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A DISRUPTION NEIGHBOURHOOD APPROACH TO THE AIRLINE SCHEDULE RECOVERY PROBLEM

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***Abstract**: Operations research (OR) has been used successfully in aviation industry and its impact in today's airline operations is significant. All major airlines plan their operations based on various OR models and algorithms including the important aspects of airline scheduling. However, operations do not always proceed as planned due to unforeseen disruptions whichmay lead to flight delays and customer dissatisfaction. Operations research methods can also be applied to the schedule disruption problems which results from irregular operations. The aim of schedule recovery is to getback to the original schedule (after a disruption) as soon as possible by means of re-scheduling the originally assigned flights. In this paper we use different approaches torecover the disrupted schedule.In the first approach we delay the flight(s) in the network without changing the originally planned aircraft and crew tasks whereas in the second approach we considered the recovery problem using the concept of disruption neighbourhood. The test instances are performed on real data on Air New Zealand's domestic operations.*

***Keywords**: Aviation, Schedule recovery, Disruption management*

1. INTRODUCTION

Schedule recovery in airline industry has been an area of interest for researchers for quite some time. A schedule is recovered after the disruptions by applying various recovery approaches such as delaying and/or cancelling flights at different stages of the recovery process. Airlines operate in a dynamic and uncertain environment whereinefficient planning and management of the resources such as aircraft and crew at various stages of operations is important and determines the success or failure of an airline. Over the years OR models and techniques have had a significant impact on planning and managing operations in the airline industry. Exponential growth in computing capabilities, both in software and hardware, and considerable advances in optimization algorithms have helped substantially in solving complex problems in airline scheduling. Operations Research techniques used in airline operations range from long term strategic planning to short term operational planning. Long term planning consists of flight schedule construction, fleet assignment, aircraft routing and maintenance while short term planning includes crew scheduling, revenue management, gate assignment and dealing with irregular operations. The traditional sequential way of airline schedule construction is elaborated in the following section.

2. AIRLINE SCHEDULING PROCESS

2.1 Schedule Design

Schedule design or flight schedule construction is considered as the first stage in airline planning and operations. A schedule is a timetable consisting of origin-destination pairs and departure/arrival times for flights that the airline intends to operate. Airline scheduling can be classified in different phases. The first phase corresponds to market evaluation where lists of routes, flight frequencies etc. are considered. Generally, it is conducted as early as one to two years before the day of operation. In the second phase a schedule is obtained for the flights to be operated. This phase is around 8-12 months before the day of the flight. In this phase flight departure and arrival times, while satisfying resource constraints such as the number of available aircraft with their overall maintenance requirements, are established. Among others, attempts have been made by[1],[2], [3] and [4] to solve the schedule design problems.

2.2 Fleet Assignment

Once schedule design is completed the next step is to assign a fleet type to each flight in the schedule. This process is called fleet assignment. Airlines generally operate with different fleet types, each having different seating capacity, maintenance requirements, fuel consumption etc. The aim of fleet assignment is to maximize the profit by assigning the appropriate fleet type to the flights in the schedule. Aircraft seats are an airline's perishable product i.e. unsold seats at the departure of the flight are wasted. Among others, the fleet assignment problem is considered by [5], [6], [7] and [8].

2.3 Aircraft Routing

Aircraft routing or tail assignment follows fleet assignment. It is a process of assigning each available aircraft within a fleet to each flight in the schedule. The main objective of aircraft routing is to either maximize revenue or minimize operating costs. Certain important issues are considered while routing an aircraft such as each flight must be covered by exactly one aircraft (*flight coverage*), overwater flying capability (*equipment check*) and maintenance check of the aircraft (*maintenance requirements*). Attempts madeto solve aircraft routing found in the literature are from [9], [10], [11] and [12].

2.4 Crew Scheduling

Once aircraft routing is accomplished then the next stage is to assign crew to the flights. Crew scheduling is a process of identifying sequences of flights and assigning both cockpit (captain and first officer) and cabin crew (purser and air-hostess) to these sequences by minimizing the cost of these assignments. Crew scheduling is completed 1-3 months prior to the actual day of operations and it is one of the most computationally intensive combinatorial optimization problems [13]. Crew scheduling can further be segmented into two phases: crew pairings and crew assignment.

