A STOCHASTIC OPTIMISATION APPROACH TO AIR TRAFFIC FLOW MANAGEMENT: ADDRESSING PREDICTABLE AND UNPREDICTABLE WEATHER EVENTS

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A Stochastic Optimisation Approach to Air Traffic Flow Management: Addressing Predictable and Unpredictable Weather Events

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CERTIFICATE OF ORIGINALITY

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_______________________________ (signed)

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Abstract

With the increasing number of flights, flight delays occur more frequently due to limited airspace and airport capacity. Additionally, adverse weather conditions are becoming more severe and frequent, exacerbating the issue of flight delays. Therefore, it is essential to address this problem. In this thesis, two significant aspects are considered: predictable and unpredictable weather events. The methods required to handle these problems differ slightly due to their particular characteristics. Thus, two different models have been presented to address the corresponding issues and reduce flight delays caused by adverse weather conditions.

Predictable weather events refer to those with more stable weather conditions, causing their trajectories are relatively easier to forecast. In this thesis, tropical storms are selected as an example of predictable weather event. A two-stage stochastic optimisation model, considering the effects of tropical storms, is proposed to maximise the punctuality of flights. Various scenarios are used for computation and testing to assess the performance of the proposed stochastic model. It is concluded that the performance of the model is satisfactory.

Unpredictable weather events, on the other hand, refer to more dynamic weather conditions. Rainfall is selected as an example of this category. Therefore, a scenario-based two-stage stochastic optimisation model is presented. The proposed model combines the aircraft landing problem and the terminal traffic flow problem to reduce the total time of flight delays. Several computational improvement procedures have been suggested to enhance the performance of the proposed model. It is determined that the performance without using any computational improvement procedures is optimal. A comparison between the traditional scheduling method (i.e. first-come-first-serve strategy), the proposed deterministic model, and the proposed stochastic model has also been performed, and the stochastic model is concluded to be the best among the three methods.

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Nomenclature

AIP	Aeronautical Information Publication
ALP	Aircraft Landing Problem
ATCOs	Air Traffic Control Officers
ATFM	Air Traffic Flow Management
EEV	Expected Value of the Expected Value Solution
ETA	Estimated Time of Arrival
FAA	Federal Aviation Administration
FCFS	First-come-first-serve
IATA	International Aviation Trade Association
ICAO	International Civil Aviation Organisation
HKCAD	Hong Kong Civil Aviation Department
HKIA	Hong Kong International Airport
MAR	Multiple Airport Region
NTSB	National Transportation Safety Board
SAA	Sample Average Approximation
SAPRs	Standard and Recommended Practices
SIDs	Standard Instrumental Departures
STARs	Standard Terminal Arrival Routes
TMA	Terminal Manoeuvring Area
TTFP	Terminal Traffic Flow Problem
VSS	Value of the Stochastic Solution

Chapter 1 Introduction

1.1 Background

Aircraft is one of the essential modes of transport nowadays since people rely on flights for trading and tourism, leading to an increasing number of flights in recent years (Presto et al., 2022; Wittmer & Bieger, 2011). According to IATA (2023a), the total number of flights in 2019, before the COVID-19 pandemic, was 38.9 million. Despite the impact of COVID-19, which led to a sudden drop in 2020, an increasing trend has been observed from 2020 to 2022. Limited airspace is one of the causes leading to severe flight delays, which typically refer to delays that exceed 15 minutes of the scheduled time of departures and arrivals (Zámková et al., 2022).

Another primary reason causing severe flight delays is weather events. According to the FAA (2023), over 75 percent of flight delays from June 2017 to May 2022 were caused by weather conditions, such as tropical storms and thunderstorms. As the climate changes, extreme weather events are rising significantly, with their intensity increasing notably (Zhang & Li, 2022). This significantly affects various industries, with aviation being one of the major sectors affected in terms of flight operations (Thompson, 2016; Vansteelant et al., 2015; Zhang & Li, 2022). An increase in safety margins and a decrease in runway capacity are two of the effects caused by meteorological events (Pejovic et al., 2009). Hence, the number of flight delays recorded is probable to rise in the coming years.

Different types of weather events can be classified into two categories based on the characteristics of the events.

The first category is the "unpredictable weather events". This kind of weather event is defined as weather events that are hard to predict and their trajectories are more dynamic. Rainfall and thunderstorms are two of the events belonging to this category. Rainfall prediction remains challenging due to its dynamic nature (Aftab et al., 2018; Manandhar et al., 2019). Sudden heavy rainfall can occur without any prior notification or warnings, which can adversely affect flights. Pilots are necessary to respond quickly to these unexpected changes, including rerouting to avoid severe turbulence and thunderstorms. Therefore, it increases the difficulty for flights to adhere to their schedules, increasing the number of flight delays.

Conversely, “predictable weather events” is the other category, which refers to meteorological events that are easier to predict, with relatively more stable trajectories. Tropical storms are an example of predictable weather events. With the development of advanced prediction technologies and research conducted by numerical scholars, the accuracy of tracking predictions of tropical storms has reached over 80% (Heming et al., 2019). Additionally, the translation speeds of tropical storms are slow. Kossin (2018) stated that there has been a slowdown in translation speed in recent years.

Despite the predictability of tropical storms, effects including precipitation, strong winds, coastal sediment change, and storm surge cannot be ignored (Correia & Smee, 2022). Each tropical storm may have different effects on cities, depending on the strength of the tropical storm and the locations of the cities. These effects may impact airport operations, including departures and arrivals. Therefore, consideration of predictable weather events is required.

Various scholars have formulated different approaches to mitigate the consequences of climate change. The most efficient and effective method is to review the current practices of the aviation industry. Afonso et al. (2023) systemically reviewed six significant areas that different scholars are investigating: operations, energy sources, propulsion systems, aerodynamics, structures and materials, and manufacturing processes. Each area encompasses numerous methods and approaches to address the effects of climate change. However, some of the reviewed methods require time to become widespread. For instance, air-to-air refuelling for aircraft is one solution to reduce the seriousness of climate change. However, this newly proposed method requires time for widespread adoption. Hence, short-term approaches have to be examined.

