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Aircraft Schedule Recovery Problem – A Dynamic Modeling Framework for Daily Operations

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Abstract

In this paper we present an innovative dynamic modeling framework to the aircraft schedule recovery problem (ASRP). The ASRP can be defined as the problem of modifying the flight and aircraft schedules to compensate the presence of irregular operations that result in the temporary or permanent unavailability of aircraft. Previous works on this topic often make use of static disruption test scenarios, simulating a set of disrupted events in a single time evaluation. The modeling framework here presented, named Disruption Set Solver (DSS), is innovative because it tackles aircraft schedule disruptions in a dynamic way (i.e., the recovery problem is solved as disruptions happen, involving the solutions of new disruption but also considering decision the incumbent solution) and because it is the first time that parallel time-space networks are used to track individual aircraft in the fleet. The framework relies on the combined usage of an efficient aircraft selection algorithm and a linear-programming model based on parallel aircraft specific time-space networks. The goal of the optimization model used to solve the ASRP is to minimize costs, including operational, passengers delay and cancellation costs. The decision variables involve the cancellation of flights, the delay of flights and the swap of aircraft between flights. The validation of the framework is done applying it to a set of real disruptive days in the operation of a major African airline. The results suggest two conclusions: (1) that the traditional static approach can lead to unreliable solutions, neglecting practical challenge and underestimating the disruption costs; and (2) that the proposed dynamic DSS framework can solve real aircraft schedule disruption problems within a time-window suitable for real-time operations.

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Keywords: aircraft recovery; dynamic modeling; time-space networks

1. Introduction

The operation of an airline requires the allocation of resources such as aircraft and crew members to air services. The allocation plan is defined in advance of the day of operations, aiming at the most efficient use of the resources available. However in practice, operations are usually associated with disturbances such as severe weather or aircraft

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mechanical failure. If these disturbances are not properly managed they can cause a large impact on operations, not only locally but also through the airline network.

To minimize the effect that disruptions have on planned operations there are two approaches. The first is a proactive approach, making sure that there is enough buffer within a schedule to cope with disruptions. This approach is often referred to as robust scheduling. The second is a reactive approach, which consists on the re-planning of resources once a disruption has occurred, referred to as recovery operations. When the focus of the recovery effort is on the aircraft, the problem of recovering operations is called the aircraft schedule recovery problem (ASRP). The ASRP can be defined as the problem of modifying the flight and aircraft schedules to compensate the presence of irregular operations that result in the temporary or permanent unavailability of aircraft.

This paper is focused on ASRP and presents an innovative dynamic modeling framework to solve the problem. The modeling framework, named Disruption Set Solver (DSS), was developed by Delft University of Technology in a collaborative project with Kenya Airways Vos (2015). Dynamic modeling refers to the technique where disruption are solved as they become known, which is in fact a simulation of reality. This approach is compared to the approach where a set of disruptions is solved as if all disruptions were known at the beginning of the day of operations. To this last approach we call the static approach, which is the traditional approach in the literature. This research is based on the assumption that this traditional approach is not suitable to solve the ASRP in real world applications.

The structure of this paper is as follows. It starts with a brief summary of the literature and research trend on the topic (Section 2). Section 3 describes the DSS framework and methodology used. The framework is tested on real-life disruption cases provided by and tested at Kenya Airways. A description of the the situation at Kenya Airways and the case study used to test the proposed framework are described in Section 4. Section 5 discuss the results achieved by the created model in terms of computational performance and provides a comparison between the dynamic and the static approach. The last section summarizes the main conclusions.

2. Literature Context

The research on recovery operations problems started in the 1980's. The early research simulated the manual approach that airline operators use, splitting the recovery of aircraft, crew and passengers into separate problems and solving them sequentially (e.g., see Teodorović and Guberinić 1984 and Yan and Yang 1996 for the case of the aircraft problem). Doing so resulted in problems which were more tractable, however still required considerable simplifications in order to solve them within a reasonable time.

In the late 1990's the use of heuristics in airline recovery operations started with the research presented by Arguello et al. (1997). This research inspired other researchers to follow similar approaches. As the research moved forward new works discussed the integrated version of the recovery operations problem, combining the aircraft recovery problem with crew and passenger recovery problems. The attempt by Petersen et al. (2012) is the most comprehensive research in the integrated recovery of aircraft, crew and passengers. However, the computation times are arguably not fit for real time use. For a recent review on the recovery operations topic, please refer to Clausen et al. (2010).

