	Number of delays	Number of changed pairings	Crew on duty
1	$339,834	0:00:07.626	1/6	0	2	114
2	$475,843	0:00:04.125	2/7	0	4	112
3	$476,301	0:00:05.730	3/6	2	6	112
4	$543,210	0:00:04.096	4/8	2	10	110
5	$707,327	0:00:03.548	9/5	2	10	110
6	$707,347	0:00:03.888	9/5	3	12	110

In the first iteration, a flight is cancelled (canx) and therefore an upcoming flight has to be cancelled as well. However, the model considers this flight as uncovered (unc) since STD is in the near future. The second input disruption is a sick crew member. The original flights from this crew member become uncovered. As a result of the input time, the flight that was left uncovered because of the previous disruption is cancelled instead of uncovered. In the third iteration, a flight is delayed and therefore the upcoming flight is delayed as well. At the same time, an uncovered flight is cancelled since STD of that flight has passed. The fourth iteration, considers an aircraft change. Two crew members have a day-off instead of a duty due to the disruption. Both flights are operated by the crew members who had to operate flights KQ442a, KQ442b and KQ442c. These triangle flights are cancelled/uncovered in the recovered situation. In the fifth iteration, two extra flights are cancelled and in the last iteration no other flights are affected by the input delay.

The final objective function of this full day scenario is $707,347. In total, three flights are delayed with a maximum of 15 minutes, five flights are uncovered (all at day 3) which are the same as in the original situation and nine flights had to be cancelled at the day of operation. The total computation time of the model is around 30 seconds for this full day scenario.

The recovered schedule after the last iteration is illustrated in Figure 7.2. Only the crew pairings which are changed regarding the original pairings are illustrated. In addition, only the first day is illustrated since only changes are applied to the pairings at the first day.

Figure 7.2: Recovered schedule of Day scenario 1.



7.3.2. Day scenario 2

The start case for this day scenario is the same as described in Section 7.3.1 and Section 7.2. The start case includes 114 crew members on duty at the considered day of operation. One set (CP and FO) are standby for the aircraft type 788 and one set is standby for the aircraft type E90. There are five uncovered flights at day 3 in the original schedule. The second test case considers the next set of disruptions as input:

- Aircraft change for KQ554 and KQ555 to E90 at 05:00
- Flight KQ605 cancelled at 07:00.
- Crew19 (CP 737) called in sick at 12:00.
- Crew15 (CP 788) called in sick at 13:30
- Crew18 (CP E90) called in sick at 15:00
- Flight KQ488 delayed with 20 minutes at 19:00

Table 7.4 illustrates the solutions obtained by the model per iteration.

Table 7.4: Recovery solutions per iteration of Day scenario 2.

Iteration	Total cost	Iteration time	Number of canx/unc	Number of delays	Number of changed pairings	Crew on duty
1	\$273,964	0:00:06.308	0/5	0	4	114
2	\$336,082	0:00:05.922	2/5	0	9	114
3	\$633,035	0:00:03.537	4/8	0	13	114
4	\$633,308	0:00:04.108	4/8	0	14	113
5	\$805,133	0:00:03.084	4/11	0	15	111
6	\$805,331	0:00:03.603	5/10	1	17	111

The reader is referred to Appendix E for more detailed information about the results of day scenario 2.

7.3.3. Day scenario 3

The start case for this day scenario is described in Section 7.2 and includes 114 crew members on duty at the considered day of operation. There is no standby crew available and there are five uncovered flights at day 3 in the original schedule. The third test case of an entire day of operation considers the next set of disruptions as input:

- Aircraft change for KQ706a, KQ706b and KQ706c to E90 at 03:00
- Kisumu airport unavailable from 7:20 till 8:20 at 06:00.
- Crew10 (FO E90) called in sick at 09:00.
- Flight KQ616 delayed with 30 minutes at 16:00
- Flight KQ348 cancelled at 19:00
- Flight KQ492 delayed with 25 minutes at 20:30

Table 7.5 illustrates the solutions obtained by the model per iteration.

Table 7.5: Recovery solutions per iteration of Day scenario 3.

Iteration	Total cost	Iteration time	Number of canx/unc	Number of delays	Number of changed pairings	Crew on duty
1	\$296,380	0:00:10.642	2/7	1	7	112
2	\$296,698	0:00:05.379	4/5	2	9	112
3	\$363,803	0:00:04.150	6/6	4	13	110
4	\$365,445	0:00:04.241	7/5	8	15	110
5	\$507,741	0:00:03.680	9/5	6	15	110
6	\$508,151	0:00:03.784	9/5	7	17	110

The reader is referred to Appendix E for more detailed information about the results of day scenario 3.

7.3.4. Day scenario 4

A different data set is used for day scenario 4. A new initial run has to be performed to eliminate the changes applied by the model to the original schedule. The initial test case is described in more detail in Appendix E. The start case for this day scenario includes 112 crew members on duty at the considered day of operation. There is no standby crew available and there are 49 uncovered flights in the original schedule from which 10 at the first day of operation. The last test case of an entire day of operation considers the next set of disruptions as input:

- Aircraft change for KQ550a, KQ550b and KQ550c to E90 at 03:00
- Flight KQ411 delayed with 30 minutes at 5:00
- Crew3 (CP E90) called in sick at 8:00
- Flight KQ670 delayed with 20 minutes at 13:00
- Flight KQ204 cancelled at 15:00
- Flight KQ492b delayed with 20 minutes at 22:00

Table 7.6 illustrates the solutions obtained by the model per iteration.

Table 7.6: Recovery solutions per iteration of Day scenario 4.

Iteration	Total cost	Iteration time	Number of canx/unc	Number of delays	Number of changed pairings	Crew on duty
1	\$3,262,191	0:00:21.232	3/41	0	4	112
2	\$3,251,459	0:00:04.438	3/41	5	8	112
3	\$3,501,267	0:00:10.582	4/43	5	12	110
4	\$3,501,855	0:00:04.275	5/42	7	14	110
5	\$3,691,803	0:00:04.528	6/42	8	18	108
6	\$3,692,028	0:00:03.717	9/39	10	20	108

The reader is referred to Appendix E for more detailed information about the results of day scenario 4.

7.3.5. Dynamic versus Non-dynamic

The difference between the dynamic and the non-dynamic approach are the input times of the disruptions. In the dynamic case the input times are spread over the day and based on the time the operation controller becomes aware of the disruption. In the non-dynamic case, the input times are all the same, namely at the start of the day.

In Table 7.7 the differences are presented between the dynamic and non-dynamic approach. The test cases from previous paragraphs are used and the value for selected crew members is set to eight.

Table 7.7: Results dynamic versus non-dynamic approach considering a selection of eight crew members.
*Flights that are uncovered at the first day are considered as cancelled.

Day scenario	Approach	Computation time	Recovery costs	Canx/Unc	Delays	Changed pairings	Crew on duty
1	Dynamic	0:00:29.602	$707,347	9/5	3	12	110
	Non-dynamic	0:00:05.543	$848,494	8*/5	2	11	110
2	Dynamic	0:00:27.180	$805,331	10/5	1	17	111
	Non-dynamic	0:00:06.274	$706,792	5*/8	1	13	110
3	Dynamic	0:00:34.500	$508,151	9/5	7	17	110
	Non-dynamic	0:00:06.904	$526,180	9*/5	6	13	110
4	Dynamic	0:00:49.366	$3,692,028	9/39	10	20	108
	Non-dynamic	0:00:27.302	$3,500,423	8*/39	17	26	109

In general, the non-dynamic case solves the problem with less cancellations, delays and pairing changes. Only for day scenario 4 this is not the case. Day scenario 4 has many uncovered flights and therefore the non-dynamic case can make a better trade-off in which flights to cancel and which one to delay. Therefore, other flights are cancelled which have lower cancellation costs. However, this is accompanied with more small delays of other flights. This declares the difference in numbers for day scenario 4.

The non-dynamic approach needs only one iteration due to the same input time which results in lower computation times. In day scenario 1 and 3, the dynamic approach generates lower costs than the non-dynamic approach. Due to the selection of crew members the best candidates for the disruptions in the afternoon are not considered in the non-dynamic approach. Therefore, the costs of the non-dynamic approach may be higher in some cases.

The results presented in Table 7.7 are obtained by using a selection of eight crew members. The computation times are low and therefore the same tests are done by considering all crew members. The results are presented in Table 7.8.

Table 7.8: Results dynamic versus non-dynamic approach considering all crew members.
*Flights that are uncovered at the first day are considered as cancelled.

Day scenario	Approach	Computation time	Recovery costs	Canx/Unc	Delays	Changed pairings	Crew on duty
1	Dynamic	0:02:05.197	$605,446	8/5	9	24	110
	Non-dynamic	0:00:37.976	$563,260	8*/5	9	26	111
2	Dynamic	0:01:30.639	$667,356	6/8	1	22	111
	Non-dynamic	0:00:37.415	$534,093	2*/8	10	26	114
3	Dynamic	0:02:19.185	$476,381	6/5	8	22	111
	Non-dynamic	0:01:23.574	$461,334	6*/5	8	23	110
4	Dynamic	0:02:52.070	$3,445,345	6/39	13	27	109
	Non-dynamic	0:02:05.461	$3,442,205	6*/39	14	24	109

In all cases the non-dynamic approach generates lower costs than the dynamic approach. In addition, for all cases better results are obtained than with the selection of crew members. Due to the selection of all crew members, the best possible recovery solution per disruption can be applied which was not always possible with the selection of eight crew members.

In test case day scenario 2 there was standby crew available. All disruptions are considered in assigning standby crew to (disrupted) flights. The best choice can be made considering all disruptions which is not possible in the dynamic situation. This declares the difference in cancellations and the recovery costs.

