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Original Article

MODELLING AND OPTIMIZING FLIGHTS DIVERSION DUE TO DESTINATION AIRPORT CLOSURE

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Highlights:
- a multi-objective linear programming model was developed to determine the aircraft diversion after an abrupt major destination airport outage based on the concept of CDM;
- from an airline operation perspective, it takes into account the expectation of alternate airports, remaining travel time, aircraft cruising speed, en-route wind, air traffic congestion, and so on;
- alternative airports are selected based on their capacity, the categories of aircraft they can accommodate, and the assigned arrival flight slots;
- according to the case study, most flights divert in less than 60 min and may go to one of their top 3 expected alternative airports.

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Abstract. With the fast development of civil aviation, large number of flights operate in major airports in rush hour. Extreme natural disasters, terrorism, and incidents may interrupt its normal operation, even lead temporary closure. Abrupt airport outage causes significant flights diverting to alternate airports. In this article, a centralized optimization method is proposed for the management and optimization of widespread flight diversion. Based on the idea of Collaborative Decision-Making (CDM), a linear programming model formulation is developed to assign flights, who are inbound to a temporary closed destination airport in an emergency, to divert to appropriate alternate airports. The objectives are minimizing total diverting time of flights as well as maximizing the expectation to alternate airports for airlines. Incorporating relevant real-world features, flights remaining flying time available and expectation of alternate airports are taken into account from airlines operation perspective. Airport alternate capacity, the category of aircraft could be accepted and the arriving flight slots assigned are considered for alternate airports. In addition, aircraft cruise speed, en-route wind, air traffic congestion and so on is considered. In the case study, it is found that under the given condition of 50 flights and 8 alternate airports, all flights can be accommodated within the remaining flying time, 33 (66%) flights are less 60 min and 48 (98%) flights are less than 120 min. The model solving time expenditure is less than one 2nd. It can meet the emergency condition and prevent a longer decision-making process. Comparing with the objective of the shortest diverting time as literature, the total diverting time is suboptimal but the formulation can get a better expectation of alternate airports for flights, which provides more flexibility of operations in airlines.

Keywords: flight diversion, alternate airport, rerouting, collaborative decision-making (CDM), air traffic control, airport closure.

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Notations

Abbreviations:

ATC – air traffic controller;
CDM – collaborative decision-making;
ZBAA – Beijing Capital International Airport.

Variables and functions:

a – index of alternate airports;
BT – beginning time when all flights begin to divert to their alternate;
BM – big number;
D_{ia} – distance en-route from the position of flight i to alternate airport a when destination shutdown suddenly;
i – index of flights;
M – total number of alternate airports;
N – total number of flights;
p_{ia} – expectation value of flight i to alternate airport a;
Q_a – the alternate capacity of airport a, which is a limit number of diverting flights of alternate airport a can accepted within a period of time;

s – index of a slot of an alternate airport;
S_a – total number of slots assigned for alternate flights in airport a;
ST_{as} – the time of slot s of airport a;
T_i – the remaining flying time available of flight i;
V_i – selected speed when flight i is diverting to an airport;
$Wind_{ia}$ – wind speed in route from the position of flight i to alternate airport a;
x_{ias} – decision variable that determines whether the flight i is assigned to the slot s of the alternate airport a;
α – weighted coefficient;
λ_{ia} – correction factor for cruising time in diversion from the position of flight i to alternate airport a.

1. Introduction

With the fast development of civil aviation, major airports are operating a larger number of flights in rush hour than ever before. Some may be at the edge of, or beyond its capacity saturation. More than 597000 flights were token-off and landed in ZBAA in 2018, and there were 1635 flights every day in mean, and more than 1900 flights on rush day, and more than 110 flights in rush hour, whereas its hourly peak estimated capacity is 88 flights. Airports are facing a capacity crunch in Europe and America too (ACI Europe 2020; García 2017). Air traffic will nearly double and 19 key European airports will be at saturation by 2030 in Europe (EC 2011). If the major airport with large volumes of flights and passengers is closed temporarily, many schedules will be disrupted.

In modern aviation operations and management, uncertainty and risks are increasing (Petrović *et al.* 2018). Because of extreme natural disasters, terrorism, and incidents sometimes occurred nearby major airports around the world, their normal operation is interrupted, even lead temporary closure. Significant flights inbound to the impacted airport have to be diverted and accommodated to alternate airports immediately.

The eruptions of the Eyjafjallajökull Volcano (Iceland) caused a significant impact on most of the northern European airports and caused more than 100000 flights diversion and cancellation in April and May 2010 (Bolić, Sivčev 2011). The 2011 Great Tōhoku earthquake (Japan) caused the immediate outages of Narita International Airport and Tokyo International Airport (Ryerson, Churchill 2013. Japan Kansai International Airport set to be closed for a week in wake of deadly Typhoon Jebi and more than 200 flights were cancelled or diverted on 5 September 2018.

On 11 September 2001, under the attack of terrorist in the US, widespread airports were shut downed and all aircrafts were diverted to the nearest airport. On 21 December 2018, London's Gatwick Airport, the UK's 2nd-biggest airport, was closed over 17 h for the unprecedented drone attack. About 110000 passengers on 760 flights scheduled to depart and land at Gatwick were instead arriving in Manchester, Luton or Heathrow in the UK, or even as far afield as Paris (France) and Amsterdam (Netherlands).