It is a recent trend in the general airline operations decision-support research field to look at practical challenges in the implementation of solution techniques. That is, to consider more realistic features of the problem in the formulation of decision-support tools. This includes, for instance, the incorporation of the dynamics aspects of the problem or the improvement of the human-machine interface in the decision-support tool. Nonetheless, this is still an emerging trend in the airline recovery literature.

This papers contributes to the literature by presenting an realistic dynamic approach to the particular case of the recovery operations problem, the ASRP. Although Stojković et al. (2002) and Babić et al. (2010) have already proposed decision support tools to handle the ASRP problem in real-time, our approach is the first to model multiple aircraft types in the decisions support system.

3. Methodology

The dynamic characteristic of the modeling framework proposed is given by two key feature. The first is that in the framework the set of disruptions is not known at the beginning of the disruption scenario. Instead, the information of these disruptions is made available as they happen, with the evolution of time. This way, the ASRP problem is

solved with the same information an airline operations control center operator would have when trying to solve real disruptions. The other important feature is the capability of the framework to re-adapt previous recovery measures when receiving new information. That is, within a certain time-window, previous decisions can be amended if with new disruption information they are no longer a good decision. This way, the incumbent schedule solution evolves in time in a truly dynamic way.

The goal of solving the ASRP will be to reduce the disruptions cost. In our work, this cost is split in two different parts, the hard and the soft cost. The hard cost refers to the direct measurable costs, which includes passengers compensations and operational costs. The soft cost refers to the opportunity cost of a passenger not choosing the same airline in the future due to an endured delay. Given that the solution with minimum costs is also the solution that less differs from the initial aircraft schedule, the objective of minimizing disruption costs also corresponds to the goal of returning to the initial operations plan.

3.1. Model Framework

The model framework developed and the simulation environment created to test the framework are schematically depicted in Figure 1. The framework, called *Disruption Set Solver* (DSS), is an aircraft disruption solver that tackles a set of disruptions in a multi-period dynamic context. The DSS is run every time t when a new 'aircraft disruption' information is made available. At each time, it solves the new disrupted situation by considering not only the new disruption events but also the potential disruptions that have become known earlier in time. To do so, the DSS makes use of a *Selection Algorithm* (SA) and of a *Selected Aircraft Linear Solver* (SALS):

- The SALS takes a small given selection of aircraft of which some are disrupted and, using a linear solver, finds an optimal solution to the disruptions for the given selection of aircraft. The SALS is explained in more detail in Section 3.2.
- The SA is a structured procedure used to look at a fleet of available aircraft and to find the best selection of aircraft to be used in solving the disruptions. Section 3.3 explains this algorithm in more detail.

The combination of the SALS and SA forms the DSS framework. The DSS finds a solution to a given set of disruptions that are known at a certain point in time. The input to the DSS is the set of disruptions, the initial aircraft schedule, the incumbent aircraft schedule (perhaps previously disrupted and containing already a set of disruption mitigation measures), information regarding costs of delay, passengers booked in each flight, aircraft information (such as range, passenger capacity, maintenance requirements and operating costs) and airport information such as distances and closure times. The DSS objective is to find the solution that minimizes the disruption costs for that given point in time, with the information that is available at that time.

To use and test the DSS within the context of this research, the model framework was enclosed in a simulation environment. The simulation environment was developed in a way that both the dynamic approach and the static approach to the problem can be equally run. In the dynamic situation the disruptions become known at a given point in time as they would become known in real life. In the static situation a single time t is used and it is assumed that all disruptions are known at the beginning of the day of operations.

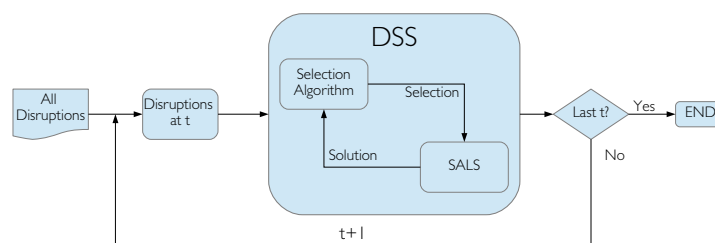


Fig. 1. A schematic representation of the Disruption Set Solver (DSS) and the simulation environment