In general, the non-dynamic approach anticipates on all disruptions at the same time which results in better solutions than the dynamic approach. However, considering a selection of crew members may sometimes result in better solutions using the dynamic approach. In most cases, the hypothesis stated in Chapter 3 is correct.

7.4. Conclusion of the validation

In this chapter, several test cases are performed to validate the model. The initial run already optimized the original input schedule and therefore it provided a cost reduction. The changes made by the model are not always preferred, however it provided insight in several solutions. The schedule can already be optimized before the operation starts.

Performing the test cases was an iterative process to solve issues and improve the model. Several meetings with crew planners and trackers provided insight in the quality of the solutions and it can be concluded that, regarding the scope of the project, the model is valid. The computation times were found valid which indicated that the model can be used in real-time operations. In addition, all changes applied by the model were found logical. None of the flights or crew members were swapped without any reason.

The model is able to provide solutions within a few seconds by using a smaller set of selected crew members. However, this affects the quality of the solutions and is associated with higher costs. Considering all crew members results in the best recovery solutions. It can be concluded that with a selection of crew members the non-dynamic approach does not always guarantee better recovery solutions.

8 Sensitivity analysis

This chapter describes the sensitivity analysis of the model. In the sensitivity analysis variables are given different values to analyse the robustness of the model. First in Section 8.1, the performances of the model are described in case the number of selected crew members are adapted. Thereafter, in Section 8.2 the performances are described in case a different selection option is used. In Section 8.3, the global optimums are compared with the results from the selection of crew members. Finally, in section 8.4, the conclusion about the sensitivity analysis is described.

8.1. Number of selected crew members

Different numbers of selected crew members influence the performance of the model. In this section, the differences in costs are analysed for different numbers of selected crew members.

The full day scenarios, described in Chapter 7, are tested with different numbers of selected crew members. Figure 8.1 illustrates the total costs per iteration per number of selected crew members of day scenario 1, Figure 8.2 for day scenario 2, Figure 8.3 for day scenario 3 and Figure 8.4 for day scenario 4. In some cases, lines are on top of each other since the same results are obtained.

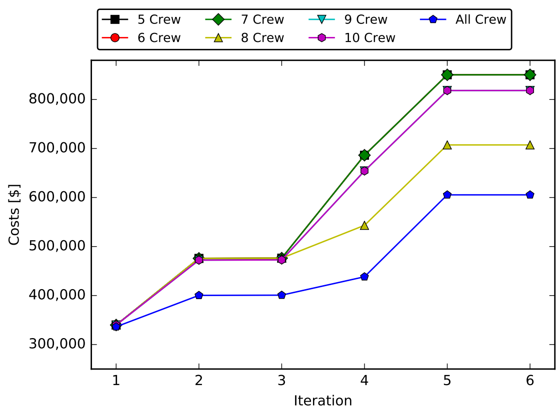


Figure 8.1: Selection crew: Total costs day scenario 1

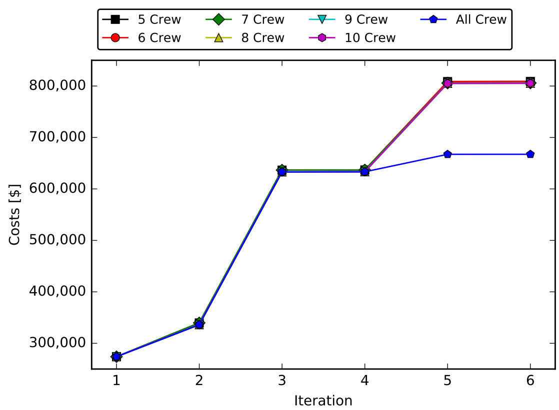


Figure 8.2: Selection crew: Total costs day scenario 2

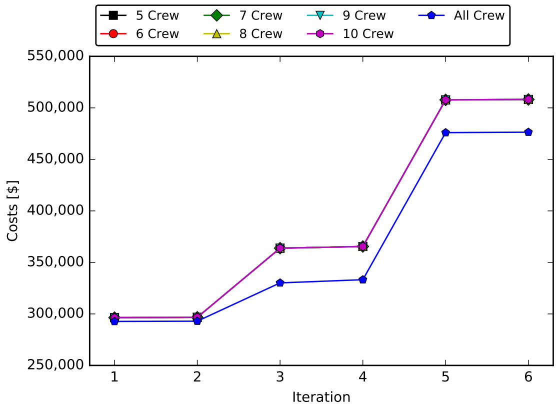


Figure 8.3: Selection crew: Total costs day scenario 3

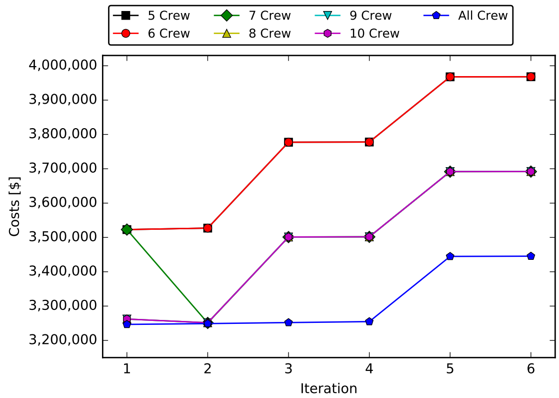


Figure 8.4: Selection crew: Total costs day scenario 4

Figure 8.1 illustrates an improvement in costs when selecting eight crew members instead of seven. However, selecting nine or ten crew members generates higher costs than eight crew members. For the second disruption (iteration), another recovery decision is made with lower costs for selecting nine and ten crew members. However, at the end this results in higher recovery costs. For day scenario 2, Figure 8.2, slightly improvements are gathered when selecting eight crew members instead of less. Day scenario 3, Figure 8.3, does not illustrate improvements when selecting more crew members except for the selection of all crew members. For day scenario 4, Figure 8.4, the results are improved when selecting seven crew members instead of less.

In all cases, selecting all crew members provides the best solutions. In case of defining a selection of crew members, it can be concluded that selecting eight crew members will provide the best solution. The differences in computation times are small and therefore it does not influence the quality of the solutions. In some cases, selecting more crew members will result in higher costs. The reason for this is that in the beginning certain decisions are taken which are the best for that moment. However, during the day these solutions were not the best to chose due to other disruptions. The decisions made in the beginning were not possible in the case of selecting eight crew members, since those crew members were not selected. That defines the differences in costs when selecting more crew members.

8.2. Selection option

The selection option is another parameter which may have an impact on the performance. The selection of crew members is of great importance to have the best set to solve the problem. Therefore, in this section different selection options are tested with eight selected crew members as input value. The costs are analysed with the different settings.

Every selection option is tested with the full day scenarios described in Chapter 7. Figure 8.5 illustrates the total costs per iteration per selection option of day scenario 1, Figure 8.6 for day scenario 2, Figure 8.7 for day scenario 3 and Figure 8.8 for day scenario 4. The same as in Section 8.1, lines are on top of each other since the same results are obtained.

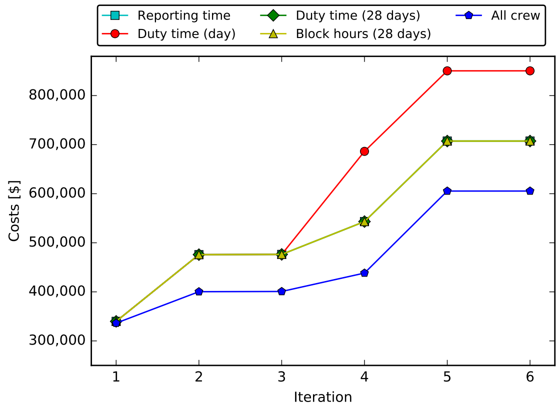


Figure 8.5: Selection option: Total costs day scenario 1

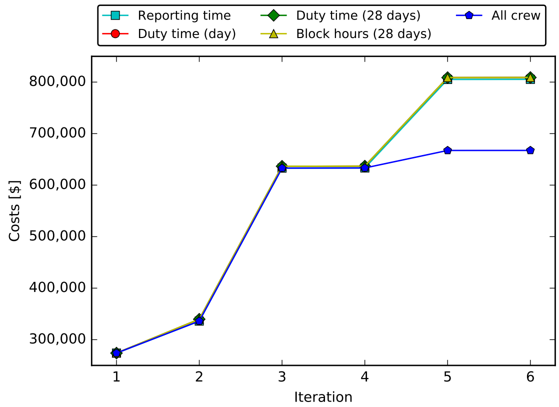


Figure 8.6: Selection option: Total costs day scenario 2

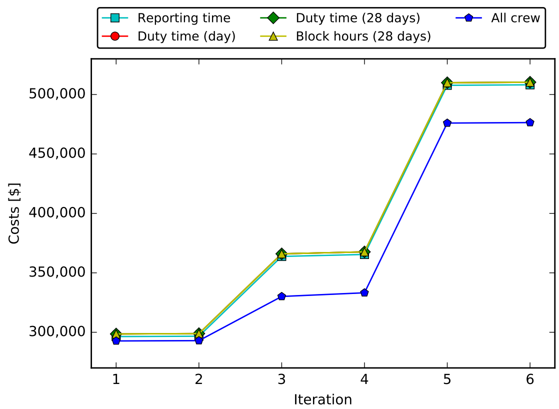


Figure 8.7: Selection option: Total costs day scenario 3

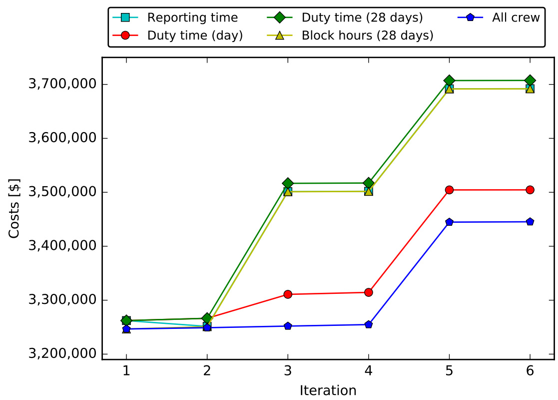


Figure 8.8: Selection option: Total costs day scenario 4

The figures illustrate that in all cases the 'reporting time' option provides the best solutions, except for day scenario 4. In that case, the 'duty time (day)' provides the best solutions. However, in day scenario 1 that option provides the highest costs. In addition, in all cases there is almost no difference between the selection option 'duty hours 28 days' and 'block hours 28 days'.