Trajectory optimisation, a subtopic under operations, will be the primary focus of this thesis. It involves using specific indexes to form flight mechanical equations and to create optimal flying trajectories through optimal parameters using equivalent mathematical methods (Huang et al., 2012). This is one of the stages in air traffic flow management (ATFM) (Dal Sasso et al., 2019).

The concept of ATFM has existed for several decades. During this period, extensive research has been conducted in various directions, summarised by Kistan et al. (2017). In their paper, four major areas have been identified: airport, approach, en-route, and regional. Each area includes sub-areas have been individually identified. Optimised trajectories under the approach section will be the focus of this thesis, according to the divisions from Kistan et al. (2017).

To the best of my knowledge, planes could only fly in sunny weather before 1933 (Gilbert, 1973). With the development of advanced technology, planes can now travel in various weather conditions. However, the effects brought by these events are unforeseeable.

In recent years, several scholars have focused on trajectory optimisation related to adverse weather conditions to mitigate these effects. Rodríguez-Sanz et al. (2022) reviewed the relationship between weather and flight operations. Yet, they stated that a network view had to be implemented to provide a more strategic approach. Zeng et al. (2021) developed a data-driven model to optimise flight schedules. Integration of sector capacity and delay propagation were some areas to be extended from the original work. Aditya et al. (2024) formulated a static model for the departures and arrivals' optimisation, and the consideration for delays with weather-related disruptions could be included in their research. Therefore, it is necessary to conduct further investigation on optimisation models related to weather uncertainties.

1.2 Contribution

This research aims to answer two questions:

1. For predictable extreme weather events (like tropical storms), how can we reschedule the flight routes to ensure punctual departures and arrivals at airports?
2. For unpredictable extreme weather events (like rainstorms), how should we react when the event occurs, and how can immediately reschedule flights?

Understanding how to reschedule the flight routes under predictable weather events can improve flight punctuality since rerouting with a shorter distance is expected. Though some delays may still occur due to overloading capacities, the number of recorded delays should be minimised.

Meanwhile, rescheduling beforehand is less feasible for unpredictable meteorological conditions due to their unpredictability and dynamic nature. However, actions can be achieved once the situation changes. This should mitigate the effects of weather events, thereby reducing the number of delays recorded.

Therefore, the three goals of this research are as follows:

1. To design networks to better handle adverse weather conditions within a specific airspace. A significant number of airports are in the area, some of which are busy. Thousands of flights take off, land, or transit through the area. The designed network should help organise the routing properly.
2. To derive optimisation models to minimise the effects of extreme meteorological events. The proposed model should reduce the impact of weather events on the flights, benefiting airlines.
3. To reduce the likelihood of aircraft being affected by different kinds of extreme meteorological events by the designed optimisation model and to improve the punctuality performance of flights. While people cannot control or accurately predict the occurrence of many weather events, reactions to these events can be conducted when there is a possibility that they will occur.

1.3 Outline of the thesis

The remaining thesis is organised as follows. The state of the art, including the literature review, development and trends of the terminal manoeuvring area (TMA), a brief introduction to local traffic regulations, and the characteristics of related TMA, is introduced in Chapter 2. Chapter 3 discusses the methodology used for the models in response to the first research question. Chapter 4 proposes a joint optimisation model for unpredictable weather events. The conclusion and future works are presented in Chapter 5.

Chapter 2 The State of The Art

In this chapter, literature on flight trajectory optimisation, air traffic flow management, terminal traffic flow problems (TTFPs), aircraft landing problems (ALPs), the combination of TTFP and ALP, and optimisation problems concerning uncertainties will be reviewed. The International Civil Aviation Organisation (ICAO) has regulations for every state to ensure a high safety standard. Each country or city might have minor differences from one another. A brief review of the airspace and a detailed review of the terminal manoeuvring area, including the development and trends of TMA, and traffic regulations and the characteristics of TMA, will therefore be discussed.

2.1 Literature Review

2.1.1 Flight Trajectory Optimisation

Flight trajectory refers to the paths of flights, including the departure, en-route, and approach stages. In typical situations, there are waypoints for flights to follow so that they can travel through all required waypoints to reach their destinations. However, air traffic control officers (ATCOs) can also communicate with the pilots for rerouting and vice versa. For instance, when a flight is expected to experience severe turbulence, pilots can request a change in flight level or direction to avoid the turbulence. Hence, flight trajectory optimisation is necessary. Numerous scholars have conducted research in this area.

Tsuchiya et al. (2009) developed a real-time flight trajectory optimisation model using nonlinear programming. Their goal was to apply it to emergency situations, though they did not achieve this goal. Wickramasinghe et al. (2014) presented a mathematical model to improve the operational performance of domestic flights in Japan using equations of motion. They discovered that flight time was extended in their model if fuel consumption was reduced. Gardi et al. (2014) presented a multi-objective 4D optimisation problem framework to obtain the optimal trajectory with relevant cost functions, which was extended in their later research (Gardi et al., 2016). Their paper used dynamic constraints, path constraints, and boundary conditions in their model formulations. A statistical approach was adopted by Patrón et al. (2014) in evaluating flight costs, which include the sum of fuel burned, cost index, and flight time. Their objective was to reduce carbon emissions through the minimisation of flight costs. An aircraft trajectory optimisation algorithm that combined time- and energy-managed operations was developed by Prats et al. (2015). Their objective was to minimise fuel consumption, noise, carbon emissions, etc., while reaching the required times of arrival with at least one waypoint.

From the above scholars, it is noticeable that even for flight trajectory optimisation problems, there are numerous ways to tackle them, including programming models, equations of motion, and control theories. Each method represents a different approach to tackling the same problem – the flight trajectory optimisation problem. In every optimisation problem, the objective obtained is different. Some focus on the airline and airport perspectives, while others focus on the environmental perspective, including carbon emissions. This thesis adopts the network programming model approach to achieve objectives related to airline and airport aspects. Hence, relevant papers are reviewed in Section 2.1.2.