3.2. Selection of Aircraft Linear Solver (SALS)

The SALS is a module which is based on a linear programming (LP) optimization model and on time-space networks representing the ASRP. Thengvall et al. (2003) used a similar approach in which in a single time-space network, interchangeable aircraft are able to be re-planned in a quick manner. One of the limitations of using a single time-space network is that it is not possible to differentiate between the different aircraft within the network. This is not a problem if all aircraft are interchangeable. For example if the problem has only one aircraft type, all in the same state and no maintenance is planned within the given time-frame. However, using such an approach greatly limits the number of solutions. Thengvall et al. (2003) suggest using a time-space network for each fleet type, however this still restricts the model from using single aircraft constraints. To overcome the limitation of using a single time-space network this research uses the approach of using parallel time-space networks, creating a time-space network for each aircraft (Figure 2). This results in a problem of larger size, however accurately depicts the real-life situation and makes it possible to add any aircraft specific constraints.

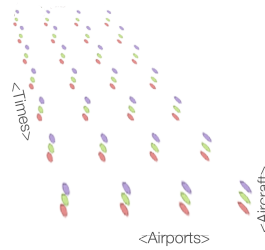


Fig. 2. Graphical depiction of the nodes in a parallel time-space network with three aircraft

The LP optimization model reflects this multi time-space network context adopted in our approach. The decision variables in the optimization model are related with binary selection variables of ground arcs for each ground arc in each time-space network, flight arcs for each flight in each time-space network, delay arcs, which are copies of flight arcs for each delay step up to a maximum delay and a cancellation variable for each flight. The objective function is created by determining the cost of selecting each of the decision variables and can be formulated as follows:

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

, where by order of appearance,

- $\delta_{AF_{p,i}}$ is the binary decision variable equal to 1 if flight arc i is operated by aircraft p (and equal to 0 otherwise);
- $C_{OP_{p,i}}$ is the operational cost of operating flight arc i with aircraft p ;
- $\delta_{AD_{p,i,j}}$ is the binary decision variable equal to 1 if 'delayed flight' arc i , with a delay of $j + 1$ timesteps in the time-space network, is operated by aircraft p (and equal to 0 otherwise);
- $C_{D_{i,j}}$ is the delay cost of operating a 'delayed flight' arc i with aircraft p imposing a delay of $j + 1$ timesteps in the time-space network;
- δ_{Canx_i} is the binary decision variable equal to 1 if flight i is canceled (and equal to 0 otherwise);
- C_{C_i} is the cost of canceling flight i ;
- $\delta_{AG_{p,n}}$ is the binary decision variable equal to 1 if ground arc n is used by aircraft p (and equal to 0 otherwise);
- $C_{AG_{p,n}}$ is the cost of using ground arc n with aircraft p

The first term of equation 1 refers to the cost of operating specific flights. For each flight arc the cost depends on the specific flight and which aircraft operates it. This cost is determined using data received from the airline for which the problem is solved. The second term refers to the cost of using 'delayed flight' arcs, computed based on the number of timesteps used in the time-space network of aircraft p . This cost corresponds to the operating cost, as determined for the flight arc, plus the sum of hard and soft costs for the delay imposed on all passengers on that flight. The hard cost of a delay depends on the compensation that each passenger receives and can be determined by the airline. The soft cost of a delay represents the monetary value of inconvenience as perceived by the passenger. Contributing to this cost is the fact that because of delays, passengers may choose to avoid the same airline in the future. This results in

potential future revenue losses for the airline which are not available from the airlines annual reports. These cost were determined based on the work from Cook et al. (Cook et al. (2004), Cook et al. (2009), Cook and Tanner (2011) and Cook et al. (2012)) and adopted to the current African market. The third term of the objective function corresponds to the cost of canceling a flight. These costs can also be obtained from the airline company and should be estimated according to the number of passengers booked for the flight canceled. Finally, the last term refers to the costs of keeping the aircraft on the ground and using the ground-arcs in the time-space network.