2.4.1 Crew Pairings

The first phase in crew scheduling is to generate crew pairings, also known as Tours of Duty (ToD). A crew pairing is a sequence of flights that starts and ends at the same crew base. The objective of crew pairing is to find a set of legal duties and pairings that cover all flights and minimize the total crew cost. Literature on crew pairing problems and an overview of state-of-the art solution methods can be found in the articles of [14], [15], [16] and [17]. Most of the crew pairing problems in the literature are related to cockpit crew.

2.4.2 Crew Assignment

The second phase in crew scheduling is called crew assignment. In this phase crew pairings are gathered into work schedules and assigned to individual crew members. Crew rostering is the process of assigning individual crew members to crew pairings based upon the individual’s preferences. The airline then attempts to grant these rosters, also known as lines of work (LoW). Crew assignments can be made on a monthly, fortnightly or weekly basis. In the literature the crew rostering problem is addressed by [18], [19] and[20].

2.5 Other Scheduling Techniques

2.5.1 Robust Scheduling

Robust airline scheduling is an approach to minimize schedule disruptions by making the airline schedule less vulnerable to disruptions. However, incorporating robustness into schedules is a difficult task because of the unknown severity level of the disruptions and the complexity associated in estimating costs related with robust scheduling. In the literature, robust airline scheduling caught the attention of researchers for a decade or so. Robust fleet assignment is considered by [21] whereasrobust crew scheduling is addressed by [22].

2.5.2 Integrated Scheduling

Apart from the traditional sequential approach of airline scheduling, as described earlier, there has beena substantial number of attempts to integrate various components of the airline scheduling problem. The sequential problems of schedule design, fleet assignment, aircraft routing and crew scheduling have interdependencies on one another. Therefore, the optimal solution for these problems considered separately may not yield a solution that is optimal for the integrated problem. Integration of these problems may result in increased revenue, improved flight connection opportunities, cost savings etc. Among others, contributions using this approach are from[23] and [24].

3. AIRLINE SCHEDULE DISRUPTIONS

Over the years air traffic has augmented considerably whereas many airlines fail to increase the number of their resources such as aircraft and crew to cater to the ever-increasing passenger demand. This lead to the highly optimized utilization of the resources in the schedule. In other words, airlines develop optimal schedules leaving very little slack to deal with any unplanned operation. A slack is the time period when a resource is not assigned a flight/duty after exhausting mandatory ground time. The tight coupling of resources often results in operational problems for the airlines (especially during disruptions).

Throughout the planning process it is assumed that an airline schedule would be implemented as planned without taking unforeseen events such as disruptions into consideration. However, disruptions do occur during operations and result in undesirable expenses to the airline, passenger dissatisfaction andbroken aircraft routings and crew pairings. Disruptions are of different kinds and their level of impact on the schedule varies. The reasons for disruption in the schedule vary from situation to situation and place to place. Some reasons of disruptions are: inclement weather, unscheduled maintenance, unavailability of crew and/or aircraft, passenger delay, security issues, airspace congestion etc.

During recovery from disruptions the aircraft routing and crew pairing problems may arise i.e., an aircraft and crew may not operate a flight as scheduled. A delayed flight affects other flights in more than one way and may result in broken aircraft routings, crew pairings and passenger itineraries. A significant delay in flight departure time or flight arrival time may affect the aircraft, crew and passengers. If aircraft routes are changed during schedule recovery, planned ToD's may not be feasible anymore. Other reasons for infeasibility of ToD's could be missed connections, lack of available flying time or flight cancellations. The objective of the airline crew rescheduling problem is to find a minimum cost reassignment of crews to a disrupted flight schedule, taking into consideration flown hours of the crews, partially flown pairings, and future rosters.