2.1.2 Air Traffic Flow Management Problem

ATFM refers to the management of air traffic flow to minimise delays and maximise airspace usage within a certain area, considering regulations in different states (Chen et al., 2024; Philipp & Gainche, 2005). Significant research has been conducted to address ATFM challenges. Bertsimas and Patterson (1998) presented an integer programming model to minimise total delay costs in the U.S. airspace, focusing on the en-route stage and the capacities for departures and arrivals. The departure and arrival of aircraft were considered through the total number of capacities being able to undertake. Lulli and Odoni (2007) proposed a deterministic optimisation model to minimise ground and airborne delays in the European airspace, which generally limited the movement of aircraft crossing through sectors. De Giovanni et al. (2024) proposed an integer programming model to minimise airborne delays, considering multiple routes from the origin to the destination and the variation of airspace capacities. These studies highlight the diverse methodologies employed to tackle ATFM problems, ranging from integer programming to deterministic optimization. Two common approaches have been identified in the reviewed research.

Sectorisation is a common technique used in ATFM problems since the problem usually considers a large area of airspace. Developing sectors in an airspace consider the combination of air traffic management, users, and the environmental considerations (Gerdes et al., 2018). By utilizing airspace sectors, aircraft can fly more efficiently from origin to destination (Soh & Zhong, 2020). However, as the number of flights increases while sector capacities remain unchanged, sectors can become overwhelmed. To address this issue, various research efforts have been undertaken. Bertsimas and Patterson (2000) introduced an integer programming model to minimise delay costs. In their paper, the sectorisation of airspace in the U.S. was considered, and the capacities of sectors varied due to the effect of weather events. Xu et al. (2020) integrated four different models to minimise the total delay of aircraft due to the excess demand for airspace. In their paper, they considered the French airspace, and through sectorisation, the aircraft could avoid the congested sectors and reroute. Agustı et al. (2012) proposed a deterministic mixed-integer programming model to minimise the delay cost of flights. They considered capacities of sectors in their model, and alternative routes were examined if the capacities were full. The stochastic case from their paper was also investigated with the uncertain capacities (Agustı´n et al., 2012). Corolli et al. (2017) proposed a two-stage stochastic integer programming model for ATFM to minimise the total delay costs. This model aims to address the uncertainty in air traffic demand and capacity by considering multiple scenarios. These studies highlight the necessity of adaptive and robust airspace sectorisation strategies to manage increasing flight volumes.

The development of network models is another common approach used by scholars in the optimisation of ATFM. In network models, nodes and links represent the transitions of capacities (Bell & Iida, 1997). Bertsimas et al. (2011) proposed an ATFM rerouting problem using the network flow problem approach to minimise ground holding and airborne costs. Their approach aimed to handle a large number of flights in the considered area. García-Heredia et al. (2019) presented a combinatorial optimisation model for ATFM, utilising the network model to minimise the operation costs. The use of the network in their paper helped simplify the complexity of the model, enhancing the efficiency of computations. Cai et al. (2017) proposed a multi-objective air traffic network flow optimisation model to minimise airspace congestion and delay costs. The network framework in their paper facilitated the analysis of different traffic scenarios, including variations in flight demand and airspace capacity. These studies demonstrate that the network approach provides the benefit of more realistic and systematic traffic flow models. Despite the increase in preparation work required for formulating the models, since the network approach demands a significant amount of input data for calibrations, it remains the most common approach in programming models.

2.1.3 Terminal Traffic Flow Problem

Other than flight rerouting, the schedule of flights may also change due to different flight routes. Therefore, TTFP, which refers to the sequences of departure and arrival flights and the sequences of when the flights are on the ground, has to be formulated to achieve the objectives (Ng et al., 2019).

D'Ariano et al. (2015) proposed a real-time aircraft scheduling model using the alternative graph. Various algorithms were evaluated in the paper, and the branch and bound algorithm was concluded to be the most effective among those studies. Zhou and Jiang (2015) presented a multi-objective real-time nonlinear programming model, which had been linearised, to minimise the weighted delay cost of arrival flights and quantify the workload of ATCOs. The genetic algorithm, first-come-first-served approach, and an optimised algorithm proposed by the scholars were used for comparison through the formulated models. The optimal result for minimising the weighted delay cost was observed when using the genetic algorithm, while the optimised algorithm was the most effective in minimising of the workload of ATCOs. Ng et al. (2021) proposed another real-time two-stage robust optimisation model aimed to control the traffic flow of arrival flights, thus reducing the effort needed from the ATC to reschedule the aircraft. The first stage of the model formulated the basic structure, while the second stage incorporated possible robustness into the model. Various decomposition approaches were suggested for the computation, with the min-max criterion is concluded to be the best for minimising the effects caused by weather uncertainties in their study.

The studies have employed different types of heuristic algorithms in solving the programming problems and optimising the corresponding objectives. By addressing TTFP, these approaches could enhance the efficiency of airports and air traffic control, reduce delays and improve overall safety and reliability. Therefore, adapting to increasing air traffic demands and evolving technological landscapes is crucial.

2.1.4 Aircraft Landing Problem

This section focuses on the ALP, which refers to the runway landing sequence and the schedule of arriving flights (Salehipour et al., 2013).

Lieder et al. (2015) proposed a mixed-integer programming formulation and a dynamic programming approach to solve the problem. The model formulation aimed to minimise the total delay cost of all landing aircraft, which involves classification of aircraft on multiple runways. Liu et al. (2018) introduced a two-stage stochastic programming approach for the ALP. In the first stage, the sequence of the aircraft weight classes is determined, while in the second stage, position assignment is performed for individual flights. Monte Carlo simulation was used to evaluate the model results. Rogovs et al. (2022) presented a mixed-integer linear programme to minimise the sum of weighted deviations from the planned landing times of aircraft. Their paper analysed complexity reduction and considered multiple runways. Silva et al. (2023) presented a mathematical formulation using the job shop scheduling approach to minimise the earliness and tardiness in aircraft landing times. Their study compared the model with those constructed by other scholars, which used different separation constraints. Their paper also employed a metaheuristic approach to address problem size that includes a large number of aircraft.