The LP formulation is complemented with a set of constraints that reflect operational disruptions and time-space continuity requirements. An overview of all the constraints used in SALS can be summarized as follows:

- **Time-space constraints** There are several constraints which are generic to the use of a time-space network. The node continuity constraints ensures that the aircraft entering a node also leaves that node. The flight coverage constraints guarantee that each flight is either flown, delayed or canceled. Start and end point constraints ensure that each aircraft starts and ends at the right place in the time-space network.
- **Aircraft specific constraints** The use of parallel time-space network means that it is possible to constrain a aircraft as well as a aircraft type. The maintenance constraints ensure that each aircraft receives the planned maintenance at the planned time and location. Passenger capacity constraints and range constraints ensure that each flight can only be flown by an aircraft type which is able to carry all the planned passengers and for the correct range. Other aircraft specific constraints, such as landing category limitations, are not implemented in this model but it can be easily extended to do so.
- **Dynamic modeling constraints** There are several constraints related to the moving time horizon and the dynamic model. For instance, in dynamic model there should be the possibility to recover delays or to readjust aircraft allocation decisions from previous solutions. For a particular disruption case, several flight and 'delayed flight' arcs need be set as unable for selection. For example, it should not be possible to select a flight or a 'delayed flight' arc of a flight that has already departed or that is already defined to depart in a short time. Dynamic modeling related constraints restraint these 'unable' arcs from being selected and fix the selection of certain arcs which cross the time window defined for solving the disruption case.
- **Disruption constraints** The manner in which disruption are loaded in the model is by limiting certain arcs from being selected. A user friendly disruption writer is currently being created, so that disruptions can be easily input. The type of disruptions that can be input are the following:
 - A flight can be delayed up to a certain point in time;
 - A flight can be canceled;
 - An aircraft can be made unavailable/grounded for a certain period of time;
 - An airport can be made unavailable for a certain period of time;

For the full discussion of the LP formulation of SALS the reader is referred to Vos (2015).

3.3. Selection Algorithm (SA)

As explained in the introduction of this section the SALS module is not able to find a solution to a large problem in a short computation time. It is thus imperative that the problem size to be solved by SALS is kept small. To do so an algorithm was developed, which for a given total fleet and a set of disruptions finds a best selection of aircraft to use for the solution. The manner in which this selection is found is by testing different combination of aircraft in the SALS module. This iterative process is illustrated in Figure 3 and it can be described by the following steps:

Step 1 – Include and fix the aircraft that are directly affected by disruptions in the selection pool.

Step 2 – From all the aircraft that are not disrupted or blocked to solve previous disruptions, filter the aircraft by aircraft type. This step does not necessarily mean that only aircraft of the same type are selected but could, for example, divide the fleet by long and short haul flights. This selection of filtered aircraft defines the aircraft solution space.

Step 3 – Sort all the aircraft in the aircraft solution space by time on ground at the airports where the disrupted aircraft are flying to/from. This step is inspired on actual operations at Kenya Airways.¹

Step 4 – Iteratively run the SALS with different selection pools composed by α selected aircraft from aircraft solution space. The value of α depends on the number of disruptions, the size of the problem and the computation capability to find a good solution within reasonable time. In this step, for each iteration i , starting with i equal to 1, the following steps are done:

Step 4a – Select the selection pool. The pool should include the aircraft already fixed in the selection pool and the set of aircraft with indexes $\alpha * (i - 1) + 1$ and $\alpha * (i)$ in the sorted aircraft solution space. If the $\alpha * (i)$ value is higher than the last index of the aircraft solution space then the last α aircraft are selected, ensuring that the selection of candidate is as large as possible.

Step 4b – Run the SALS with the set of selected aircraft. Save the aircraft selection, the schedule solution and the solution cost.

Step 4c – Check if all aircraft in the solution space have been run. If so, move to Step 5. Otherwise, increase i by 1 and return to Step 4a.

Step 5 – From the solutions found in Step 4 select the solution with the lowest cost. From this solution determine which aircraft are actually used for the solution, i.e., which aircraft have a changed schedule. When there are solutions with equal cost, one of the solutions affecting less aircraft is select. Fix these aircraft, together with the disrupted aircraft, in the selection pool for future iterations.

Step 6 – Place all aircraft that are not fixed in random order.

Step 7 – Repeat steps 4, 5 and 6 until the selection of aircraft used in the solution does not change for X iterations. Where X is a pre-defined value.

Step 8 – Save the schedule, the delays and determine where the aircraft is at the end of the recovery period. If aircraft are at different locations than planned, then the tail numbers are changed in the remaining schedule.

4. Case Study

The model framework presented has been tested on a number of cases provided by Kenya Airways. This section briefly describes the current situation at Kenya Airways and the manner in which recovery operations occur. This explanation is followed by a description of the disruption test cases upon which the DSS framework is tested.