On 3 August 2016, Emirates Boeing 777-300 crashed on landing at Dubai (UAE) and the airport was shut down. All flights to Dubai were diverted to alternate airports. On 6 July 2013, Asiana Airlines Flight214, a Boeing 777-200 ER aircraft, crashed just short of runway 28L's threshold at San Francisco International Airport (US). The crash resulted in a 5 h total closure of the runways at the airport and cancelation or redirection of all fights (Marzuoli *et al.* 2016).

Widespread flights alternate not only cause huge economic loss to airlines but also disturb the normal operation of alternate airports, even may obstruct the operation of the entire air traffic network. A case study of a hypothetical short-term closure at London Heathrow is indicated that the costs can be substantial (Pejovic *et al.* 2009). Therefore, it is a very crucial work for the management and optimization of widespread flights diverting when the original major airport is abrupt outage.

Normally, the pilots and airline dispatchers have the right to decide which alternate airport to divert based on the knowledge of airplane conditions, such as safety of flight, remaining fuel, the possibility of successful alternate, passengers' intention and accommodation, and so on. ATCs arrange alternate airports as pilots' wish under normal conditions.

Because of the competitive market within the airline industry, high-quality service has become a global marketing need (Badi, Abdulshahed 2019). This decision gives operation flexibility for airline companies to satisfy their passengers. But it will bring several shortages when widespread flights diverting. For airlines' cost and benefit, many flights may concentrate on some same alternate airports when preparing diversion. By analysing America diverted flight data between 2010 and 2016, airlines are more likely to divert to small airports nearby their intended destination and waiting until the outage clears when faced with a full or partial airport outage (Ryerson 2017).

While this strategy allows airlines the possibility of recovering their operations, it may not offer a resilient outcome when airlines are recovering from uncertain climate events and not focus on passenger re-accommodation. Moreover, many passengers were diverted to airports where their airline operates at low frequency and many more issues arose when flights were diverted to airports in which their carrier does not operate (Marzuoli *et al.* 2016). Besides, the incidence of low fuel in diversions sometimes occurs. Major hub airport outages create a challenging reroute and diversion situation. If select alternate airports are congested either from their schedules or from the volume of reroutes, flights must endure long holding time and potentially leading to emergency fuel (Ryerson, Churchill 2013). On 20 January 20 2018, a United Boeing B737-824 performing flight UAL342/UA342 from Chicago to Boston (US) was unable to land at Boston due to poor weather conditions, and a low fuel emergency happened in its diversion.

Additionally, it relies on individual experience rather than technical support mostly for ATCs to guide and direct diverting flights rerouting to an alternate airport. Workload will be increased for monitoring and directing extra diverting flights, which might increase the probability of human error. Because the dynamical and rapidly change of transport, methodologies should be developed and strategic aims should be coordinated efficiently (Kondroška, Stankūnas 2012). For maintaining the expect capacity of air traffic and reacting to these unplanned conditions, real measures are required (Rodríguez-Sanz *et al.* 2018). So, for avoiding the shortages of decentralized decision-making in diversions of different airlines, the research of the central control and optimization for diversion is required. However, the research in this area is rare.

2. Literature review and contributions

We have identified 3 cases in the majority of extant literature that concerns airport temporary closure:

- the 1st is the cases of the impact of different airport closure. Some of the works are: Pejovic *et al.* (2009), Bolić & Sivčev (2011), Carslaw *et al.* (2012), Chan (2012), Ding & Rakas (2015), De Armon *et al.* (2016), Marzuoli *et al.* (2016), Malandri *et al.* (2020) and Zhau & Xiao (2025). However, there are not approaches provided to cope with that impact in there works;
- the 2nd is how to recover airlines and airport operations when normal flight schedules are disrupted as destination airport closure. The main literature include: Yan & Lin (1997), Thengvall *et al.* (2001, 2003), Sherali *et al.* (2002), Rosenberger *et al.* (2003), Yang *et al.* (2016), Wu *et al.* (2017), Voltes-Dorta *et al.* (2017a, 2017b) and Lin & Wang (2018a, 2018b). The works provide rescheduling approaches from different perspectives. One of the different approaches provided by Zhou *et al.* (2019), who reveal the "alternative pair" existence in the airport network and provide an identifying method. The alternative pair is a pair of airports that, if one of them is closed, the other one can take over part of its traffic load. It is like a special alternate airport. Despite aircrafts rescheduling and alternative pair approaches are provided in this study. Their research is at the strategic level, not concern flights in flying as the destination airport closure;
- in this article, we focus on the 3rd case that how to deal with the flights in flying to divert to an appropriate alternate airport when destination in an abrupt outage. To the best of our knowledge, there are few works of literature researching diversion. We find only 3 literature provide approaches to flight diversion. Furthermore, optimization models are quite similar and the objectives of all the models are minimized diverting time for rerouting and diversion. The present contribution can be considered as an extension of these works.