The above papers have formulated the ALP and identified different objective functions for optimisation, including delay and tardiness costs. By addressing this problem, these approaches can enhance scheduling efficiency, reduce delays and improve utilisation. This is crucial for ensuring that landing strategies remain effective and sustainable in a rapidly evolving aviation landscape.

2.1.5 Combination of ALP and TTFP

The combination of ALP and TTFP has also been developed in recent years. Huo et al. (2021) proposed an optimisation model within the TMA of Paris to enhance the efficiency of arrival flights. Another paper by Huo et al. (2023), which extends the work of Huo et al. (2021), presented a dynamic optimisation model to improve the efficiency and safety of arriving aircraft using the concept of the Extended Arrival MANager (E-AMAN). In their paper, they considered flights arriving at the same airport within a range of 500 NM. In both papers, the solution approach was simulated annealing. Chen et al. (2020) proposed a stochastic integer linear programming model to maximise airport throughput and flight quality of service. Their paper considered both departure and arrival flights in Shanghai, with simulations conducted using Monte Carlo methods. Samà et al. (2013) addressed a real-time aircraft scheduling optimisation problem in the TMAs of Rome Fiumicino and Milan Malpensa to minimise flight delays. They compared first-come-first-serve (FCFS) strategy and the branch-and-bound method in their paper.

By addressing this problem, more efficient and coordinated airport operations can be achieved, which is crucial for managing the complexities of modern air travel.

2.1.6 Optimisation problem under uncertainties

Various factors, including severe weather, air traffic delay propagation, technical challenges, and security considerations, introduce variability in the ETA for aircraft. Consequently, this uncertainty affects the input data for runway scheduling operations. Extensive numerical research has been conducted to address traffic flow problems under various uncertainties, particularly in the aviation sector, where efficient flight scheduling is crucial.

Khassiba et al. (2020) proposed a two-stage stochastic mixed-integer programming model to minimise the makespan of flights. In their paper, they consider the actual flying time of aircraft as an uncertainty, and Benders decomposition was used to solve the model. Chen et al. (2017) proposed a stochastic integer programming model to minimise flight delays. The brute-force mixed-integer linear programming model was employed as the solution method in their paper. Huo et al. (2021) presented an optimisation model within the TMA to enhance the efficiency of arrival flights. A simulation model based on the Monte Carlo method was used to evaluate the results. Solak et al. (2018) proposed a two-stage stochastic runway scheduling algorithm considering early arrival uncertainties. A probabilistic vector was introduced in their paper converted to the form of expected value for the modelling purposes. Ng et al. (2020) proposed a two-stage stochastic programming model minimising the penalty costs, considering aircraft flight time as an uncertainty. Comparisons were performed between several computational methods. Ng et al. (2021) considered weather conditions as uncertainties in the construction of a two-stage robust optimisation model. When considering uncertainty, the optimisation model could become either stochastic or robust to account for various specific factors. For example, severe weather conditions may affect the arrival time of aircraft at a particular waypoint, leading to flight delays.

These studies highlight the diverse methodologies employed to tackle uncertainties in flight scheduling, ranging from decomposition techniques to brute-force optimization and simulation models. The results from these studies emphasise the potential of stochastic and simulation-based approaches to improve traffic flow under uncertainty, which is crucial for addressing the inherent variability and unpredictability in many real-world problems.

2.2 Airspace and Traffic Regulations

2.2.1 Development of Airspace

Airspace is defined as the airspace above a country and its territorial waters, extending 12 nautical miles from its coastline (Kareng, 2020). International airspace, which refers to airspace not within any nation's jurisdiction, is managed by countries based on signed international agreements. Therefore, the size of airspace varies in each country. According to ICAO (2018a), airspace is further classified into seven classes (namely Class A to Class G), where each state selects the classes based on its needs. Thus, the establishment of airspace is nationally based. Based on the regulations adopted by ICAO, each state can develop its own guidelines and regulations suitable for its operations.

2.2.2 Development and Trend of TMA

According to ICAO (2013), TMA is defined as the airspace surrounding an airport and within its air traffic control service area. Various factors, such as the number, length, and duration of departure or arrival trajectories, runway system capacity, and operational rules, affect the size of the TMA in each state (Chandra et al., 2022). In each TMA, standard instrument departures (SIDs) and standard terminal arrival routes (STARs) are published by the state (Netjasov et al., 2011). These documents include details such as the speeds and altitudes at each waypoint and the paths that flights should travel in the TMA. Hence, standards and procedures are well-defined in every TMA to ensure every flight can easily follow the designed path.

With the development of airports, the size of the TMA may change when the aforementioned factors change, and the SIDs and STARs may also be updated accordingly to facilitate a better flow of aircraft. For instance, the Hong Kong International Airport (HKIA) began construction of a third runway in 2016, and the runway became operational in 2022 (HKIA, 2022). The corresponding documents, including the STAR and SID for the third runway, have been updated accordingly (HKCAD, 2021a, 2023). Figure 2-1 and Figure 2-2 show the STARs in HKIA before and after the commencement of the third runway and reconfiguration of the centre runway. Slight changes in waypoints, arrival, and go-around routes have been observed from the STARs. Thus, after different considering factors such as terrain of the state and the potential flight paths, flight routes may require redesign. For airports that remodel of flight routes, the TMA may change correspondingly so that the airports and ATCOs can monitor flight movements effectively. As the number of passengers is predicted to rise, it is expected the number of runways will increase in the future to enhance the airport runway capacity (Ali et al., 2023; Ricardianto et al., 2022). Hence, the TMAs of states are expected to change continuously to fulfil the demands of the states.

2.2.3 Traffic Regulations and the Characteristics of TMA

In the aviation industry, regulations are established to ensure safety. ICAO has published several regulations, including those related to aircraft standards, flight rules, and airspace division. Based on these regulations, each state can adapt and modify them according to their specific circumstances. In this section, traffic regulations in Hong Kong and its characteristics of the TMA are introduced and discussed.