4.1. Context

Kenya Airways (KQ) is a full service hub-and-spoke carrier based in Nairobi. In the international airport of Nairobi, called Jomo Kenyatta International Airport, passengers from domestic, African and intercontinental flights are connected. At the point in time when this research was done KQ operated 43 aircraft, serving 53 destination to and from Nairobi. The outlook is that both the network and the fleet of company will grow in the future Kenya Airways (2011).

Daily disrupted operations at KQ are centered around the Duty Manager Operations (DMO) at the Operations Control Center (OCC). As soon as disruptions become known they are relayed to the DMO and it is his responsibility to devise (with help of his team at OCC) a new plan of operations. The recovery decision process is mainly done based on human judgment. The DMO uses a schedule display software to help him understand the implication of the disruption and the current state of the system, but limited computer-based decision support tools are used to support the DMO in developing a recovery plan.

According to a breakdown analysis of the sources of delay in KQ operations, it was estimated that almost half of the daily delays experienced by the company (direct and reactionary delays) are caused by aircraft disruptions. For this reason, it was decided in this research project to focus on the ASRP. During this work, data from KQ as well as expert opinions were used to calibrate the model framework and validate the results obtained.

¹ Interviewing duty operations managers and seeing how they go about their work, it becomes clear that one of the criteria when looking for aircraft to solve a disruption is seeing how much 'free' time the aircraft has.

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

Fig. 3. Illustrative example of the Selection Algorithm (SA) for α equal to 3

4.2. Test Cases

Four test cases, representing full days of disruptions from the Kenya Airways network in October 2014, are used to test the DSS framework and to illustrate the difference between a dynamic and a static approach. The data that define these cases include information on the scheduled operation, the number of passengers in each flight, aircraft maintenance requirements, the disruptions that have occurred and the times at which the disruptions become known. The selected cases can be summarized as follows:²

- *Case 1*: Two short-haul aircraft unavailable all day due to unplanned maintenance; one short-haul aircraft with a technical issue unavailable from 4:00 until 16:30; and one short-haul aircraft unavailable from 3:00 until 7:40.
- *Case 2*: Two aircraft unavailable at the beginning of the day due to technical issues – one unavailable until 6:00 the other until 7:00; and three delays due to late fueling and other ground issues – two of 30 min and one of 60 min.
- *Case 3*: One aircraft unavailable from 4:30 to 5:20 (a knock-on delay from previous day/shift); an aircraft unavailable due to technical issue from 16:30 to 17:30; three delays of approximately 45 min due to ground operations issues – one of 30 min in flight delay and two passenger related delays of 40 min and 2 hours.
- *Case 4*: One aircraft unavailable due to a technical issue between 4:50 and 6:20; four different delay reasons of 30, 50, 120 and 170 min.

In general, the two last cases involve larger operations complications than the first two cases. Besides the data specific related to the cases tested, other sort of data was collected and used in the test and validation phases of the modeling framework. This additional data includes aircraft technical data, operation costs data and airline passenger compensation costs.

5. Results

This section presents the results of the application of the model framework to the four full day test cases. The final results obtained were validated by KQ DMOs, which confirmed that the aircraft schedule adaptations suggested by the DSS are realistic, valid for implementation and similar to the solutions that would be adopted in practice. A full comparison between the solution adopted by the DMOs and the solution proposed by the DSS was not possible because during the four days of operations other factors (e.g., crew delays, passenger services or ground operations) have influenced the decisions adopted by the DMOs.

To better analyze the results, this section is divided in three subsections. In the first subsection a discussion on the computational performance of the framework is provided. In the second subsection a summary of the results obtained for the four test cases is presented, followed by a discussion on the impact of not using dynamic modeling when tackling the ASRP.

5.1. Computational performance

In airline recovery operation handling speed of the OCC can make the difference between having to delay or cancel flights or not. Decision at OCC must happen quickly, but must not be made hastily. The DMO must make sure that he has all the important input to make a proper decision. The goal set out in this research is that the model is able to provide solutions to problems for real time operations. Interviews with KQ DMOs have determined that a decision support tool should provide a feasible solution to a disruption within a time-span of 10-15 minutes.