In the literature we have found that disruption management in the airline industry has been given significant attention, especially during the last two decades. Over this period numerous techniques and approaches have been applied in aircraft and crew recovery, mostly using heuristics, in various disruption scenarios to get the disrupted schedule back to normal operations. Recent survey or review articles on airline schedule perturbation and disruption management are from [25], [26] and [27].

4. SOLUTION METHODOLOGY

4.1 The Delay Approach

We considered two approaches for the airline schedule recovery problem. In the first approach we solve the airline schedule recovery problem by propagating delays in the airline network. In this approach all the resources (aircraft, captain and first officer) follow the same flights(even after the disruption is observed) which are assigned to them at the start of the day's operations in the schedule. However, some resources may wash out delay in the schedule itself before the end of the day’s operations depending on the time and duration of the delay.As observed in real operations, this approach is primarily usedin dealing with schedule perturbations of small (1-15 minutes)and medium (15-30 minutes)durations in the network. However, for large disruptions (30 minutes or more) this approach may be expansive for the airline to get back to normal operations.

4.2 Disruption Neighbourhood Generation Approach

In the second approach to solve airline scheduling problem we use the concept of disruption neighbourhood. In this novel idea of disruption neighbourhood generationto tackle airline schedule recovery problems we start with a small set of disrupted resources and flights and solve the problem to recover the schedule within a certain recovery period. If a feasible solution is not achievedthe disruption neighbourhood is expanded until all disrupted resources are assigned a feasible flight to perform in the neighbourhood. In the beginning, we generate an initial neighbourhoodin which we try to recover the schedule in a small time window with as little change as possible to the planned schedule. This can be achieved by swapping of resources and/or by using idle resources in the recovery period or by delaying flights. However, if we do not get a feasible recovery solution then we modify the neighbourhood by extending the time window to add more resources tosolve the problem and get back to normal operations. This process of neighbourhood generation continues until we get back to originally planned schedule or we reach at the end of the day's operations. The concept of disruption neighbourhood is implemented successfully by [28]for solving the train driver recovery problem (TDRP) for Danish passenger railway operatorDSB S-tog A/S.

The following notations are used in the schedule recovery algorithm and computational experiments presented in the results section.

- **S** is the original schedule
- **R** is the set of resources in the schedule
- **resources** is the data struct that contains disrupted resources
- **delays** is the data struct that contains delayed flights
- **av_time** is the availability time of the resource r?R
- **av_port** is the availability port of the resource r?R
- $\mathbf{D_t}$ is the time when disruption is known
- $\mathbf{D_p}$ is the port of disruption
- $\mathbf{D_{dis}}$ the duration of disruption
- $\mathbf{N_t}$ is the total number of affected flights
- $\mathbf{N_{tod}}$ is the total number of affected ToDs
- $\mathbf{T_m}$ is the total number of delayed minutes

- $\mathbf{R_a}$ states whether recovery is achieved or not
- $\mathbf{R_d}$ is the recovery duration (in minutes)
- $\mathbf{F_a}$ is affected flights

We present a schedule recovery algorithm which is implemented using C++ in Linux environment. All the problem instances tested were solved in less than a second.

Schedule Recovery Algorithm

```
In: S
In: D_t
In: resources
In:av_time, av_port
delays ← empty map
for all r ∈ resources do
    t ← first flight done by r afterDt
    delay ← max(av_time[r] - S.begin_time[t], 0)
    if delays contains t then
            delays[t] ← max(delays[t], delay)
    else
            delays[t] ← delay
    end if
end for
for all {t ∈ S.flights: S.departure_time[t] >D_t} do
    if delays does not contains t then
            continue
    end if
    av_time ← S.end time[t] + delays[t] + S.turnaround
    for all {r ∈ S.resources : r associated with t} do
            tr ← next flight done by r after t
            delay ← av_time - S.begin_time[tr]
            if delays contains trthen
                    delays[tr] ← max(delays[tr], delay)
            else
                    delays[tr] ← delay
            end if
```

```
    end for
end for
Out: delays
```