The computation times are fairly constant and small in all cases. Therefore, it does not influence the quality of the solutions and it can be concluded that in general the 'reporting time' is the best option to choose.

8.3. Global optimum versus selection

All day scenarios consider a set of input disruptions. In this section, per disruption the global optimum is defined and compared with the results obtained from the selection of crew members. The global optimum is the best solution for a certain problem. In this research project, the global optimum per disruption can be defined by selecting all crew members. Figure 8.9, illustrates the solutions per disruption of day scenario 1, Figure 8.10 for day scenario 2, Figure 8.11 for day scenario 3 and Figure 8.12 for day scenario 4.

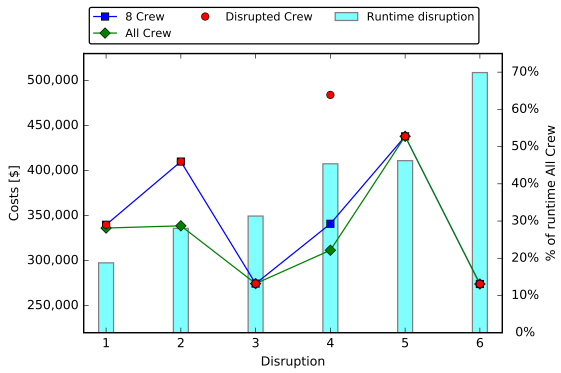


Figure 8.9: Global vs. Selection: Day scenario 1

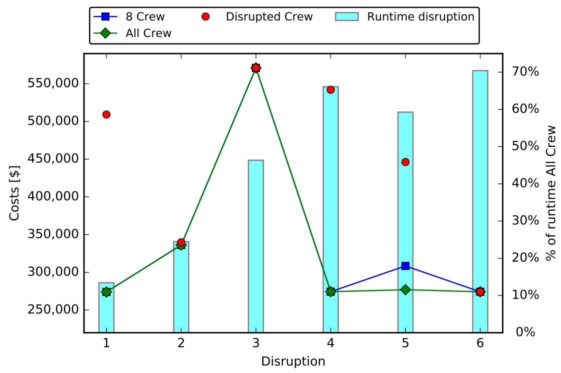


Figure 8.10: Global vs. Selection: Day scenario 2

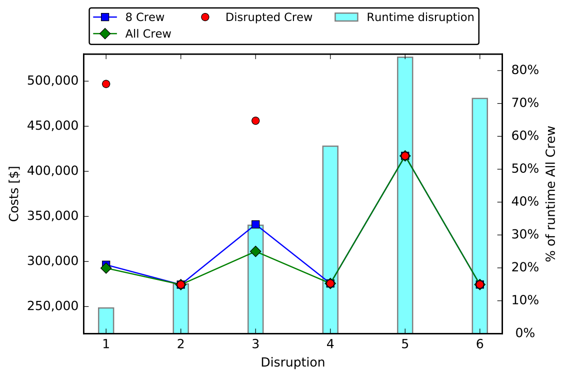


Figure 8.11: Global vs. Selection: Day scenario 3

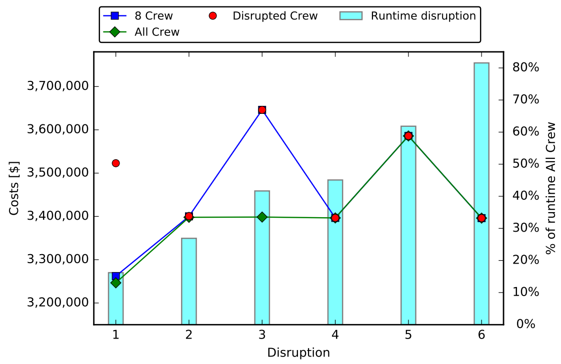


Figure 8.12: Global vs. Selection: Day scenario 4

The global optimums are indicated with the green line and the selecting of eight crew members with the blue line. The solutions of selecting only the disrupted crew members are indicated in red. The computation times of the selection of eight crew members are illustrated with the bars. The times are expressed in percentages of the computation times of selecting all crew members. The same order of disruptions is used as in the day scenarios. E.g. for day scenario 1, disruption 1 is the cancellation of flight KQ605, disruption 2 is the sickness of Crew1, etc. The higher the disruption number, the later the disruption is notified on the day.

In all cases, an improvement in computation times for the first two disruptions can be achieved. A reduction in computation times of at least 70% is obtained by using the selection of crew members instead of all crew members. However, for the second disruption at day scenario 1, the cost is 20% higher than the global optimum. The higher the disruption number and therefore the later on the day, the lower the difference is between computation times, since less recovery options are available.

For every disruption and selection, the differences in costs are compared with the global optimums. Table 8.1 presents the differences with the global optimums in percentage.

Table 8.1: The differences in percentage of to the global optimums. - In these cases there is no difference in costs. * Difference is less than 0.02%

	Day scenario 1		Day scenario 2		Day scenario 3		Day scenario 4	
Disruption	Sel Crew	Dis Crew	Sel Crew	Dis Crew	Sel Crew	Dis Crew	Sel Crew	Dis Crew
1	1	1	-*	86	1	70	1	9
2	21	21	-*	1	-	-	-*	-*
3	-	-	-	-	10	47	7	7
4	9	55	-	98	-	-	-	-
5	-	-	11	61	-	-	-	-*
6	-	-	-	-	-	-	-	-

In 55% of the cases, the selection of crew members (sel crew) obtain the same results as the global optimums. However, in 45% of the cases, the global optimum was equal to the solution of selecting only the disrupted crew members (dis crew). This implies that there were no other solutions possible. It can be concluded that in all cases the selection of crew members provides solutions that differ to a maximum of 21% with the global optimum. It depends on a great extend to the input disruption if improvements in recovery costs are possible.

8.4. Conclusion Sensitivity Analysis

Different parameters of the model were adapted to test the influence on the performance. All tests were analysed based on the costs (objective function) and the computation time of the model.

The first parameter that was analysed is the maximum number of selected crew members. The results concluded that a maximum number of eight crew members provide the best results. No improvements were obtained by selecting a larger number of crew members, except for selecting all crew members.

Different selection options are available in the model and the differences in performances were tested. The results concluded that the selection option based on the reporting time of crew members is the best option. The same as in the previous case, selecting all crew members provides the best solutions.

In general, it can be concluded that differences between parameters become visible during the second iteration. Previous recovery decisions become important from that point. In addition, the performance of the different parameters depend on a great extent of the input disruption.

Finally, the global optimum was defined for every disruption in a day scenario. The results were compared with the results obtained from the selection of crew members. In all cases the selection of crew members provided solutions that differ to a maximum of 21% with the global optimum. Over 70% reduction in computation times are achieved with the selection of crew members. This reduction is gained with disruptions that are notified at the start of the day. The percentages became lower with increasing time of notification of disruptions at the day of operation.

9

Conclusion and Recommendations

This chapter describes the conclusions about the research project and recommendations are given for future research. In Section 9.1 conclusions are drawn from the research project. The most important recommendations are described in detail in Section 9.2. These recommendations can be used in future research to improve the quality of the model. At the end, a list is provided of small limitations of the model.

9.1. Conclusions research project

The conclusions drawn from this research project are divided in several parameters. Separate conclusions are drawn about the research objective obtained from the test cases, the contribution to literature and the developed model.

9.1.1. Research objective

The research question and objective described the importance of costs and computation times of the model. These two parameters determined whether the model can be used in real-time operation by airlines. Several tests were performed to validate the model and it concluded that the model was valid within the scope of the research project. This indicates that the model is suitable to use by airlines. All test cases provided solutions within one minute. Even testing the model with the entire set of crew members provided solutions within a few minutes which was associated with the best recovery solutions.

Cost improvements were obtained by the model even before the implementation of disruptions. However, the model provided some solutions which were not always preferred by the airline. Nevertheless, a better overview of the recovery costs was gathered by using the model. Therefore, regarding the research objective it can be concluded that the model provided cost improvements in computation times that were considered useful for airlines. In addition, the selection of crew members provided solutions that differ to a maximum of 21% with the global optimum.

9.1.2. Contribution to literature

Conclusions about the contribution to literature are described per element. Respectively, dynamic recovery, individual schedules and recovery options.

Dynamic recovery

The main contribution was set as the dynamic approach of the model. This implied that the model solved the problem when the disruptions were notified. In addition, previous recovery decisions were reconsidered if possible. In literature, two types of models were described: One in which a disruption is solved at the moment of notification, however previous recovery decisions are not reconsidered. The other type is in which a set of disruptions is solved. Within this set, future disruptions were considered as well. Therefore, the dynamic approach is more realistic compared to the non-dynamic approach. However, based on the solutions of the test cases, the dynamic approach provided higher costs.

Individual schedules

In literature there was one paper present *(Q. Liu et al., 2013)* that considered individual crew members. However, costs were not taken into consideration. In the current research, costs were taken into account which resulted in an extension of previous work. Moreover, using individual crew schedules improved the recovery possibilities. In previous papers, the entire cockpit crew was changed even when there was only a problem with one of the cockpit crew members. In the current model, swaps were applied for only one of the cockpit crew members. Therefore, the remaining original crew member could still operate the flight with another crew member.