An early study by Zhao *et al.* (2013). They described the flights diversion as a classical bin packing problem that n flights need to divert to m alternate airports. The objective was to minimize the total diverting time and the only constraint was the capacity of alternate airports. They had ideal assumptions that all flights' fuel remain was enough to every alternate airport, and alternate airports could accept any category of aircraft. The diverting time was assumed as a straight-line distance from decision point to alternate divided by a given cruise speed. They gave a data experience of 20 flights diverting to 6 airports due to the weather in ZBAA in 2012. The result showed that it could save 9.7% of the total diverting time comparing with practical history data.

Zhang *et al.* (2018) using the same model of Zhao *et al.* (2013), designed an artificial bee colony algorithm and 7.35% of the total diverting time was reduced given a test of 10 flights and 5 airports. They compared bee artificial colony algorithm, genetic algorithm, and particle swarm algorithm, and found that all had a fast convergence speed and good performance for this problem.

Ryerson & Churchill (2013) developed a deterministic routing model for airport outage that assigns flights an arrival time at a diversion airport following the destructive 2011 Tōhoku earthquake (Japan). The objective seeks to minimize the time during holding and rerouting. The constraints of diverting time windows, remaining fuel limit and airport capacity were considered. The reroute flying time was an orthodromic distance, from decision point to alternate, being divided by a given average speed or economy speed without considering the impaction of wind and traffic. It was found that under reasonable assumptions about diversion airports and capacities, all flights can be accommodated without reaching a fuel-critical state for a decision occurring 20 min after the disaster.

The operation as works of literature seeking to save time instead of companies' voices, could reduce the total diversion time of flights, but airlines lost their expected alternate airports and require more time and cost from recovery. Zhang & Hansen (2008) designed an intermodal strategy for flights recover, where flights bound for a major hub experiencing an outage are rerouted to a nearby airport and the passengers are bussed to the hub airport experiencing an outage.

Additionally, there are 2 works related to flight diversion. As destination airport closure has a significant impact on connecting passengers, Suh & Ryerson (2017) provide a strategy to reroute to a hub airport that is not disrupted, with the goal of accommodating passengers on existing flights departing the non-disrupted hub. The objective of the model is to minimize the sum of passenger travel time to an alternate airport and wait time for connecting flight, and subjects to the on-board fuel and diversion airport capacity constraints. They develop a large neighbourhood search heuristic to solve the model. Li (2015) researched the problem of whether the arriving flights wait at the airport for landing or divert to an alternate airport when destination airport capacity decreases. They provide a simulation analysis by comparing the waiting cost and alternated cost.

Our contributions as following. The objectives of total time saving and airlines' expectations for alternate airports are combined in our approach. It is a flexible model that always has central control and optimization, and that also can satisfy claims of airlines. This approach reflects the idea of CDM that we have been advocating. Furthermore, different from previous works, a penalty function as a soft constraint is given so that the model could process emergency diverting flight that not following constraints. Besides, the model improves on previous work by incorporating relevant real-world features, e.g., the diverting time includes both rerouting time and holding time, and the influence of wind and air traffic delay is considered. The constraint for the acceptability of the airport to the category of aircraft is given as well.

3. Model formulation

A major destination airport shutdown urgently. All flights bound to the destination have to divert to alternate airports. With some practical constraints, a set of N flights need to be assigned to a set of M alternate airports $M < N$, so that shorting the total flying time and satisfying the airlines desired alternate airports as possible, as shown in Figure 1.

3.1. Fundamental assumption

In the real-world, there are some acceptable fundamental assumptions for reducing the complexity of the operation process as follows. To be consistent with the practical situation, we follow these assumptions in our model:

- remaining flying time is available. Pilot in air could gain this time from flight management computer, while airline dispatcher could obtain the time by aircraft performance calculating based on remaining fuel and normal cruise condition;
- the beginning time that all airlines make decisions on their flights to divert is the same. It could be a "start" time for destination airport outrage;
- airports have capacity limits and aircraft category is required. We do not take into account landing operations in an emergency, which beyond constraints of capacity or category;
- p_{ia}, the expectation value of every flight i to alternate airports a, is available. Here the expectation value is using a value to express the expectation degree that the aircraft divert to an alternate airport. ATCs can get the flight plan in the day before the flight take-off, which includes the flight alternate information. There are 3 alternate airports for a flight in its plan for most airlines in China. Normally, the 1st one is which airline wanted most, then the 2nd and the 3rd. We give the alternate airports a number as expectation value following the sequence, e.g., p_{ia} = 0.5 means the expectation value of the flight i to alternate airport a is 0.5.