5. MATHEMATICAL BACKGROUND

5.1 Set Partitioning Problem Formulation

In the set partitioning problem (SPP) a set of entities is partitioned in subsets such that no entity is contained in two or more subsets and the union of all elements of all the subsets is the same as elements of the set. The airline schedule recovery problem can be formulated as set partitioning problem as represented below;

$$\text{Minimize } Z = c^T x \tag{1}$$

$$\text{subject to } Ax = b \tag{2}$$

$$x \in \{0, 1\}^n \tag{3}$$

where A is a binary matrix of order $m \times n$, and c is the objective coefficient vector. Eachcolumn a_j, where $j = 1,.., n$ of A represents a duty with an associated cost c_j and thecorresponding variable x_j is a binary variable. If the jth column is included in thesolution x_j would be 1, and 0 otherwise. The jth duty a_j has elements $a_{ij} = 1$ (if duty j performs flight i), and 0, otherwise. An optimal solution of the SPP is given by asubset of duties with $x_j = 1$, which satisfy (1) at minimal cost. The constraint (2) require that each of the mflights (or resources) is performed (or covered) exactly once inany solution whereas constraint (3) defines integer restrictions.

5.2 Integrated Airline Schedule Recovery Problem (IASRP)

We formulate the integrated airline schedule recovery problem (IASRP) as a set partitioning model to solve schedule disruption instances using the concept of disruption neighbourhood. Let A, C and F be the set of aircraft, captains and first officers, respectively, whereas N^a,N^c, and N^f represent the corresponding set of flight copies for aircraft, captains and first officers that need to be covered. Let R^a be the set of feasible recovery duties for aircraft $a \in A$, R^c be the set of feasible recovery duties for captain $c \in C$ and R^f be the set of feasible recovery duties for first officer $f \in F$. The costs c_j^a ,c_k^c and c_l^f represent the unattractiveness of the recovery duty $j \in R^a$ for aircraft $a \in A$, cost of unattractiveness of recovery duty $k \in R^c$ for captain $c \in C$ and cost of unattractiveness of recovery duty $l \in R^f$ for first officer $f \in F$, respectively. A binary decision variable x_j^a equals 1 if the duty $j \in R^a$ for the aircraft $a \in A$ is included in the recovery solution and equals 0 otherwise. Similarly, binary decision variables x_k^c and x_l^f equals 1 if duties $k \in R^c$ for captain $c \in C$ and $l \in R^f$ for first officer $f \in F$, respectively are included in the solution and equals 0 otherwise. A binary null variable wa equals 1 if an aircraft $a \in A$ is idle in the neighbourhood andequals 0 otherwise. Also, binary null variables w_c and w_f equals 1 if a captain $c \in C$ and a first officer $f \in F$ respectively are idle and 0 otherwise. A binary parameter p_{ij}^a reflectswhether or not the aircraft task $i \in N^a$ is covered by the duty $j \in R^a$. Likewise, binary parameters p_{ik}^c and p_{il}^f represents whether or not the captain and first officer tasks $i \in N^c$ and $i \in N^f$ are covered by duties $k \in R^c$ and $l \in R^f$ respectively. Binary artificial variabletaitakes value 1 if flight $i \in N^a$ is not covered by aircraft $a \in A$, otherwise is equal to 0. Similarly, if flight $i \in N^c$ is not covered by captain $c \in C$ then binary artificial variable t_i^c is set to 1, otherwise it is set to 0 and binary artificial variable tkiequals 1 if flight $i \in N^f$ is not covered by first officer $f \in F$, else is equals 0. Whereas, M is a very large number. The integrated airline schedule recovery model for a single fleet is presented and described as the following:

$$\begin{aligned} \min\ & \Sigma\Sigma c_j^a x_j^a + \Sigma\Sigma c_k^c x_k^c + \Sigma\Sigma c_l^f x_l^f + \Sigma d_a w_a + \Sigma d_c w_c + \Sigma d_f w_f \ \ a \in Aj \in R_c \in Ck \in R^c \ f \in Fl \in R^f + \Sigma M t_l^a \\ & + \Sigma M t_l^c + \Sigma M t_l^f i \in N^a i \in N^c t \in N^f \end{aligned} \tag{4}$$