Recovery options

Several recovery options were available for operation controllers to recover schedules after disruptions. However, in literature a distinction can be made between papers that implemented the option to cancel flights and papers that implemented the option to delay flights. To the knowledge of the author of this research project, there were no papers available in which delays and cancellations are both possible in a crew recovery model. Thus, the possibility in the model to cancel and delay flights is a contribution to literature. More options were obtained by using both recovery options in the model.

9.1.3. Model

One of the goals of the project was to support the recovery process of operation controllers. The model should provide recovery solutions to operation controllers. In some cases, the optimal solution depends on human factors. Therefore, it is important to have several options available for operation controllers. The model generated multiple solutions from which operation controllers can choose.

Despite several limitations of the model, it was found useful to use in operations of KQ. Furthermore, several input options were available to model the preference of other airlines in the best possible way.

9.2. Recommendations

Crew recovery is a complex task due to all involved regulations. Therefore, in the development of the crew recovery model, several assumptions had to be made. In this section recommendations are given for future research.

Aircraft and passenger recovery

The model considered only crew schedules and therefore recovery decisions were based on crew members only. However, some crew recovery decisions may be impossible for the aircraft routing or passenger connections. Therefore, considering aircraft and passenger recovery will improve the quality of the recovery solutions of the model.

Cabin crew

The model only considered cockpit crew members and therefore decisions were based on cockpit crew. However, it may occur that decisions made for cockpit crew influence the cabin crew. Worst case scenario may be that certain decisions cause infeasibility of cabin crew schedules. Considering cabin crew in the model as well will result in a more complete solution of the entire set of crew schedules. Implementing the cabin crew in the model will be a great improvement. The reason cabin crew was not implemented in the model was because of the different involved regulations for cabin crew members.

Selection algorithm

The selection algorithm used in the model was limited to one selection. Based on the selection option, the best set of candidate crew members was chosen. An improvement for the model should be to test several selections per iteration. Currently, the best set of candidate crew members were chosen based on the selection option. However, this set did not guarantee the best solutions. Therefore, testing several selections of crew members will improve the recovery solutions.

In addition, the selection of crew members was based on one selection option which was used for every disruption. An improvement will be to select the best selection option per disruption. This will result in better solutions since the best selection and selection option can be defined per disruption.

Time period
Currently, the model considers three days of operation. The recovery decisions may have consequences for the schedule after those three days. In addition, pairings which consider more than three days of operation can be problematic for the model (infeasibility). Therefore, the time period should be extended. Considering a larger time period will make it possible to consider monthly schedules and the balancing of the schedules as well.

A drawback of the extension of the time period will be the computation time. Increasing the time period is associated with longer computation times. Therefore, improvements in computation times are necessary when the time period is increased.

Input disruptions
The set of possible input disruptions was described in Chapter 4. However, some disruptions are not possible to implement in the model. Therefore, the possible input disruptions should be extended.

Crew members coming late at the airport is one example of an additional input disruption. There may be several reasons why crew members coming late. Currently, the model has to process this disruption as crew calling sick. However, the crew member is still able to operate flights at a later point in time. Therefore, an additional input disruption can be implemented for these problems.

Another option is to extend the input disruption of diverted flights. Currently, the option for diverted flights is limited in the model. When a new flight is not added to the schedule, infeasibility will appear for the considered crew members. They will get stuck at the diverted airport from which no flights are departing.

9.3. Limitations model

Many assumptions had to be made to the model. Otherwise, it would be too complex and time consuming to come up with a recovery model. In this section limitations of the model are described.

Cancellation costs
In the determination of the cancellation costs of a flight, is determined if passengers can be rebooked on other flights. There was only searched for exactly the same flights. Therefore, routes with an additional transfer were not considered in the model. Only the network from the airline was considered. Hence, the possibility to rebook passengers on same flights from other airlines was not possible.

Another limitation in the determination of the cancellation costs is the fact when two same flights (e.g. flight 1 and 2) are cancelled in the recovery. The passengers from flight 1 can be rebooked on flight 3, however the passengers from flight 2 can be rebooked on flight 3 as well. The model does not check if same flights are cancelled and what the consequences are for the passengers and cancellation costs.

Delay options
A maximum delay time was used in the model. However, when a delay input disruption was above the maximum delay time the model was not able to delay upcoming flights with the input delay as well. It will result in cancellations of flights.

Another limitation in the model based on the delay was the fact that the model only considered the minimum needed delay per flight. In some cases, it was preferred to delay a flight with more than the minimum needed delay to cover the flight. For example, a flight needs to be delayed with 30 minutes for Crew1 and the same flight needs to be delayed with 35 minutes for Crew2. Currently, the model is not able to delay the flight with 35 minutes and assign Crew1 and Crew2 to the flight. This delay of 35 minutes for Crew1 was not considered.

Times
The dates and times were processed in the model and rewritten to UTC times. The determination of the maximum allowed duty hours were based on the duty start time. In this case, these starting times were based on the times at NBO, the home base of KQ. However, times were based on NBO as well for crew members who started their duty at an outstation located in a different time zone. In addition, late arrivals were based on NBO times as well. All times were based on the home base of the airline which is a limitation in the model.

Other limitations

- The transition time was set to one standard input time. However, the transition time depends on and therefore differs per aircraft type.
- In some cases, trainees are assigned to flights and therefore an extra crew member has to be present in the cockpit. However, this was not considered in the model.
- Crew members who are travelling as passengers on flights (deadheading crew) were not considered in the model. Deadheading crew is used to reposition crew members to recover schedules.

A

Crew Regulations

Crew scheduling becomes extremely difficult due to many crew regulations and labour agreements. In general, these regulations are similar for all countries. The regulations are imposed by the aviation authorities of the country. In the United States the regulations are produced by the Federal Aviation Administration (FAA). In Europe, the state members use the regulations of the European Aviation Safety Agency (EASA).

Many rules regarding working hours and rest hours are stated in the regulations. Maximum duty hours, the maximum flight duty period (FDP) hours and minimum rest hours are some examples which are further examined in this section.

A.1. Duty period

A duty period is a period which starts at the moment crew is reported for duty and ends when the crew is free of all duties *(European Aviation Safety Agency (EASA), 2014)*. A duty period consists of flight legs, stand-by periods, training hours and other business related tasks. Table A.1 illustrates the maximum duty hours and the maximum pure flying hours imposed by the FAA and Table A.2 illustrates the values imposed by the EASA.

Table A.1: Maximum duty period hours and maximum pure flying hours. *(Federal Aviation Administration (FAA), 2012)*

Duty Periods		Total Flight Time	
Consecutive	**Maximum hours**	**Consecutive**	**Maximum hours**
7 days	60	28 days	100
14 days		1 calender year	1000
28 days	190	12 months	

Table A.2: Maximum duty period hours and maximum pure flying hours. *(European Aviation Safety Agency (EASA), 2014)*

Duty Periods		Total Flight Time	
Consecutive	**Maximum hours**	**Consecutive**	**Maximum hours**
7 days	60	28 days	100
14 days	110	1 calender year	900
28 days	190	12 months	1000

A.2. Flight Duty Period (FDP)

A FDP is a period which starts at the moment crew is reported for duty, which includes a flight leg or a series of flight legs. The period finishes at the end of the last flight leg of a duty period from the crew member. In general, the period finishes 30 minutes after the engines of the aircraft of the last flight leg are shut down *(European Aviation Safety Agency (EASA), 2014)*.

Table A.3 illustrates an overview of the maximum FDP hours depending on the start time and the number of flight legs imposed by the FAA. Table A.4 illustrates the hours imposed by the EASA.

Table A.3: Maximum flight duty period hours based on the number of flight legs *(Federal Aviation Administration (FAA), 2012)*

Scheduled time of start	Number of flight legs						
	1	**2**	**3**	**4**	**5**	**6**	**7+**
0000-0359	9	9	9	9	9	9	9
0400-0459	10	10	10	10	9	9	9
0500-0559	12	12	12	12	11.5	11	10.5
0600-0659	13	13	12	12	11.5	11	10.5
0700-1159	14	14	13	13	12.5	12	11.5
1200-1259	13	13	13	13	12.5	12	11.5
1300-1659	12	12	12	12	11.5	11	10.5
1700-2159	12	12	11	11	10	9	9
2200-2259	11	11	10	10	9	9	9
2300-2359	10	10	10	9	9	9	9

Table A.4: Maximum flight duty period hours based on the number of flight legs *(European Aviation Safety Agency (EASA), 2014)*

Scheduled time of start	Number of flight legs									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
0000-0459	11	11	10:30	10	09:30	9	9	9	9	9
0500-0514	12	12	11:30	11	10:30	10	09:30	9	9	9
0515-0529	12:15	12:15	11:45	11:15	10:45	10:15	09:45	09:15	9	9
0530-0544	12:30	12:30	12	11:30	11	10:30	10	09:30	9	9
0545-0559	12:45	12:45	12:15	11:45	11:15	10:45	10:15	09:45	09:15	9
0600-1329	13	13	12:30	12	11:30	11	10:30	10	09:30	9
1330-1359	12:45	12:45	12:15	11:45	11:15	10:45	10:15	09:45	09:15	9
1400-1429	12:30	12:30	12	11:30	11	10:30	10	09:30	9	9
1430-1459	12:15	12:15	11:45	11:15	10:45	10:15	09:45	09:15	9	9
1500-1529	12	12	11:30	11	10:30	10	09:30	9	9	9
1530-1559	11:45	11:45	11:15	10:45	10:15	09:45	09:15	9	9	9
1600-1629	11:30	11:30	11	10:30	10	09:30	9	9	9	9
1630-1659	11:15	11:15	10:45	10:15	09:45	09:15	9	9	9	9
1700-2359	11	11	10:30	10	09:30	9	9	9	9	9

EASA defines more different groups according to the scheduled time of start. In addition, the maximum FDP hours are defined for more flight legs than is done by the FAA. The values of the maximum FDP hours of EASA and the values of the FAA differ slightly. However, the values indicate that it would be impossible to perform flight legs that take more than 14 hours (13 hours in case of the EASA regulations). However, there are some extensions to the maximum FDP hours. These extensions depend on the additional crew members on board of the aircraft and the in-flight rest facilities. The in-flight rest facilities are divided into three classes *(European Aviation Safety Agency (EASA), 2014)*:

Class 1: A bunk separated from the cockpit and passenger cabin in which crew members can take a flat sleeping position, control the light and are isolated from noise and disturbance.