Thus, in practice this means that the DSS model framework developed needs to respect this time limit for each time a new disruption information is received. The four full day cases were used to test this capability of the model framework. In total, for the four cases, the DSS is run 38 times, processing new information about aircraft schedule disruptions. The DSS met the 15 minute requirement in all of the 38 runs of DSS and in 93.3 percent of the times

² In these summaries, only the major delays are mention and minor delays of less than 20 min are omitted.

the DSS found the solution in less than 10 min. This illustrates the capability of the model framework to solve in real aircraft schedule disruption problems within a time-window suitable for real-time operations.

5.2. Test Cases Results

Table 1 gives an overview of the results for the runs that have been done for the dynamic and the static approach. The results represent the difference in the Direct Operating Cost (DOC) between the original schedule and the disrupted schedule; the soft and hard costs caused by the delay experienced in the disrupted schedule; and the total costs, which reflect the sum of the former cost parcels. The costs presented are based on KQ values but are equally scaled to generic monetary units. In this subsection we will focus on the dynamic results.

As expected, the total costs for the two last cases are much higher than the ones obtained for the two first cases. This is mainly due to the fact that in the two last cases the disruptions were not possible to solve without canceling one or more flights. As a result of this the soft costs are considerable higher and there are hard costs to be considered. It is also important to mention that the simulation of disruptions in a full day of operations revealed the fact that delay costs can be of several thousands of dollars (this is particularly the case for the two last cases). This fact highlights the importance of doing recovery operations in a realistic and comprehensive way.

Test case	Situation	Difference DOC	Soft cost	Hard cost	Total cost
1	Dynamic	8.18	3.74	0	11.92
	Static	2.02	0	0	2.02
2	Dynamic	-17.41	35.87	0	18.46
	Static	-33.69	36.47	0	2.11
3	Dynamic	-57.09	249.55	31.25	223.71
	Static	-78.27	204.38	23.96	150.07
4	Dynamic	-98.19	384.15	39.50	325.47
	Static	-98.97	308.90	36.74	246.67

Table 1. Dynamic and static approach results for the four disruption test cases (values in generic monetary units)

Another important observation is the fact that in some cases the DOC decrease with the identification of a solution that solves the disruption cases. This can be explained by two facts. The first is that in most cases one or more flights are canceled, not operated, thus reducing the total DOC. The second fact is that in some cases the disrupted solution finds better aircraft allocation solutions than the solution proposed by KQ in their initial schedule. This happens because the initial schedule not always is the most efficient in terms of DOC. Other factors, such as cargo opportunities, the revenue passenger profile in specific markets or branding/marketing decision, seem to influence the fleet allocation process in KQ. These factors have not been considered in our analysis since it was assumed that most of these factor can be disregarded in a context of disrupted operations.

5.3. Dynamic vs Static

By comparing the results from the dynamic and the static approaches, it can be seen that in all cases the static approach leads to solution with much lower costs. This is the expected outcome given that in the static approach all the disruptions are assumed to be known at first instance and thus proactive measures can be taken to solve the disruptions. This leads to complete different aircraft schedule solutions. However, this also reveals that the results from the static approach can be unrealistic and misleading, both in terms of the estimated costs and of the schedule solution. In fact, the difference between a more reliable dynamic approach and the traditional static approach can be very significant. According to the first two cases, the error of estimating costs based on a static approach can be of more than 80%. For the two last cases, involving more challenging disruptions, this value is lower, but still over 24%.

It should be mentioned that one option could be to run the static approach multiple times in the day, when new delay information is made available. This iterative approach would be much more suitable to tackle real-world problems than the pure static approach discussed here. This is also the common approach followed in most commercial ASRP tools available on the market. Nevertheless, this iterative approach still has the problem of solving each time the ASRP as an isolated problem, independent of the previous runs. The disrupted solution and the initial solution are the only

schedule solutions considered. No correction of disruption recovery measures assumed in past iterations is possible. This myopic process can only lead to results that are less efficient solutions than the ones found by a fully dynamic approach as the one presented in this work. Despite that, the comparison of the dynamic approach and the iterative (static) approach can be interesting for future work.

6. Conclusions

This paper presented an innovative dynamic modeling framework to the aircraft schedule recovery problem (ASRP). The framework relies on the combined usage of an efficient aircraft selection algorithm and a linear-programming model based on parallel aircraft specific time-space networks. This approach allows for very detailed aircraft specific constraints, and thereby closely portrays reality. The conclusions which can be drawn from the work presented are the following: (1) The chosen approach provides realistic solutions which have been validated by industry professionals. (2) The results show that in all the test cases a solution is found within a short and appropriated time window, confirming the validity of the model framework for real-life application. Currently Kenya Airways is in the process of implementing the model framework developed in this research.