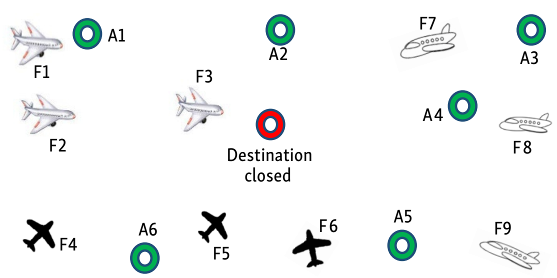

Figure 1. Problem description

3.2. Decision variable

$$x_{ias} = \begin{cases} 1, & \text{if the flight } i \text{ is assigned to the} \\ & \text{slot } s \text{ of the alternate airport } a; \\ 0, & \text{otherwise;} \end{cases}$$

$$\forall i = 1, 2, \ldots, N;$$
$$a = 1, 2, \ldots, M;$$
$$s = 1, 2, \ldots, S_a. \quad (1)$$

3.3. Objective functions

2 objectives are considered here:

$$\min \sum_{i=1}^{N} \sum_{a=1}^{M} \sum_{s=1}^{S_a} \left(ST_{as} - BT\right) \cdot x_{ias}. \quad (2)$$

Equation (2) is the objective to minimize the total diverting time as literature for central control and optimization; $ST_{as} - BT$ is the reroute flying time and holding time required if a flight deciding to divert to the airport a at slot s.

$$\max \sum_{i=1}^{N} \sum_{a=1}^{M} p_{ia} \cdot \sum_{s=1}^{S_a} x_{ias}. \quad (3)$$

Equation (3) is the objective to maximize the total expectation for the flexibility of operations in airlines; p_{ia} is the expectation value that the airline selects the airport a as the alternate of their flight i, e.g., a base airport is a better choice in diverting for cost-saving and convenient service; $0 \le p_{ia} \le 1$, and the greater of p_{ia}, the more expected to divert to the airport.

2 objectives are put together with a weighted coefficient $\alpha\left(0 \le \alpha \le 1\right)$.

$$\min\left(\alpha \cdot \sum_{i=1}^{N} \sum_{a=1}^{M} \sum_{s=1}^{S_a} \frac{ST_{as} - BT}{T_i} \cdot x_{ias} - \left(1-\alpha\right) \cdot \sum_{i=1}^{N} \sum_{a=1}^{M} p_{ia} \cdot \sum_{s=1}^{S_a} x_{ias} + BM \cdot \sum_{i}^{N} \left(1 - \sum_{a=1}^{M} \sum_{s=1}^{S_a} x_{ias}\right)\right), \quad (4)$$

where: relative time $\frac{ST_{as} - BT}{T_i}$ is used here for the same order of magnitude for 2 objectives;

$BM \cdot \sum_{i}^{N} \left(1 - \sum_{a=1}^{M} \sum_{s=1}^{S_a} x_{ias}\right)$ is a penalty function to avoid flight i do not divert to any of alternate airports.

If flight i is assigned to an airport, the function is 0, otherwise, it equates to BM. BM is a big number and $BM \gg T_i$. This penalty function could permit the model to solve the scenario of emergency alternate, which diverting flight could not follow the given constraints. For instance, the "mayday" flight for minimum fuel permits landing 1st without considering airport capacity and category limit.

3.4. Mathematic constraints

Each flight must not be assigned to more than one slot of an airport, and each slot is assigned one flight at most:

$$\sum_{a=1}^{M} \sum_{s=1}^{S_a} x_{ias} \le 1,\ i = 1, 2, \dots, N; \tag{5}$$

$$\sum_{i=1}^{N} x_{ias} \le 1,\ a = 1, 2, \dots, M,\ s = 1, 2, \dots, S_a. \tag{6}$$

Nevertheless, the flight may be assigned to none of the airports under the condition of other constraints. For instance, if the remaining fuel of aircraft is too small to approximately minimum fuel and no enough ability to fly to a suitable airport under the condition of the model constraints, it will be no alternate airport assigned for the model. For this emergency event in the real-world, the flight has the privilege to land the nearest airport without regard to limitation of capacity, aircraft category, runway pavement strength or others. So less-than-equal, rather than equal, is used in the constraint of Equation (5). To avoid x_{ias} tend to zero in the objective of minimize the total flight time, a penalty function is given.

3.5. Slots time window constraints

The alternate time window of slots has to be smaller than the flight remaining flying time and greater than the time of flight arriving at the alternate airport. Because the remaining fuel in the tanks of flight i is limited, the diverting time required $ST_{as} - BT$, from the diverting point to the alternate airport a and holding over the airport to wait the assigned slot s to land, is in the limit of T_i.

$$\left(ST_{as} - BT\right) \cdot x_{ias} \le T_i;$$
$$\forall i = 1, 2, \dots, N,$$
$$a = 1, 2, \dots, M,$$
$$s = 1, 2, \dots, S_a. \tag{7}$$

The reroute time of flight i from diverting point to the alternate airport a, should be earlier than the time of assigned slot s of airport a.

$$\frac{D_{ia}}{V_i + Wind_{ia}} \cdot \lambda_{ia} \cdot x_{ias} \le ST_{as} - BT;$$
$$\forall i = 1, 2, \dots, N;$$
$$a = 1, 2, \dots, M;$$
$$s = 1, 2, \dots, S_a. \tag{8}$$

where: D_{ia} can be obtained by adding together the total en-route distances in diversion from aeronautical charts or using a distance of the great circle of earth from origin to destination instead; V_i can be gained from the chosen cruise speed; $Wind_{ia}$ can use a forecast equivalent wind from upper wind and temperature chart; correction factor λ_{ia} is used for considering the factors of outside air temperature, unpredictable wind variation, navigation error, air traffic congestion and so on, which may cause the flight delay $\left(1 \le \lambda_{ia} \le 1.1\right)$.