Class 2: A seat that provides leg and foot support in an aircraft cabin and is separated from passengers by at least a curtain. The seat has a width of at least 50cm, a pitch of at least 137.5cm and an angle to the vertical of at least 45 degrees.

Class 3: A seat that provides leg and foot support in an aircraft cabin or flight crew compartment and is separated from passengers by at least a curtain. The seat is not adjacent to another seat occupied by passengers and has an angle to the vertical of at least 40 degrees.

It is stated in the regulations of the FAA as well as the regulations of the EASA, that the minimum in-flight rest period has to be at least 2 consecutive hours for cockpit crew. In addition, the FDP is limited to three flight legs. Table A.5 illustrates the maximum flight duty period hours, including in-flight rest, for cockpit crew imposed by the FAA. Table A.6 illustrates the hours for cockpit crew imposed by the EASA.

FAA and EASA do not differ much concerning the maximum extended flight duty period hours regarding rest facilities. Only, the FAA makes a distinction between the scheduled time of start, where

Table A.5: Maximum duty hours regarding rest facilities for cockpit crew *(Federal Aviation Administration (FAA), 2012)*

Scheduled time of start	Class 1 rest facility		Class 2 rest facility		Class 3 rest facility	
	3 pilots	4 pilots	3 pilots	4 pilots	3 pilots	4 pilots
0000-0559	15	17	14	15.5	13	13.5
0600-0659	16	18.5	15	16.5	14	14.5
0700-1259	17	19	16.5	18	15	15.5
1300-1659	16	18.5	15	16.5	14	14.5
1700-2359	15	17	14	15.5	13	13.5

Table A.6: Maximum duty hours regarding rest facilities for cockpit crew *(Federal Aviation Administration (FAA), 2012)*

Scheduled time of start	Class 1 rest facility		Class 2 rest facility		Class 3 rest facility	
	3 pilots	4 pilots	3 pilots	4 pilots	3 pilots	4 pilots
0000-2359	16	17	15	16	14	15

EASA does not make a distinction.

The minimum in-flight rest period has to be at least 90 minutes for cabin crew stated by the FAA and EASA. However, the maximum extended FDP hours are not described by the FAA. Table A.7 illustrates the maximum extended FDP hours, including in-flight rest, for cabin crew imposed by the EASA. The amount of extended hours depends on the quality of the rest facility and the in-flight rest hours. The FDP for cabin crew is limited to 3 flight legs as well in case of extended FDP hours.

Table A.7: Maximum extended FDP hours, including in-flight rest, for cabin crew imposed by the EASA *(European Aviation Safety Agency (EASA), 2014)*

Maximum extended FDP	Minimum in-flight rest (hours)		
	Class 1	Class 2	Class 3
Up to 14:30 hours	01:30	01:30	01:30
14:31 - 15:00 hours	01:45	02:00	02:20
15:01 - 15:30 hours	02:00	02:20	02:40
15:31 - 16:00 hours	02:15	02:40	03:00
16:01 - 16:30 hours	02:35	03:00	NA
16:31 - 17:00 hours	03:00	03:25	NA
17:01 - 17:30 hours	03:25	NA	NA
17:31 - 18:00 hours	03:50	NA	NA

A.3. Rest periods

The minimum hours of rest depend on multiple factors. One of the factors is the duty time the crew member has worked. Longer duty times increase the chance of performance degradation. Another factor is the difference in time between the home base and the outstations. A major difference in time zone between the arrival and departure station has impact on the performance of the crew. Hence, longer rest periods are required with increasing time difference.

In general, EASA states that the minimum rest period at the home base is the amount of hours of the preceding duty period, or 12 hours, whichever is greater. The minimum rest period away from the home base is the amount of hours of the preceding duty period, or 10 hours, whichever is greater. At all times, crew should have the opportunity to have a minimum of 8 hours sleep *(European Aviation Safety Agency (EASA), 2014)*.

In case of a time difference of more than 4 hours, the minimum rest period is at least as long as the preceding duty period, or 14 hours, whichever is greater. When the time difference is more than 4 hours, the rest periods at the home base are determined as illustrated in table A.8 by EASA and in table A.9 by FAA.

Table A.8: Minimum allowed rest days at home base regarding time differences and elapsed time since reporting for first FDP *(European Aviation Safety Agency (EASA), 2014)*

Maximum time difference from home base	**Time elapsed since reporting for the first FDP in a rotation**			
	<48	**48-71:59**	**72-95:59**	**$\geq$ 96**
$\leq$ 6	2	2	3	3
$>$ 6 and $\leq$ 9	2	3	3	4
$>$ 9 and $\leq$ 12	2	3	4	5

Table A.9: Minimum allowed rest days at home base regarding time differences and elapsed time since reporting for first FDP. * Westward - Eastward transitions one extra rest day is required to be added to the value depicted *(Federal Aviation Administration (FAA), 2012)*

Maximum time difference from home base	**Time elapsed since reporting for the first FDP in a rotation**					
	<60	**60-84**	**84-108**	**108-132**	**132-156**	**$\geq$ 156**
4	1	1*	2*	3	3	3
5	1	2*	2*	3	3	3
6	1	2*	3	3	3	3
7	1	2*	3	3	3	3
8-9	1	2*	3	3	3	3
$\geq$ 10	1	3	3	3	3	3

There are some slightly differences between the rest requirements of the FAA and EASA. The FAA defines more different groups regarding the FDP and the maximum time away from the home base. However, EASA requires more rest days than the FAA.

Sometimes cockpit crew regulations differ from the cabin crew regulations. This makes the scheduling process an enormous complicated task. In addition, there are many extensions and exceptions to the regulations described in this section. The reader is referred to *Federal Aviation Administration (FAA) (2012)* and *European Aviation Safety Agency (EASA) (2014)* for more detailed information about the extensions and exceptions of the crew regulations.

B
Pairing Generation

In this appendix an example of the pairing generation algorithm is described. The steps in the flowchart, illustrated in Figure B.1, are used to generate new pairings for the example.

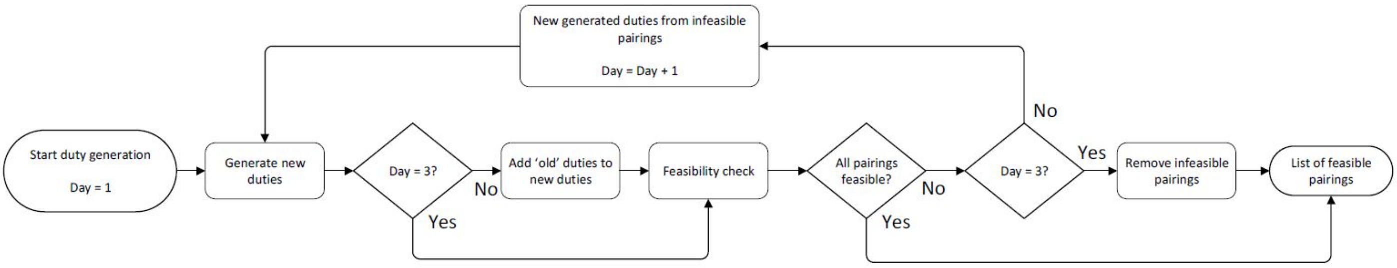


Figure B.1: Flowchart of the generation of new duties and pairings.

The example used is illustrated in Figure B.2 in which six crew members are considered.

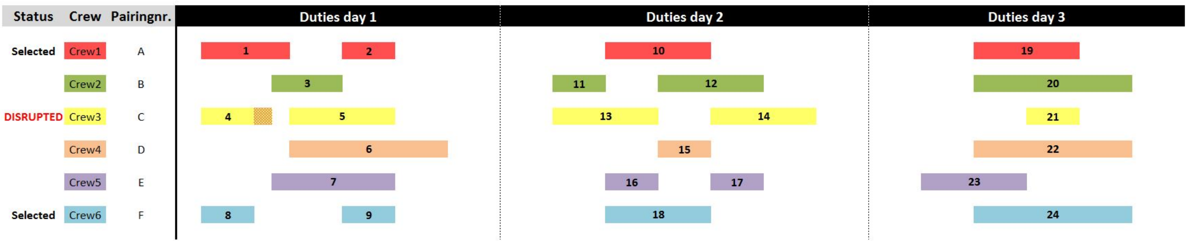


Figure B.2: Small network problem with a delay of flight 4.

The input disruption is a delay of flight 4 which causes infeasibility of the duty at day 1 for Crew3. In the column status is shown that Crew1 and Crew6 are selected to recover the schedule. This is based on the reporting times of the crew members. Figure B.3 illustrates the original duties of the selected crew members.

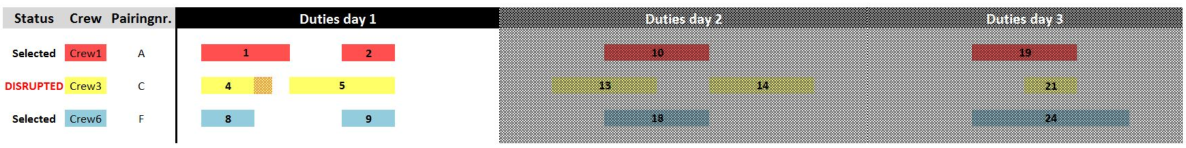


Figure B.3: Selected crew with original pairing. First, consider only day 1 in the duty generation.