$$j \in R^a \qquad \forall a \in \text{A}$$

$$k \in R^c \qquad \forall c \in \text{C}$$

$$l \in R^f \qquad \forall f \in \text{F}$$

$$\Sigma\Sigma p_{ll}{}_a^a x_j^a + t_i a = 1 \qquad \forall f \in \text{F}$$

$$\Sigma\Sigma p_{lk_c}{}_c^c x_k^c + t_i c = 1 \qquad \forall i \in \text{N}$$

$$\Sigma\Sigma p_{ll_f}{}_f^f x_l^f + t_i f = 1 \qquad \forall i \in \text{N}$$

$$x_j a \in \{1, 0\}, \forall j \in \text{R}^a \qquad \forall a \in \text{A}$$

$$x_k c \in \{1, 0\}, \forall k \in R^c \qquad \forall c \in \text{C}$$

$$x_l f \in \{1, 0\}, \forall l \in R^f \qquad \forall f \in \text{F}$$

The objective of *IASRP* is to minimize the total cost of feasible duties for each resource included within the disruption neighbourhood, such that all the flights within the recovery period are covered exactly once. During recovery it is not significant which aircraftis assigned which routings in the recovery schedule. Similarly, crew can also perform any flight(s) as long as their recovery duties are feasible in the neighbourhood. The resource constraints(5), (6) and (7) ensure that each resource is assigned to exactlyone recovery duty in the recovery network. The resource constraints have a generalised upperbound (GUB) structure because the constraints for each resource are disjoint and eachcolumn represents exactly one resource. However, flight constraints (8), (9) and (10) ensurethat each flight in the recovery network is covered exactly once whereas integer constraints(11), (12) and (13) enforce the integer solutions of the recovery problem.

6. RESULTS

6.1 Data

The problem instances were testedon real data based on Air New Zealand's domestic operations. We only consider flights which operate in mainland New Zealand. However, flights across Tasman are excluded from this work due to various operational constraints. The flight network consisted of 61 flights which operate during the day of operations from four major domestic ports - Auckland (AKL), Wellington (WLG) Christchurch (CHC) and Dunedin (DUD). The flights are operated by 10 aircraft of a single fleet type (733), 16 captains and 16 First officers.

6.2 Disruption Scenarios

We split the day of operations in three different time frames; Morning (M)flights i.e, flights departing between 0500-1100 hrs, Day(D) flights i.e, flights departing between 1100-1700 hrsand Evening (E)flights i.e, flights departing between 1700-2300 hrs. We considered three types of disruptions: small (1-15mins), medium (15-30mins) and large (30-60mins).We also consideredsimultaneous disruptions at more than one port during the day of operations.

Initially, we created small disruptionsof up to 15 minutes at a single port by considering unavailability of an aircraft and/or crew during the day of operations. Subsequently, we extended the disruption duration first, by 30 minutes and finally up to 60 minutes to observe the impact of a large disruptions in the network. Later, we considered simultaneous disruptions at two and three different ports for the same disruption durations (i.e., 0-60 minutes) to observe the impact of these disruption scenarios in the network. For conducting computational experiments we selected the flights to be included in the disruption scenarios based on the following heuristic to test the algorithm under stringent conditions.

1. Select the initially disrupted flight such that thereshould be at least two subsequent flightsfor a resource in the networkwith minimum possible turnaroundand sittime durations for aircraft and crews, respectively.
2. In case of a tie in criteria 1, select the flight that departs from a crew base.
3. For more than one disrupted ports, if possible,select the flights that departs at the same time from different portselse considerthe flights such that difference between the departure timesofthe flights is minimal.

The heuristic is generatedto identify maximum impact in the network due to different types of disruptions in terms of disruption time, number of disrupted ports and disruption duration.In Table 1 the summary of 27 disruption scenarios we considered for the computational experiments are presented.Whereas Table 2 presents the effect of the disruption scenarios on the network.