3.6. Capacity constraints of alternate airport

The total number of flights diverting to the alternate airport a, should not exceed its alternate capacity Q_a:

$$\sum_{i=0}^{N} \sum_{s=0}^{S_a} x_{ias} \le Q_a;$$
$$a = 1, 2, \dots, M. \tag{9}$$

where: Q_a is the maximum number of flights diverting to this airport; normally, it is based on the number of aircraft gates and prepared by the airport; it is specified in the *Rules for Flight Diversion 2013* of Civil Aviation Administration of China (CAAC 2013).

3.7. Aircraft categorization constraint of airport

Some Airports cannot accept any category of aircraft. The large aircrafts, such as Boeing 777, with large wheel loads, high tire pressures and complex landing gear configurations, can impact on some airport pavement life and performance. Their suitability for use in airports should be concerned (Gopalakrishnan 2008). Small airports or others, because of the limit of runway, navigation system or size of gates for aircraft, cannot accept some categories of aircraft for an alternative. ICAO (2018) provide the aerodrome reference code to define what size of aircraft the airport is able to handle – from something small like an ATR-72, all the way up to the Airbus A380 at the other end of the scale.

The categorization of airplanes is $\left\{A, B, C, D, E, F\right\}$ of the aerodrome reference code. If the airport is suitable for heavy aircraft, it can accept a smaller one too. For comparison purposes, the set of reference codes can be mapped to a set of numbers, $\left\{1, 2, 3, 4, 5, 6\right\}$. C_i is the code of the categorization of flight i and $C_i \in \left\{1, 2, 3, 4, 5, 6\right\}$. C_a is the code of the heaviest airplane that airport a can accept and $C_a \in \left\{1, 2, 3, 4, 5, 6\right\}$. Therefore, if flight i decides to divert to the airport a, $C_i \le C_a$:

$$C_i \cdot \sum_{s=0}^{S_a} x_{ias} \le C_a;$$
$$i = 1, 2, \dots, N;$$
$$a = 1, 2, \dots, M. \tag{10}$$

4. Computational experiments

In this section, we present computational results to demonstrate the effectiveness of the model developed in Section 3. The model is implemented with *Microsoft Visual Studio 2013* (*https://visualstudio.microsoft.com*) in C++ and

Table 1. Parameter settings

Item	Value
N	50
M	8
s_a	20, a = 1, 2, ..., M
α	0.5
BT	0
BM	5
λ_{ia}	random between 1.0 and 1.1
$Wind_{ia}$	random between –30 kn (heading wind) and 30 kn (tail wind)
ST_{as}	it is 0 in 10% probability and random between 30 + 5·s and 35 + 5·s in 90% probability; s = 1, 2, ..., S
V_i	random between 350 and 500 kn
T_i	random between 120 and 180 min
C_i	random between 2 and 6
C_a	random between 4 and 6
Q_a	random between 8 and 15
p_{ia}	random between 0 and 1.0
D_{ia}	random between 100 and 800 nm

solved with IBM ILOG CPLEX 12.6.1 (*https://www.ibm.com/products/ilog-cplex-optimization-studio*). The experiments run in a portable computer with an *Intel*(*R*) *Core*(*TM*) i7-4720HQ processor (CPU @ 2.60 GHz / 2.60 GHz and 8.00 RAM), and *Microsoft Windows 10* operating system. This test assumes that there are 50 flights need to divert to 8 alternate airports given following parameter settings (Table 1).

4.1. The tests result (α = 0.5)

The following is the result of the test. The total diverting time is 2968 min, with 2676 min total rerouting flying time and 292 min total holding time. The mean of flying time is 59.36 min, with the means of rerouting and holding are 53.53 and 5.83 min respectively. Comparing with the remaining flying time available T_i, the diverting time required $ST_{as} - BT$ of 33 (66%) flights are in the circle of 60 min and 48 (98%) flights are less than 120 min (Figure 2). $ST_{as} - BT$ is composed of cruising time and holding time. 37 (72%) flights diverting cruise time is less than 60 min, which is the time selected most for airlines dispatching flights and deciding alternate airports. 40 (80%) flights holding time is less than 10 min (Figure 3). For domestic operation, airlines need to fly for 45 min at normal cruising fuel consumption for hold (FAA 1964). So, this approach could reduce diverting time for aircraft.