Another goal of this research was to demonstrate the difference between following a dynamic or a static approach to solve the ASRP. It was observed for the test cases that the results for both approaches are considerably different, in terms of delay costs and schedule solutions found. These differences suggest that the static approach can lead to unreliable solutions that neglect practical challenges and underestimate the costs of the disruptions. A dynamic approach is needed to tackle real-life applications in a systematic and continues process.

References

- Arguello, M.F., Bard, J.F., Yu, G., 1997. A GRASP for Aircraft Routing in Response to Groundings and Delays. *Journal of Combinatorial Optimization* 5, 211–228.
- Babić, O., Kalić, M., Pavković, G., Dožić, S., Čangalović, M., 2010. Heuristic approach to the airline schedule disturbances problem. *Transportation Planning and Technology* 33, 257–280. URL: <http://dx.doi.org/10.1080/03081061003732318>, doi:10.1080/03081061003732318.
- Clausen, J., Larsen, A., Larsen, J., Rezanova, N.J., 2010. Disruption management in the airline industry – Concepts, models and methods. *Computers & Operations Research* 37, 809–821. URL: <http://linkinghub.elsevier.com/retrieve/pii/S0305054809000914>, doi:10.1016/j.cor.2009.03.027.
- Cook, A., Tanner, G., 2011. Modelling the airline costs of delay propagation, in: AGIFORS Airline Operations Conference, London, May 16-19, 2011.
- Cook, A., Tanner, G., Anderson, S., 2004. Evaluating the true cost to airlines of one minute of airborne or ground delay: final report. Technical Report. Eurocontrol and University of Westminster.
- Cook, A., Tanner, G., Lawes, A., 2012. The Hidden Cost of Airline Unpunctuality. *Journal of Transport Economics and Policy* 46, 157–173.
- Cook, A., Tanner, G., Williams, V., Meise, G., 2009. Dynamic cost indexing – Managing airline delay costs. *Journal of Air Transport Management* 15, 26–35. URL: <http://linkinghub.elsevier.com/retrieve/pii/S0969699708000975>, doi:10.1016/j.jairtraman.2008.07.001.
- Kenya Airways, I.R., 2011. 10 Year Strategic Plan, 'Project Mawingu'. URL: https://www.kenya-airways.com/uploadedFiles/Global/About_Kenya_Airways/Investor_Information/Investor_News/10%20year%20Strategice%20Plan%20.pdf.
- Petersen, J.D., Sölveling, G., Clarke, J.P., Johnson, E.L., Shebalov, S., 2012. An Optimization Approach to Airline Integrated Recovery. *Transportation Science* 46, 482–500. URL: <http://pubsonline.informs.org/doi/abs/10.1287/trsc.1120.0414>, doi:10.1287/trsc.1120.0414.
- Stojković, Goran, G., Soumis, F., Desrosiers, J., Solomon, M.M., 2002. An optimization model for a real-time flight scheduling problem. *Transportation Research Part A: Policy and Practice* 36, 779–788. URL: <http://www.sciencedirect.com/science/article/pii/S0965856401000398>, doi:http://dx.doi.org/10.1016/S0965-8564(01)00039-8.
- Teodorović, D., Guberinić, S., 1984. Optimal dispatching strategy on an airline network after a schedule perturbation. *European Journal of Operational Research* 15, 178–182. URL: <http://www.sciencedirect.com/science/article/pii/0377221784902078>, doi:http://dx.doi.org/10.1016/0377-2217(84)90207-8.
- Thengvall, B.G., Bard, J.F., Yu, G., 2003. A Bundle Algorithm Approach for the Aircraft Schedule Recovery Problem During Hub Closures. *Transportation Science* 37, 392–407.
- Vos, H.W.M., 2015. Minimising Cost by Dynamic Modelling of Aircraft Recovery in Disrupted Operations. A Kenay Airways Case Study. Master's thesis. Delft University of Technology.
- Yan, S., Yang, D.H., 1996. A decision support framework for handling schedule perturbation. *Transportation Research Part B: Methodological* 30, 405–419. URL: <http://www.sciencedirect.com/science/article/pii/0191261596000136>, doi:http://dx.doi.org/10.1016/0191-2615(96)00013-6.