In first instance, the duty generation only considers day 1. The flights at day 1 of the selected crew members are used to generate new duties for day 1. It is assumed that the first flight of every selected crew member is fixed and cannot be changed. When the duty generation algorithm, described in Algorithm 10, has finished the old duties of day 2 and day 3 are added to the new generated duties at day 1. This is illustrated in Figure B.4.

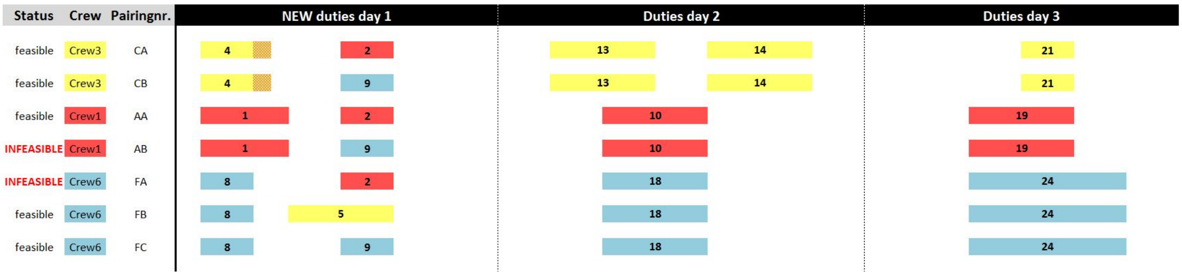


Figure B.4: New generated duties for day 1 and the 'old' duties of day 2 and day 3 are added to get the new pairings.

The new pairings are checked with the feasibility check and it shows that pairing AB and pairing FA are infeasible for certain reasons. This is stated in column 'Status' in Figure B.4 and the feasible pairings are saved in a list. New duties were only generated for day 1 and therefore the infeasible pairings are used to generate new duties for day 2. The selection is illustrated in Figure B.5.

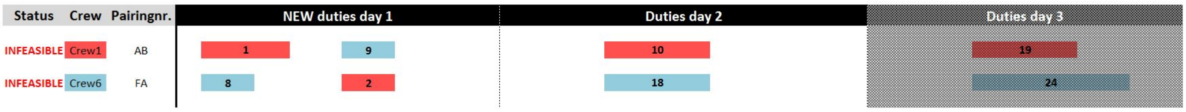


Figure B.5: Infeasible pairings and the new duties at day 1 are used as start flights for the duty generation of day 2.

The flights at day 2 are used to generate new feasible duties. Again, the duty generation algorithm generates new duties for day 2 with the generated duties at day 1 as fixed flights. After the duty generation, the old duties of day 3 are added to the new duties which results in the pairings illustrated in Figure B.6.

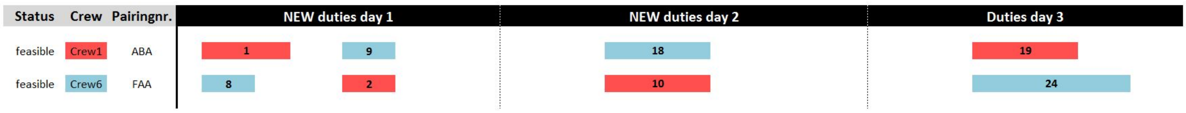


Figure B.6: New generated duties for day 2 and the 'old' duties of day 3 are added to get the new pairings.

Again, the feasibility check of the new pairings is done and in column 'Status' is illustrated that all new pairings are feasible. Therefore, the pairing generation algorithm is finished and an overview of all new generated pairings is illustrated in Figure B.7.

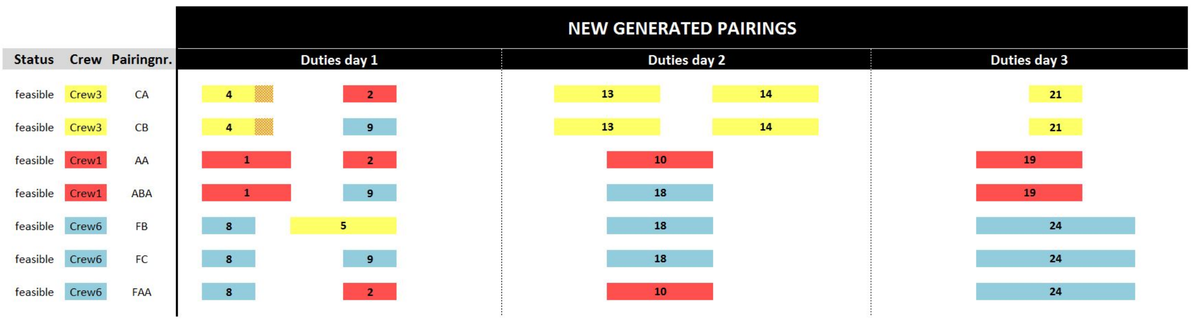


Figure B.7: List of new generated pairings for the selected crew.

The list of new generated pairings and the pairings which were not selected (pairing B, D and E) are used to solve the entire problem. It is still possible to cover all flights and therefore the model will choose that solution. The new schedule will be pairing A, B, CB, D, E and FB which is illustrated in Figure B.8.

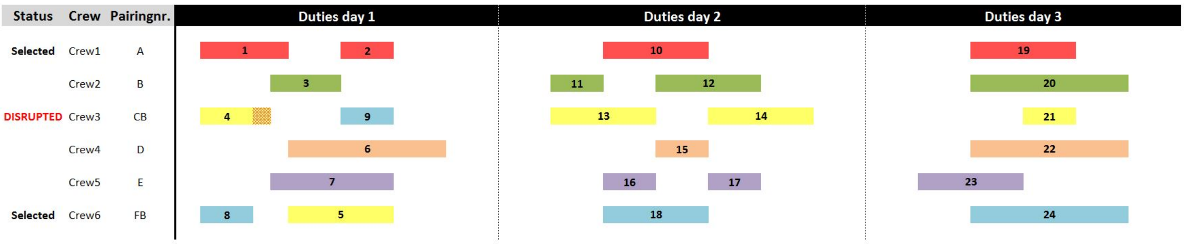


Figure B.8: The recovered schedule with new pairings for Crew3 and Crew6.

C

Crew Salaries Kenya Airways

D

Airport List

IATA	ICAO	Airport City
ABJ	DIAP	Abidjan
ABV	DNAA	Abuja
ACC	DGAA	Accra
ADD	HAAB	Addis Ababa
AMS	EHAM	Amsterdam
APL	FQNP	Nampula
ATL	KATL	Atlanta
AUH	OMAA	Abu Dhabi
BGF	FEFF	Bangui
BJM	HBBA	Bujumbura
BKK	VTBS	Bangkok
BKO	GABS	Bamako
BLZ	FWCL	Blantyre
BOM	VABB	Mumbai
BOS	KBOS	Boston
BZV	FCBB	Brazzaville
CAI	HECA	Cairo
CAN	ZGGG	Guangzhou
CDG	LFPG	Paris
CMB	VCBI	Colombo
COO	DBBB	Cotonou
CPT	FACT	Cape Town
DAR	HTDA	Dar es Salaam
DEL	VIDP	Delhi
DKR	GOOY	Dakar
DLA	FKKD	Douala
DXB	OMDB	Dubai
DZA	FMCZ	Dzaoudzi
EBB	HUEN	Entebbe
EDL	HKEL	Eldoret
FBM	FZQA	Lubumbashi
FIH	FZAA	Kinshasa
FKI	FZIC	Kisangani
FNA	GFLL	Lungi
GBE	FBSK	Gaborone
HAH	FMCH	Moroni
HAN	VVNB	Hanoi
HKG	VHHH	Hong Kong
HRE	FVHA	Harare
JED	OEJN	Jeddah
JFK	KJFK	New York
JIB	HDAM	Djibouti
JNB	FAOR	Johannesburg
JRO	HTKJ	Kilimanjaro
JUB	HSSJ	Juba
KGL	HRYR	Kigali
KIS	HKKI	Kisumu
KRT	HSSS	Khartoum
LAD	FNLU	Luanda
LBV	FOOL	Libreville
LHR	EGLL	London
LLW	FWKI	Lilongwe
LOS	DNMM	Lagos
LUN	FLKK	Lusaka
LVI	FLHN	Livingstone
MBA	HKMO	Mombasa
MIA	KMIA	Miami
MPM	FQMA	Maputo
MRU	FIMP	Mauritius
MWZ	HTMW	Mwanza
MYD	HKML	Malindi
NBO	HKJK	Nairobi
NLA	FLSK	Ndola
NSI	FKYS	Yaounde
OUA	DFFD	Ouagadougou
PEK	ZBAA	Beijing
POL	FQPB	Pemba
ROB	GLRB	Harbel
SEZ	FSIA	Mahe Island
SSG	FGSL	Malabo
TNR	FMMI	Antananarivo
WDH	FYWH	Windhoek
ZNZ	HTZA	Zanzibar

E

Test Cases

This appendix describes the remaining test cases performed in Chapter 7. Therefore, day scenario 2, 3 and 4 are described in more detail. In addition, for day scenario 4 a new initial run had to be performed. This initial run is described in this appendix as well.

E.1. Day scenario 2

The start case and the set of input disruptions are described in Chapter 7. This section describes the results in more detail. The recovery solutions of day scenario 2 obtained by the model are illustrated in Table E.1.

Table E.1: Recovery solutions per iteration of Day scenario 2.