The total expectation of flight is 35.2, the mean is 0.888. The expectation value of flight assigned to alternate airport p_{ia} is close to maximum expectation (Figure 4). Figure 5 shows the rank of the expectation value of a flight to all alternate airports. The 1st number is the expected alternate airport identifier, and the 2nd represents the number of flights, and the 3rd means the percentage of flights in the total. 23 (46%) flights are assigned to their 1st expected alternate in the result and 39 (78%) flights could divert

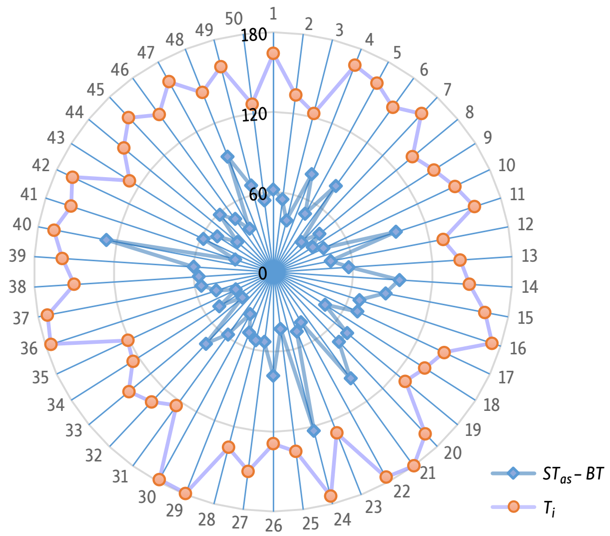

Figure 2. The flying time required vs the remaining flying time available

to their top 3 expected airports. No flight is assigned to its 7th expected alternate airport. Most of the flights' expected alternate airports are obtained.

4.2. Comparison of α = 0.5 and α = 1

Comparing the 2 objectives module (α = 0.5) with the shortest flight time objective (α = 1), it loses a few flight time but gets more expectations for airlines alternate. On the one hand, the total flight time grows from 2682 to 2968 min, and the mean of flight time grows from 53.64 to 59.36 min, increasing 10.66% (Figure 6). Flying time of 19 (38%) flights in α = 0.5 is greater than α = 1 and every flight increases 5.72 min flying time in mean. The maximum flying time is the same.

On the other hand, the total expectation grows from 26.2 to 35.2, the mean grows from 0.524 to 0.704, increasing 34.35% (Figure 7). 18 flights are greater in expectation. There are 16 flights whose expectation is not less than 0.8 and 26 flights expectation not less than 0.6 for α = 1, moreover, 28 and 39 flights for α = 0.5, respectively. Therefore, most of the flights could divert to its expected alternate airport and that will take a lot convenient for airlines.

4.3. The impacts of weighted coefficients

The 2 objectives weighted coefficient α can be changed from 0 to 1 with every 0.02 interval, and corresponding solutions of total flying time and expectation can be obtained. Figure 8 is the impacts of weighed coefficients on 2 objectives. The minimum average flying time is 53.64 min but the average expectation is only 0.524 when α = 1. If it is delayed to 60 min, the average expectation will grow more than 0.7 (0.704, α = 0.5). Therefore, within losing 6.35 min in flying time, we can obtain 0.18 additional expectations, which will give great convenience to airlines and most of the flights will have the opportunities diverting to their expected airports. If it is more than 60 min, the expectation grows slowly.

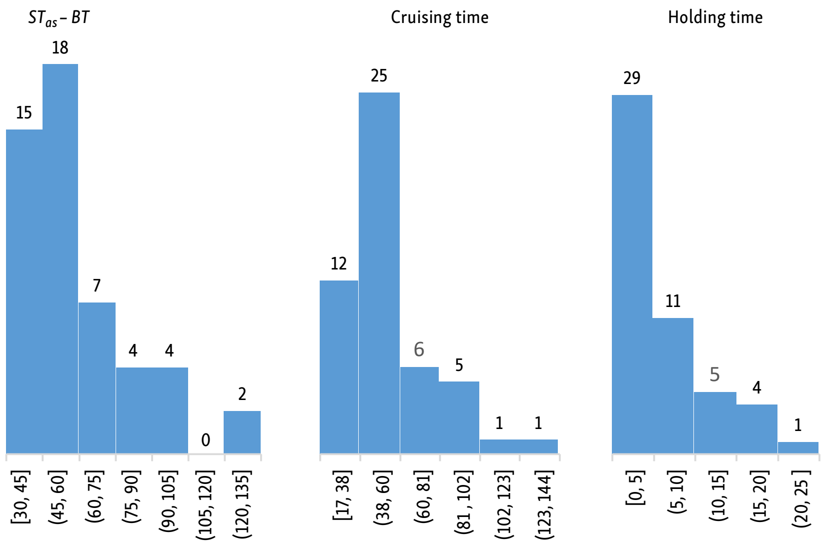

Figure 3. The number of flights in different time intervals

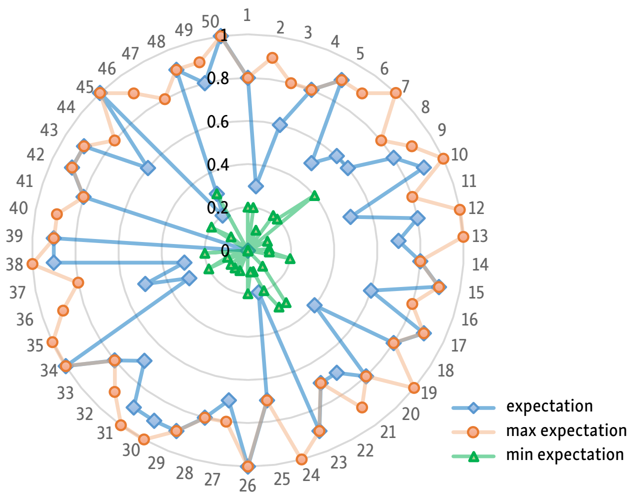

Figure 4. The expectation value of flights comparing with the max and min expectation