Table 1. Disruption Scenarios in the Network

No.	D_t	D_p	D_d	N_t	*A*	*C*	*F*
1	M	1	15	1	1	1	1
2	M	1	30	1	1	1	1
3	M	1	60	1	1	1	1
4	M	2	15	2	2	2	2
5	M	2	30	2	2	2	2
6	M	2	60	2	2	2	2
7	M	3	15	3	3	3	3
8	M	3	30	3	3	3	3
9	M	3	60	3	3	3	3
10	D	1	15	1	1	1	1
11	D	1	30	1	1	1	1
12	D	1	60	1	1	1	1
13	D	2	15	2	2	2	2
14	D	2	30	2	2	2	2
15	D	2	60	2	2	2	2
16	D	3	15	3	3	3	3
17	D	3	30	3	3	3	3
18	D	3	60	3	3	3	3
19	E	1	15	1	1	1	1
20	E	1	30	1	1	1	1
21	E	1	60	1	1	1	1
22	E	2	15	2	2	2	2
23	E	2	30	2	2	2	2
24	E	2	60	2	2	2	2
25	E	3	15	3	3	3	3
26	E	3	30	3	3	3	3
27	E	3	60	3	3	3	3

Table 2 Impact of Disruption Scenarios in the Network

No.	Subsequently Disrupted				N_t	T_m	N_{tod}	Recovery	
	Fa	A	C	F				R_a	Rd
1	1	0	0	0	2	30	2	Yes	255
2	3	0	0	1	4	90	3	Yes	510
3	3	0	0	0	4	210	3	Yes	510
4	1	0	1	1	3	35	5	Yes	250
5	2	0	0	0	4	95	6	Yes	355
6	9	3	4	5	11	335	11	No	-
7	2	0	2	2	5	65	8	Yes	305
8	3	0	2	3	6	155	9	Yes	355
9	3	3	3	5	6	435	11	No	-
10	4	0	2	2	5	75	5	Yes	495
11	4	0	2	2	5	150	5	Yes	495
12	6	1	4	3	7	345	8	Yes	630
13	4	0	3	2	6	90	7	Yes	510
14	4	0	3	2	6	180	7	Yes	510
15	6	1	5	3	8	405	10	Yes	630
16	2	1	1	1	5	105	6	No	-
17	7	1	1	1	10	255	6	No	-
18	8	2	1	1	11	575	6	No	-
19	2	0	0	0	3	45	1	Yes	315
20	2	0	0	0	3	90	1	Yes	315
21	3	0	0	0	4	210	1	No	-
22	3	0	0	0	5	70	2	No	-
23	3	0	0	0	5	145	3	No	-
24	4	0	0	0	6	325	3	No	-
25	4	0	0	0	7	90	4	No	-
26	4	0	0	0	7	195	4	No	-
27	5	0	0	0	8	435	4	No	-

7. CONCLUSION

Disruption scenarios atonedisrupted portare recovered by washing out delay in the network in all problem instances but one. In such cases the total number of affected flights range from 2 to 7,flight delay minutes (total time when flights are delayed) is between 30-345 minutes and the range of recovery duration is 255-630 minutes. Flights which are delayed during the day had significant impact on the schedule followed by the morning and the evening flights. In disruption scenarios where disruption is observed at two ports, recovery is achieved in five problem instances out of nine. Four problem instances in which recovery is not achieved had the last flight of the day delayed. In such cases the impact on the schedule is less (as long as the delay of last flight does not affect next day's operations) since there are no further flights in the network. In this scenario the total delayed flights are 3-11, with total flight delay duration ranging between 35-405 minutes. Flights which are delayed during the evening are not recovered at all whereas flights delayed in the morning and during the day are recovered in the schedule between 250-630 minutes. Schedule is recovered in two out of nine instances when disruption is created at three ports. In such cases no flight which departed during the day and in theevening was recovered however morning flightsareback to normal operations when delayed by 15-30 minutes.The schedule is recovered in almost all the problem instances by delaying the flights in small disruption scenarios(1-15 minutes)whereas for medium disruptions (15-30 minutes) most of the flights get back to the planned schedule. However, with large disruptions (30-60 minutes) few flights could operate as planned.

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