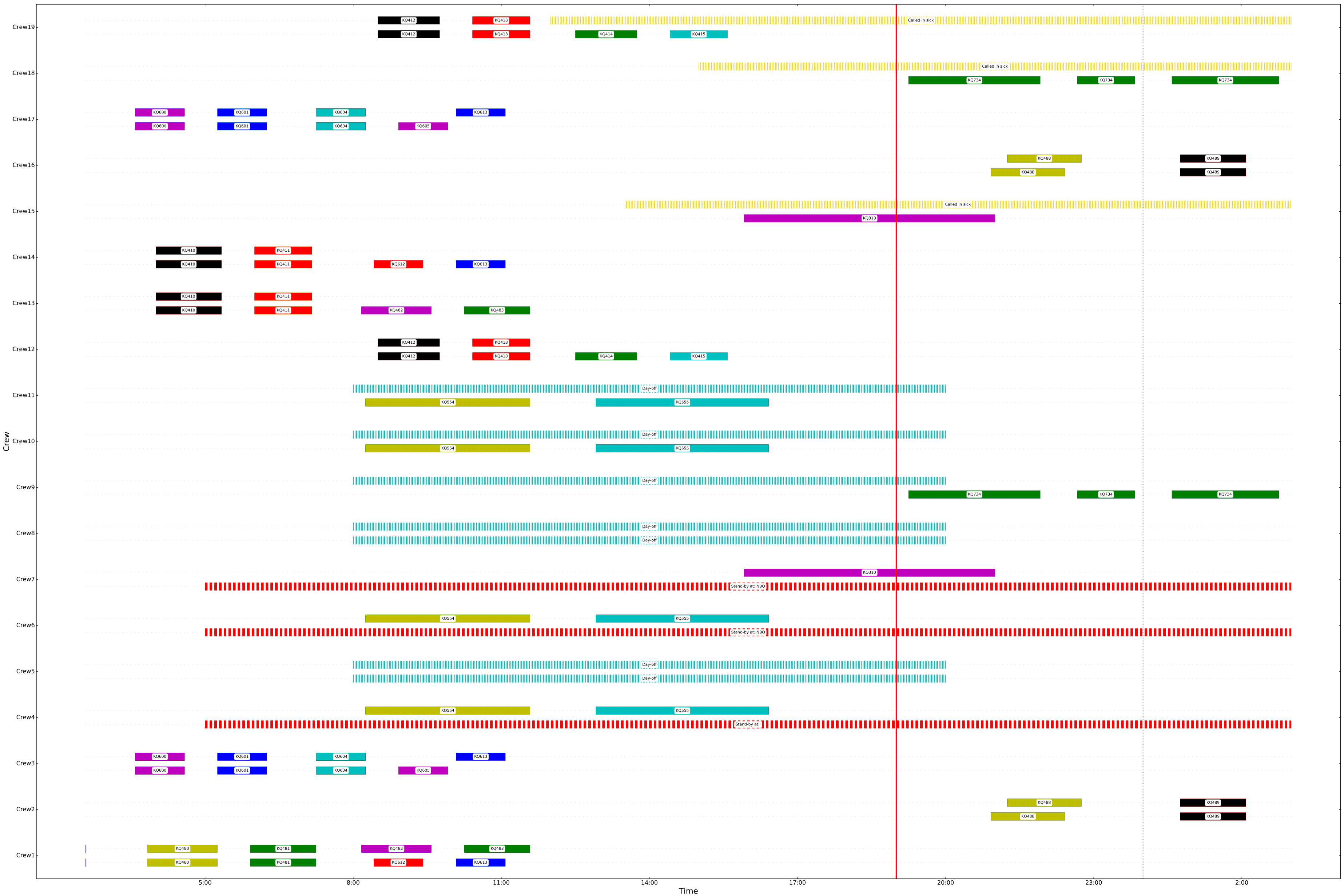
Iteration	Total cost	Iteration time	Number of canx/unc	Number of delays	Number of changed pairings	Crew on duty
1	$273,964	0:00:06.308	0/5	0	4	114
2	$336,082	0:00:05.922	2/5	0	9	114
3	$633,035	0:00:03.537	4/8	0	13	114
4	$633,308	0:00:04.108	4/8	0	14	113
5	$805,133	0:00:03.084	4/11	0	15	111
6	$805,331	0:00:03.603	5/10	1	17	111

Due to the aircraft change of flights KQ554 and KQ555, two crew members have a day-off instead of a duty. Both flights are operated by the standby crew members with the aircraft type E90. Because of the cancellation of flight KQ605, flight KQ612 is cancelled as well. Another option was to cancel flight KQ604, however the cancellation costs are higher for flight KQ604 because of the passenger numbers and alternatives for the passengers. There is no standby crew available for the aircraft type 737 and therefore flight KQ414 and KQ415 have to be cancelled. Crew19 calls in sick after flights KQ412 and KQ413. Therefore, these flights are operated and after STA of KQ413, Crew19 is planned as sick. The flights from Crew15 are operated by standby Crew7, because of sickness of Crew15. The triangle flights KQ734 have to be cancelled as well due to sickness of Crew18. Flight KQ488 is delayed and has no influence on other flights.

The final objective function of this full day scenario is $805,331. In total one flights is delayed with 20 minutes, ten flights are uncovered from which five where already uncovered in the original situation and five flights had to be cancelled at the day of operation. The total computation time of the model is around 27 seconds for this full day scenario.

The recovered schedule after the last iteration is illustrated in Figure E.1. Only the crew pairings which are changed regarding the original pairings are illustrated. Only the first day is illustrated, since at day 2 and 3 some flights became uncovered and some swaps are applied as a result of the disruptions at day 1.

Figure E.1: Recovered schedule of Day scenario 2.



E.2. Day scenario 3

The start case and the set of input disruptions are described in Chapter 7. This section describes the results in more detail. The recovery solutions of day scenario 3 obtained by the model are illustrated in Table E.2.

Table E.2: Recovery solutions per iteration of Day scenario 3.

Iteration	Total cost	Iteration time	Number of canx/unc	Number of delays	Number of changed pairings	Crew on duty
1	$296,380	0:00:10.642	2/7	1	7	112
2	$296,698	0:00:05.379	4/5	2	9	112
3	$363,803	0:00:04.150	6/6	4	13	110
4	$365,445	0:00:04.241	7/5	8	15	110
5	$507,741	0:00:03.680	9/5	6	15	110
6	$508,151	0:00:03.784	9/5	7	17	110

Due to the aircraft change of the triangle flights KQ706, two crew members have a day-off instead of a duty. The flights are operated by Crew2 and Crew17 with the aircraft type E90. The original flights of those crew members become uncovered. At a later stage these flights are cancelled, since no other crew members are available to operate the flights. Because of the airport closure of Kisumu, flight KQ655 is delayed with 30 minutes. The delay has no influence on other flights. Crew11 calls in sick and the flights are operated with a small delay by Crew13. The original triangle flight of Crew13 is cancelled which results in a day-off for Crew15. Flight KQ616 is delayed with 30 minutes and therefore flight KQ617, KQ348 and KQ349 are delayed as well. However, due to the cancellation of flight KQ348 at a later stage, flight KQ349 is cancelled as well. The delay of the first KQ492 flight has no influence on the other flights.

The final objective function of this full day scenario is $508,151. In total seven flight are delayed, nine flights are cancelled and five flights are uncovered which are the same as in the original situation. The total computation time of the model is around 35 seconds for this full day scenario.

The recovered schedule after the last iteration is illustrated in Figure E.2. Only the crew pairings which are changed regarding the original pairings are illustrated. Only the first day is illustrated, since only changes are applied to the pairings at the first day.

Figure E.2: Recovered schedule of Day scenario 3.

E.3. Day scenario 4

The set of input disruptions is described in Chapter 7. However, this day scenario considers another set of data and therefore a new initial run is performed.

Many flights were not fully covered which results in many uncovered flights. The crew members assigned to these uncovered flights are considered as standby crew. Therefore, these crew members can be assigned to flights in the optimization of the original schedule. The same as in Chapter 7, a delay disruption of 0 minutes is used as input. The flight schedule considered for this case, contains 130 flights from which nine flights are uncovered at the first day. In total, 71 flights are uncovered in the considered three days of operation. In this case, the schedule is also optimized for day 2 and 3 for the 737 and 787 fleet. The E90 fleet is only optimized at the first day. There are 253 crew members including standby crew scheduled for duty at the considered three days.

The differences between the costs are determined based on the cost determination described in Chapter 6. The original case and the solutions provided by the model in the new case are illustrated in Table E.3.

Table E.3: Recovery solutions of the initial case compared with the original schedule.

	Original Schedule (old)	**Original Schedule (new)**
Canx/Unc flights	9/62	5/39
Crew on duty	253	253
Cancellation cost	\$838,450	\$524,250
Delay cost	\$0	\$4,455
Additional duty cost	\$0	\$220
Total cost	\$838,450	\$528,925