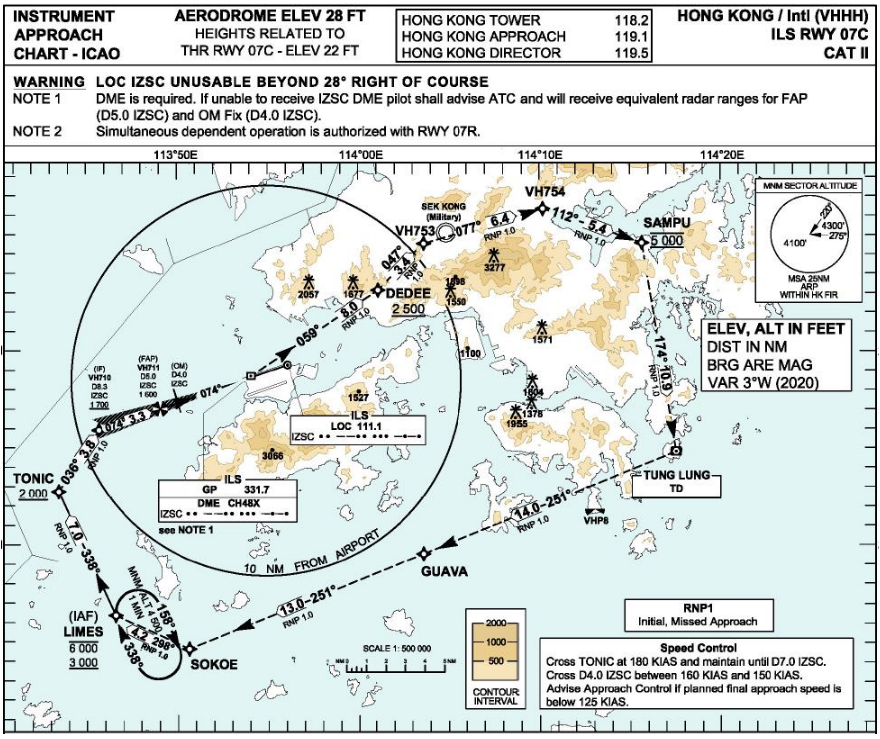

Figure 2-1: STAR of HKIA before the commencement of the third runway.

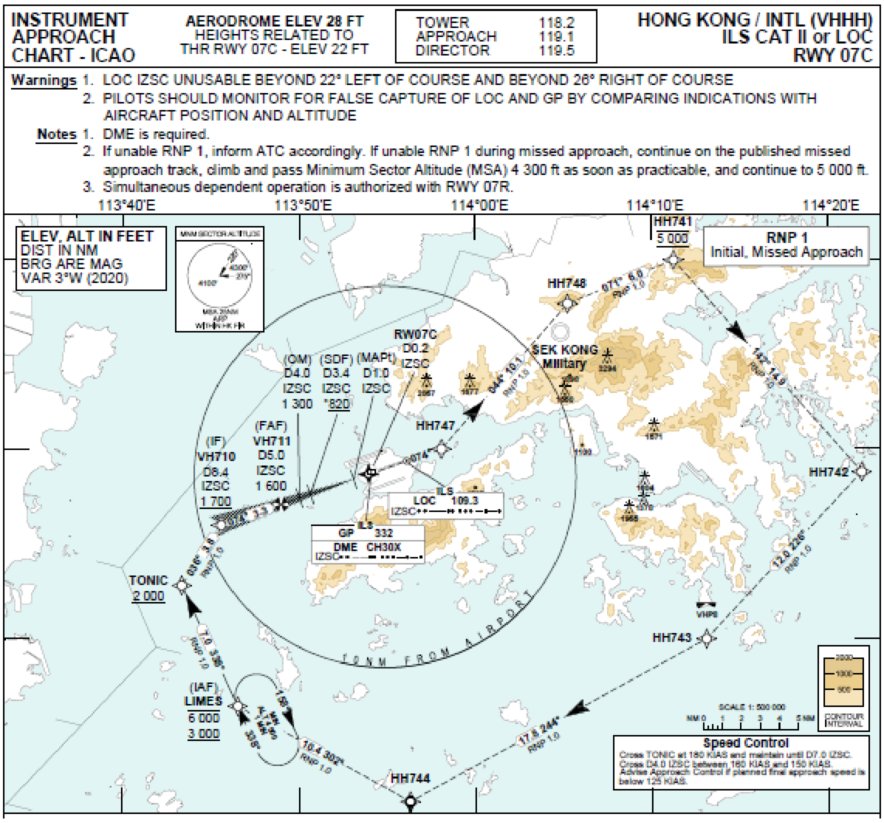

Figure 2-2: STAR of HKIA after the commencement of the third runway.

In Hong Kong, the Civil Aviation Department (HKCAD) monitors the air transport system to ensure safety, efficiency, and sustainability (HKCAD, 2021b). Consequently, regulations and standards are established by the HKCAD and are published through the Aeronautical Information Publication (AIP) Hong Kong (HKCAD, 2023). During the preparation stage, the HKCAD has referenced the documents listed below. Any differences between these documents and the AIP Hong Kong are also presented in the document (GEN 1.7).

List of Documents

- The Standard and Recommended Practices (SAPRs) of Annex 15 to the Convention on International Civil Aviation
- The Aeronautical Information Service Manual (ICAO Doc 8126)
- Procedures for Air Navigation Services – Aeronautical Information Management (ICAO Doc 10066)
- SAPRs of Annex 4 to the Convention on International Civil Aviation
- The Aeronautical Charts Manual (ICAO Doc 8697)

The AIP Hong Kong includes well-defined and detailed information. Updates to the AIP Hong Kong are conducted whenever the ICAO announces new regulations or policies to the states. The following sections extract and discuss relevant information related to this thesis.

2.2.3.1 Separation Minima Requirements

The ICAO has proposed various separation minima requirements to ensure flight safety, with each type serving a different purpose.