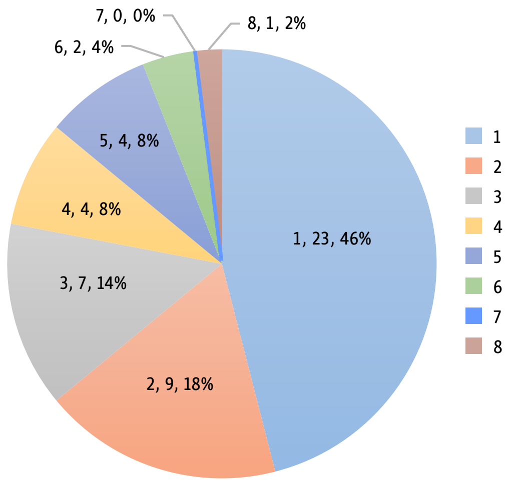

Figure 5. The number of flights in different rank of expectation (the 1st number is the expected alternate airport identifier, and the 2nd represents the number of flights, and the 3rd means the percentage of flights in the total)

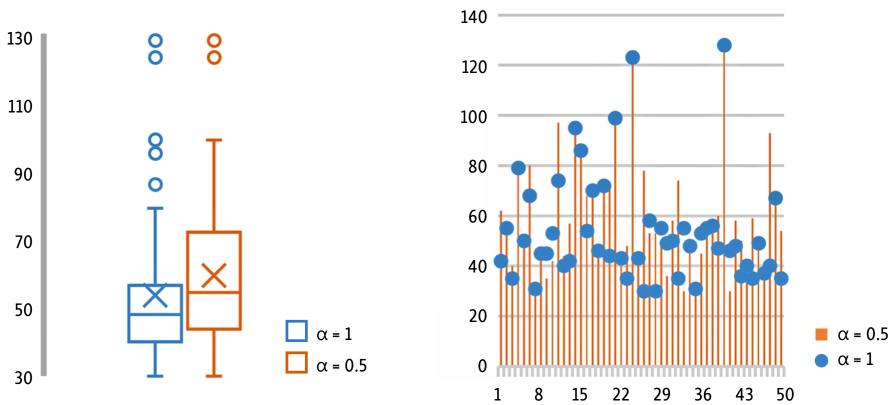

Figure 6. Time comparison

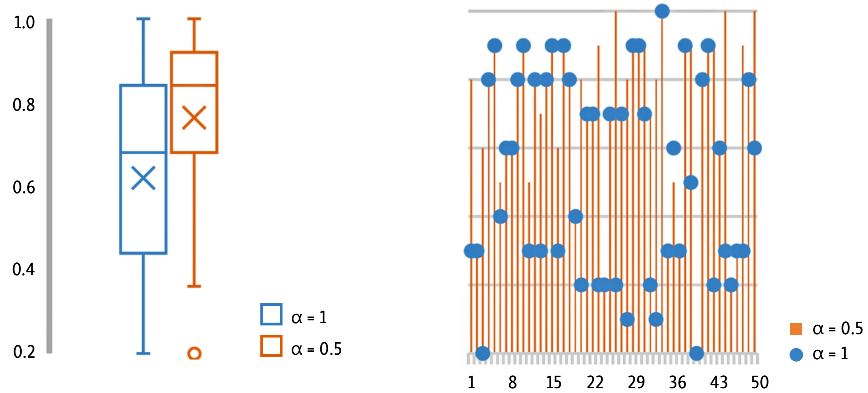

Figure 7. Expectation comparison

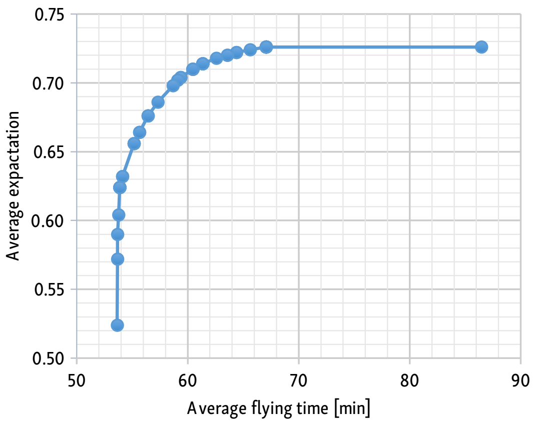

Figure 8. The impacts of weighted coefficients

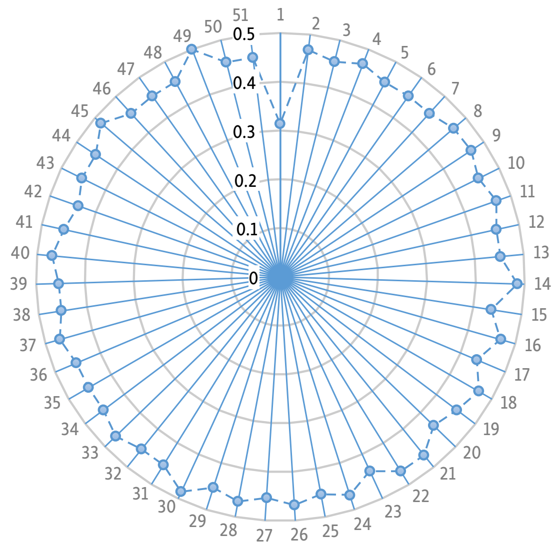

Figure 9. Experimental time

Figure 9 shows the time expenditure for every experiment. The average time of computation for these 51 tests is 0.456 s and the standard deviation is 0.024. It is acceptable in diversion decision.