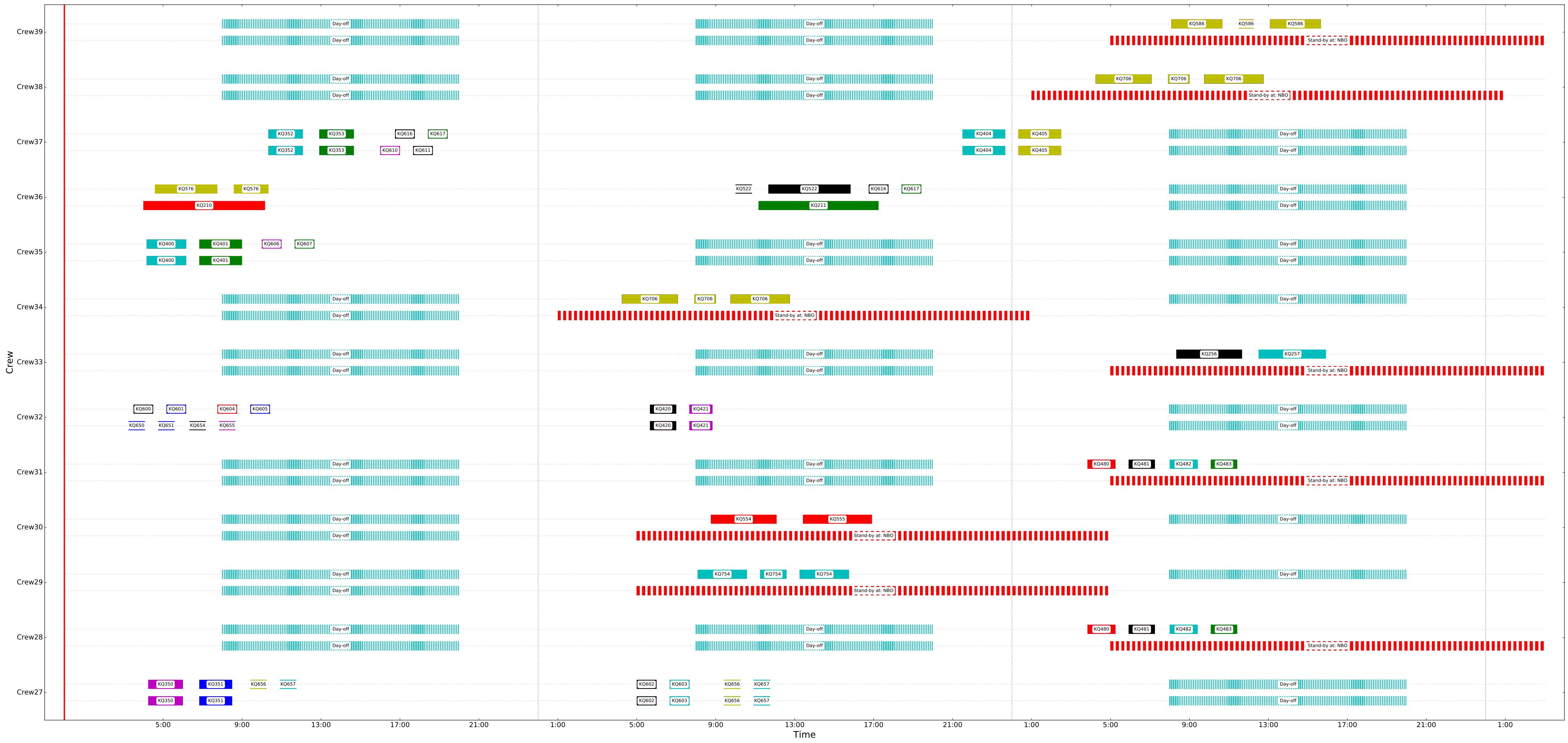
The solution from the initial test case shows that the number of cancelled and uncovered flights are tremendously reduced. Many flights are covered with standby crew members which resulted in lower cancellation costs. In addition, some flights are delayed instead of cancelled. Additional duty costs are assumed to cover the additional flights. The number is set to four based on the difference in total flight times of the cancelled flights at day 1. Overall, a cost saving of around \$300,000 can be gained by operating the new original schedule.

The schedule obtained by the model is illustrated in Figure E.3[1]. Only the pairings that are changed compared with the original case are illustrated.

[1]The graphs are developed in parts and therefore the colours of the flights in the old and new schedule may differ

Figure E.3: Schedule after the initial run of test case 4.


Crew26
Crew25
Crew24
Crew23
Crew22
Crew21
Crew20
Crew19
Crew18
Crew17
Crew16
Crew15
Crew14
Crew
Time
5:00
9:00
13:00
17:00
21:00
1:00
Day-off
Stand-by at: NBO


Crew39
Crew38
Crew37
Crew36
Crew35
Crew34
Crew33
Crew32
Crew31
Crew30
Crew29
Crew28
Crew27
Crew
Day-off
Stand-by at: NBO
KQ586
KQ706
KQ352
KQ353
KQ616
KQ617
KQ610
KQ611
KQ404
KQ405
KQ576
KQ210
KQ522
KQ211
KQ400
KQ401
KQ606
KQ607
KQ256
KQ257
KQ600
KQ601
KQ604
KQ605
KQ650
KQ651
KQ654
KQ655
KQ420
KQ421
KQ480
KQ481
KQ482
KQ483
KQ554
KQ555
KQ754
KQ350
KQ351
KQ656
KQ657
KQ602
KQ603
5:00
9:00
13:00
17:00
21:00
1:00
Time

After the initial run, day scenario 4 is tested which is described in Chapter 7. The recovery solutions of day scenario 4 obtained by the model are illustrated in Table E.4.

Table E.4: Recovery solutions per iteration of Day scenario 4.

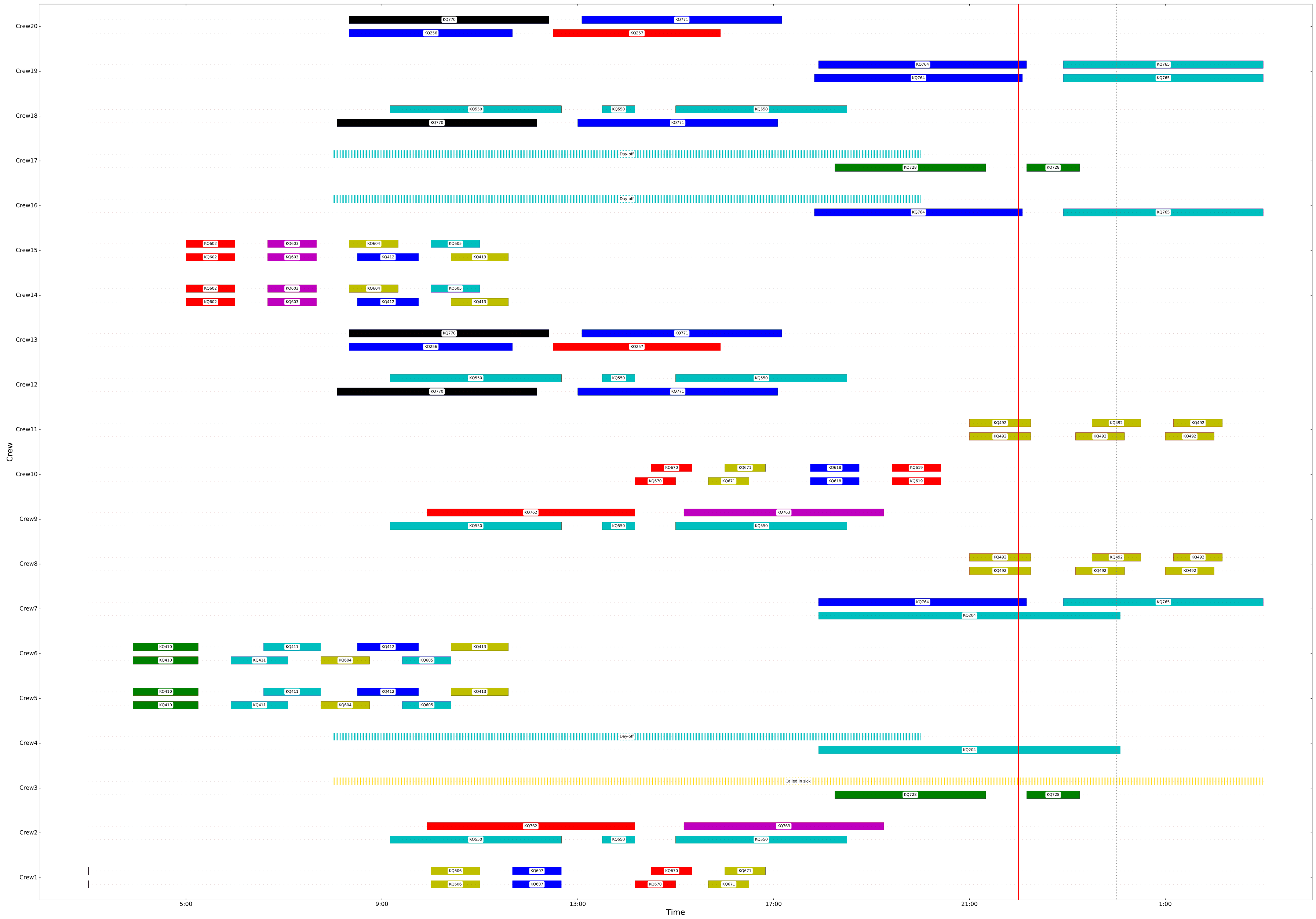
Iteration	Total cost	Iteration time	Number of canx/unc	Number of delays	Number of changed pairings	Crew on duty
1	$3,262,191	0:00:21.232	3/41	0	4	112
2	$3,251,459	0:00:04.438	3/41	5	8	112
3	$3,501,267	0:00:10.582	4/43	5	12	110
4	$3,501,855	0:00:04.275	5/42	7	14	110
5	$3,691,803	0:00:04.528	6/42	8	18	108
6	$3,692,028	0:00:03.717	9/39	10	20	108

Due to the aircraft change of the triangle flights KQ550, Crew2 and Crew9 can operate the uncovered flights KQ762 and KQ763. Crew12 and Crew18 operate the triangle flights KQ550 and their original flights are covered at a later stage. The delay of flight KQ411 causes delay for the other flights as well, however at a later stage some flights are swapped which reduced the total delay minutes. Crew3 calls in sick and therefore the triangle flights KQ728 become uncovered. In addition, Crew17 has a day-off instead of a duty. The delay of flight KQ670 causes a delay of flight KQ671 as well. The cancellation of flight KQ204 results in two crew members who have a day-off instead of a duty. Finally, the delay of flight KQ492b causes a small delay of the upcoming flight as well.

The final objective function of this full day scenario is $3,692,028. In total ten flights are delayed, nine flights are cancelled and 39 flights are uncovered which were already uncovered in the original situation. The total computation time of the model is around 50 seconds for this full day scenario.

The recovered schedule after the last iteration is illustrated in Figure E.4. Only the crew pairings which are changed regarding the original pairings are illustrated. Only the first day is illustrated, since only changes are applied to the pairings at the first day.

Figure E.4: Recovered schedule of Day scenario 4.



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