Wake turbulence separation minima, used when the flight is in the en-route stage of flight, is one of such types. The purpose of developing wake turbulence separation minima is to mitigate potential hazards caused by wake turbulence, including induced roll, loss of height or rate of climb, and possible structural stress (ICAO, 2021). Therefore, adhering to wake turbulence separation minima is essential. Table 2-1 presents the distance-based wake turbulence separation minima as outlined in the AIP Hong Kong (HKCAD, 2023). This separation is applicable during the departure and approach stages of the flights. In recent years, recategorisation has led to the formation of an enhanced wake turbulence separation minima standard. However, this standard would not be applied in this thesis.

		Trailing Flight			
		Super	Heavy	Medium	Light
Leading Flight	Super	-	5 NM	7 NM	8 NM
	Heavy	-	4 NM	5 NM	6 NM
	Medium	-	-	-	5 NM
- Indicates wake turbulence separation is not applicable					

Table 2-1: Distance-based Wake Turbulence Separation Minima

From Table 2-1, it can be observed that separation minima apply only in certain situations, typically when the category of the leading flight is higher than that of the trailing flight. No wake turbulence separation minima are required in the reversed order. It is believed that the effects caused by a lighter aircraft on a heavier aircraft are limited, so the separation minima requirement does not apply in this situation.

Another type of separation is the minimum inter-arrival spacing. The purpose of developing inter-arrival spacing is to ensure the basic safety requirement between flights. In Hong Kong, according to HKCAD (2023), the minimum inter-arrival spacing is 3.0 NM, subject to wake turbulence separation minima. Therefore, Table 2-1 can be modified to show the complete separation minima, which is presented in Table 2-2.

From Table 2-2, it is observed that the minimum separation between any flights is at least 3 NM. However, it should be noted that this requirement is the minimum requirement. If there are any unforeseeable factors, such as adverse weather conditions, the separation between the flights should be increased to ensure flight safety.

		Trailing Flight			
		Super	Heavy	Medium	Light
Leading Flight	Super	3 NM	5 NM	7 NM	8 NM
	Heavy	3 NM	4 NM	5 NM	6 NM
	Medium	3 NM	3 NM	3 NM	5 NM
	Light	3 NM	3 NM	3 NM	3 NM

Table 2-2: Distance-based Separation Minima Requirement

Other types of separation minima, including vertical separation minima, will not be discussed in this thesis.

2.2.3.2 Standard Terminal Arrival Routes

The TMA of Hong Kong covers a large area. Figure 2-3 shows the TMA of Hong Kong, which is bounded by the white region. STARs are issued separately for the red lines by the Hong Kong Civil Aviation Department (HKCAD, 2021a). The STARs are established for pilots and ATCOs to ensure a safe approach and landing stage for every flight. Various information is included in the STARs, such as flight routes, speed and altitude limitations, holding points and waypoints, go-around paths when necessary, distances between waypoints, headings, and general notes to. This provides the basis for setting up parameters and model construction frameworks in the thesis.

Four main flight paths can be identified from the STARs, with ABBEY from the east, BETTY from the south, and CANTO and SIERA from the west as the entry waypoints. Notably, there are two paths where the entry waypoint is SIERA, but the one passing through BORDA and ROCCA is used less frequently and is combined with the one from SIERA directly to CANTO. Based on multiple factors, including weather, the selection of which runway to use for landing would vary, and the go-around path would also vary.