5. Discussion of operation and management

We provide an approach of alternate airport selection for flights in routes when their destination temporarily closes at an emergency. If the closure of destination is a major and hub airport in rush hours, dozens of flights inbound to this destination may require a diversion. It will be a challenge for regional air traffic operation and management. Freely alternate airport selection by airlines may disturb normal operations and increase the burden of ATCs and alternate airports. For preventing the deficiencies of decentralized decision-making of airlines' decisions for flights diverting, we consider a centralized control and optimization method based on the idea of CDM. For the airlines, we take into account the remaining flying time available of every flight and minimize the total diverting time including reroute flying time and flight hold time over alternate airports, while still accommodate these alternate airports that airlines expected and provided. For the alternate airports, we consider their alternate capacities, the categories of aircraft can be accepted and the arriving flight slots available to avoid disrupting the normal operation of the alternate airport. For the ATC, we just use a correction factor λ_{ij} to consider the air traffic congestion, because air network selection has not considered here and it will be one of our next work. Because of the centralized optimization and CDM, we can reduce the total flying time, and satisfy the expectation of airlines, and prevent disturbing the flight flow of air network as well as alternate airport operations as the case study shown in Section 3.

From airline management and tactical perspective, it is a basic right that airlines choose to divert their flights when destination airport experiences an outage. This proposed approach does not deprive airlines right for flight diversion as Zhao *et al.* (2013), Ryerson & Churchill (2013) and Zhang *et al.* (2018) does. Airlines could choose their alternate airports as their expectation in keeping with airline ploy and strategies, such as base airports, or airports convenient for turnover, or accommodating passengers easily. Airlines can provide an alternate airport list (3 airports at least) for every flight, and submit the list as a part of the flight plan to civil aviation administration, air traffic management department, destination airport, and alternate airports on the day before the flight operation. The alternate airport list provides available airports for centralized optimization selection.

From the air traffic management department perspective, this centralized optimization method can be assembled in the air traffic flow management system. The alternate airports of every flight come from flight plan airlines submitted, and other information is from the air traffic flow management system. It works when a major airport is an abrupt outage and will provide an optimal diversion solution. This solution can provide useful reference values for the resilience of the air transport network and helpful decision support for centralized flight diversion management. The department can distribute the optimal solution to dispatchers and pilots of airlines, ATCs, and airports managers by the air traffic flow management system. Then, they should proceed as plan.

6. Conclusions

In this study, a linear programming model formulation was developed to determine flight diversion following a major destination airport outage abruptly. The formulation considers flights, whose destination airport was closed in an emergency, diverting to appropriate alternate airports by minimizing diverting time and maximizing the expectation of airlines to airports. Reroute flying time and remaining flying time available of a flight bound the earliest and latest arrival time at each alternate airport. Incorporating relevant real-world features, alternate airport capacity and aircraft categorization constraints are considered in the model.

In cases study, as expected, most of the flights diverting time are less than 60 min and could divert to their top 3 expected alternate airports. Comparing with one objective of the shortest diverting time as literature, our 2 objectives module can get more expectations for airlines alternate within losing a few flying minutes.

If the model is used in reality, it is a good way that policymakers give the weighted coefficients based on his knowledge and experience firstly and solve the model because of limited decision time. Though some practical characteristics were considered, because of the complexity of real-world urgency situation, uncertainty of a flood of affecting factors, and shortage of flight parameters, the model is simple by design and a lot of random parameters are used in computational experiment experiences. Further investigation and expansion are required in future work characterized by, high dimensional and multi-objective, then meta-heuristics such as differential evolution and estimation of distribution algorithm, such as: Tang *et al.* (2019, 2021, 2024), promising for dealing with these problems: Hubbard, S. M. L. & Hubbard, B. (2019) and Zhen *et al.* (2019). Not all flights will divert to alternate after destination outrage. Some may return to origin airports, even some may continue to destination. The decision of what the flight selects for a certain purpose is under many uncertainties, such as flying time, wind, and destination reopen time.

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Author contributions

Xiangling Zhao and *Yu Zhang* conceived the study.

Xiangling Zhao were responsible for the design and development of the model and data analysis, and wrote the 1st draft of the article.

Disclosure statement

We declare that we have none competing financial, professional, or personal interests from other parties.

Declaration on the use of Artificial Intelligence (AI)

During the preparation of this manuscript, the authors did not use generative AI or AI-assisted technologies.

The authors take full responsibility for the content of this manuscript.

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