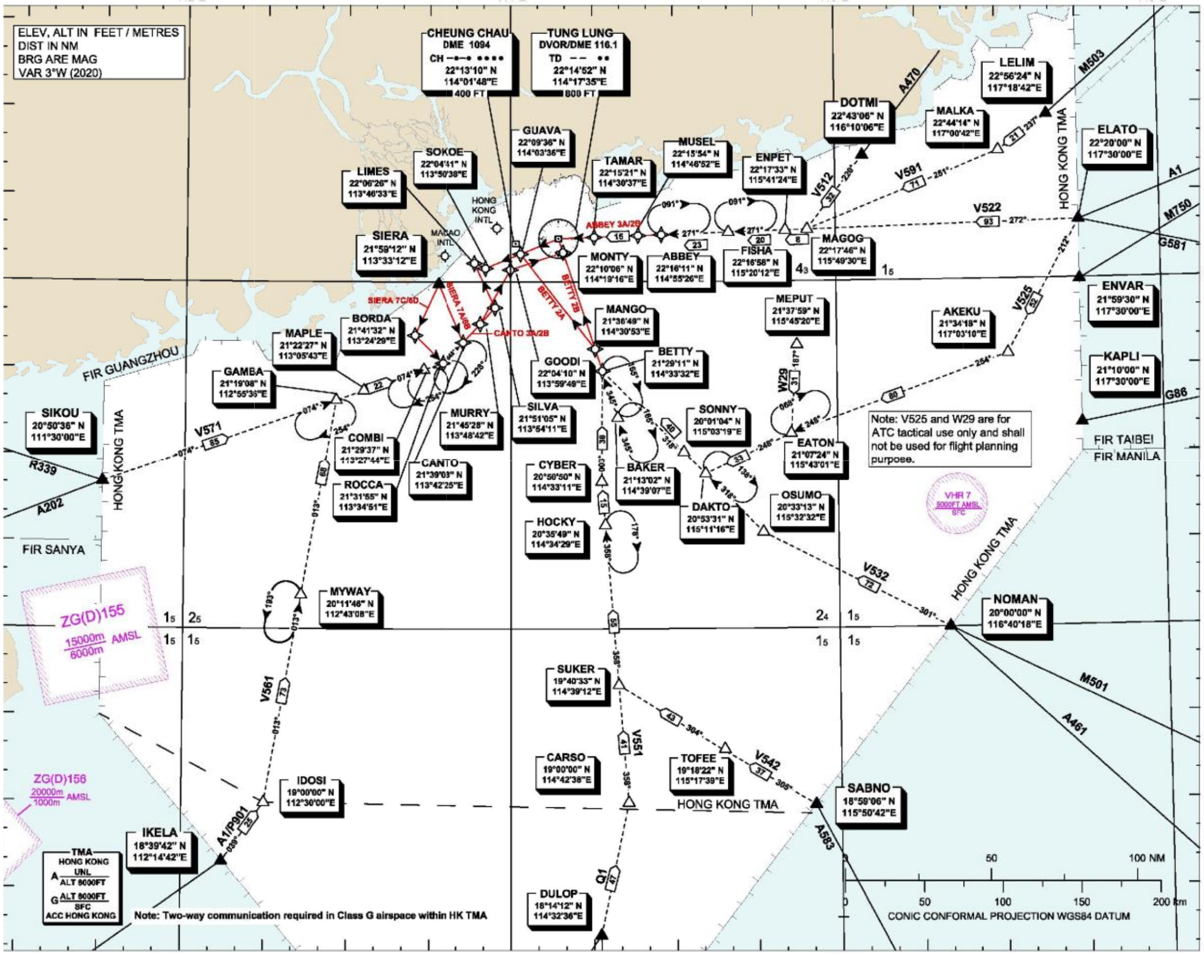

Figure 2-3: TMA of Hong Kong (HKCAD, 2021a)

2.3 Concluding Remarks

Numerous approaches have been explored by scholars in conducting research related to flight trajectory optimisation. Each of these approaches has its benefits and drawbacks. Direct comparation was unproductive due to differing foundations and backgrounds. In this thesis, optimisation programming models utilise both sectorisation and network technique in their formulation.

With this foundation, the AFTM, the TTFP and the ALP have been separately reviewed. In these problems, different approaches were adopted by scholars to achieve their goals. The combination of TTFP and ALP, as well as optimisation under uncertainties, have also been reviewed. By reviewing the above literature, foundations have been constructed for the formulation of the two-stage stochastic optimisation models in response to the research questions.

A brief review of airspace is included to provide a foundation for the discussion of the TMA. The development and trends of the TMA are then reviewed. Factors affecting the development of the TMA have been discussed, and examples have been included to illustrate these trends. Traffic regulations and the characteristics of the TMA in Hong Kong are presented. Different requirements, including separation minima and STARs, have been studied in this section. The discussion of airspace and the TMA provides a basis for developing the parameters to be inserted into the proposed mathematical models.

Chapter 3 Two-stage Stochastic Optimisation Model for Air Traffic Flow Management under Tropical Storms

With the increasing number of weather-related events, recorded flight delays continue to raise. While the occurrence and intensity of these weather events cannot be controlled, it is expected that the number of flight delays will continue to increase. Thus, it is essential to address this challenge. One frequently occurring weather event is tropical storms, whose trajectories are comparably stable and easier to predict. Therefore, in this chapter, a two-stage mixed-integer stochastic optimisation with the consideration of the effects of tropical storms is proposed in maximising the punctuality of flights in the selected area of southeastern China. Punctuality of flights includes both departing and arriving flights. Four different weather scenarios were generated from the stochastic model as uncertainties, affecting the capacities of sectors. The performance of the proposed stochastic model is satisfactory in maximising the punctuality of flights.

3.1 Introduction

Weather-related issues are a significant concern in aviation, impacting both safety and efficiency. Based on the report from the NTSB (2022), 23% of aircraft accidents from 2008 to 2020 were related to weather events, with 23% of these weather-related accidents being fatal. Among all weather-related accidents, adverse wind had accounted for 52%. The research by Long (2022) also revealed an increasing trend of fatal accidents related to weather, rising from 11% to 25% between 2016 to 2018. Other than aircraft accidents, flight delays, which are defined as delays that are more than 15 minutes than the scheduled times, are also an important key performance indicator in aviation. According to Bureau of Transportation Statistics (2024), flight delays in America from 2015 to 2023 reached 17.58%, where 51.84% of these delays in the national aviation system are caused by weather. Thanks to climate change, the number of extreme weather events is increasing (Burbidge et al., 2024). Therefore, it is expected that the number of weather-related accidents and flight delays will increase in the future.

While most weather events are difficult to predict accurately, the development and trajectories of some, such as tropical storms (or tropical cyclones), are relatively more stable (Jaseena & Kovoor, 2022; Liu et al., 2023). Thus, preparations can be performed before the tropical storms occur to mitigate the effects caused by the predictable weather events, including flight delays. With the increasing number of adverse weather conditions, it is essential to reduce flight delays.

Seldom do commercial flights fly over the tropical storms due to potential unpredictable influences (Jun et al., 2024). For example, the development of storms changes significantly, potentially affecting the safety of flights, or aircraft may experience severe turbulence (DesRosiers et al., 2023; Ming et al., 2023). This is another reason for avoiding the tropical storms in the consideration of the flight trajectory. In addition to operational effects, airport infrastructure, including the airport terminals and navigation equipment, can also be damaged by the storms (Pümpel, 2016). Tropical storms typically brings not only strong winds but also other effects such as storm surges, heavy precipitation, crosswinds, and gusts (Ayyad et al., 2023; Collins & Walsh, 2019; Shah et al., 2023; Spiridonov & Ćurić, 2021). These events would affect both the aircraft operations, including take-off and landing, and also ground services. Flight procedures are often suspended due to tropical storms, leading to cancellation and delays. Therefore, it is crucial to develop strategies to mitigate the effects of tropical storms on aviation.

Given this context, a two-stage mixed-integer stochastic programming model is proposed for the en-route stage of flights to maximise the punctuality of flights while considering sector capacity under the effects of tropical storms. The contributions of this paper are outlined as follows.

1. A two-stage mixed-integer optimisation model is proposed, considering the presence of tropical storms, to maximise the punctuality of flights.
2. A numerical study is conducted to analyse the performance of the model. The performance of the stochastic model is concluded to be satisfactory in maximizing the punctuality of the flights.

The remaining of the paper is organised as follows. Section 3.2 presents the problem description and the proposed two-stage mixed-integer stochastic programming model. The computational framework and experimental setup are proposed in Section 3.3. Section 3.4 includes the computational results and a discussion of its value. The conclusion and future work are provided in Section 3.5.

3.2 The Two-Stage Mixed-Integer Stochastic Programming Model

3.2.1 Problem Description

The proposed model considers the movements of flights in the en-route stage. Consider a set of flights I, each flight $i \in F$ has an assigned departure time $\mathrm{dt_i}$ and assigned arrival time $\mathrm{at_i}$. Each flight should depart from its origin sector $\mathrm{orig_i}$ within the time period $[dt_i - t_c, dt_i + t_c]$, where t_c refers to a 15-minute interval, and arrive at its destination sector $dest_i$ within the time period $[at_i - t_c, at_i + t_c]$. In between each flight, the flight should pass through certain sectors $k \in K$ within its maximum flight time f_i. Each flight requires at least s_{ilk} time to travel from sector k to sector l. After arriving at the destination sector (and assuming the aircraft is landed), a preparation time p_j is required for the flight to depart again from the airport.

In each sector, there is a maximum sector capacity S^k. For sectors containing airports, the capacities for departing flights D^k and arriving flights A^k are also included. Concerning the effects caused by the tropical storms, the severity of how a tropical storm affects a sector is represented by a random variable ω_t^k. If the random variable ω_t^k approaches to 1, it means that the sector is severely affected, and no flight can enter sector k at time period t.

Table 3-1 presents the definition of the notations for the proposed model.

3.2.2 Mathematical Formulation of Optimisation Model

The mathematical formulation of the two-stage optimisation model based on the problem description and notations is proposed.

Set of Indices	Explanations
I	set of flight
T	set of time period
K	set of sectors
P	Collection of possible paths for the tropical storm trajectories (must be adjacent sectors)
C	Set of adjacent sectors
C_T	Set of adjacent sectors that tropical storms would pass through
Parameters	**Explanations**
i, j	flight $i, j \in I$
t	time period $t \in T$
k, l	sector $k, l \in K$
D^k	capacity of departure of an airport in sector k
A^k	capacity of arrival of an airport in sector k
S^k	sector capacity at sector k
f_i	Maximum flight time for flight i
$orig_i$	Origin sector of the flight i
$dest_i$	Destination sector of flight i
p_j	The preparation time for flight j to depart from the airport
p^k	Probability that tropical storm would occur in sector k
dt_i	Assigned departure time of flight i
at_i	Assigned arrival time of flight i
t_c	Constant – 15 minutes interval
α	Constant – 10%
β	Constant – 0.75

Decision Variables	Explanations
$x_{i,t}^{k}$	1, if flight i at time period t is in sector k; 0, if otherwise
y_{t}^{k}	1, if a tropical storm occurs in sector k at time period t; 0, if otherwise
d_{i}^{k}	1, if it falls into the range $[dt_i - t_c, dt_i + t_c]$; 0, if otherwise
a_{i}^{k}	1, if it falls into the range $[at_i - t_c, at_i + t_c]$; 0, if otherwise
$punc_i$	1, if flight i is punctual at its departure and its arrival; 0, if otherwise
Random Variable	**Explanations**
ω_{t}^{k}	Continuous, the effect of weather convention that would cause route capacity deficiency at time period t in sector k

Table 3-1: Definition of notations for the proposed model.

3.2.2.1 First Stage Model

Based on the definition of notation in Table 3-1, the first stage of the propose stochastic programming model is presented.

$$max \sum_{i} punc_i + \mathbb{E}[\gamma] \tag{3.1}$$

$$s.t. \quad \sum_{i \in I} x_{i,t}^{k} \leq D^k, \forall k \in K, \forall t \in T, t > 0, k = orig_i \tag{3.2}$$

$$\sum_{i \in I} x_{i,t}^{k} \leq A^k, \forall k \in K, \forall t \in T, t > 0, k = dest_i \tag{3.3}$$

$$\sum_{i \in I} x_{i,t}^{k} \leq S^k, \forall k \in K, \forall t \in T, k \neq l \tag{3.4}$$

$$\sum_{k \in K} x_{i,t}^{k} \leq 1, \forall i \in I, \forall t \in T \tag{3.5}$$

$$x_{i,t-1}^{k} - \sum_{\substack{l \in K \\ (k,l) \in C}} x_{i,t}^{l} \leq 0, \forall i \in I, \forall k \in K, \forall t \in T \tag{3.6}$$

$$x_{i,t}^{orig_i} - x_{i,t+f_i}^{dest_i} \leq 0\ , \forall i \in I, \forall t \in T \tag{3.7}$$

$$x_{i,t}^{k} - x_{j,t-p_j}^{l} \leq 0\ , \forall i \in I, \forall t \in T, \forall k, l \in K, i \neq j, k \neq l \tag{3.8}$$

$$d_i^{orig_i} - \sum_{t=dt_i-t_c}^{dt_i+t_c} x_{i,t}^{orig_i} \leq 0, \forall i \in I \tag{3.9}$$

$$a_i^{dest_i} - \sum_{t=at_i-t_c}^{at_i+t_c} x_{i,t}^{dest_i} \leq 0, \forall i \in I \tag{3.10}$$

$$punc_i \leq d_i^{orig_i}, \forall i \in I \tag{3.11}$$

$$punc_i \leq a_i^{dest_i}, \forall i \in I \tag{3.12}$$

$$x_{i,t}^k \in \{0, 1\}, \forall i \in I, \forall k \in K, \forall\, t \in T \tag{3.13}$$

$$d_i^k, a_i^k, punc_i \in \{0, 1\}, \forall i \in I \tag{3.14}$$

Objective function (3.1) maximised the number of punctual flights, where a punctual flight is considered if it departs from its assigned origin airport and arrives at its assigned destination airport with no more than 15-minute delay, while minimising the effects caused by the tropical storms. Constraint (3.2) restricted the number of departing flights in sector k in time period t to be less than the maximum capacity for departures at the airport in sector k in time period t. Constraint (3.3) restricted the number of arriving flights in sector k in time period t being less than the maximum capacity for landings at the airport in sector k in time period t. Constraint (3.4) restricted the number of flights in sector k in time period t to be less than the maximum capacity of sector k, particularly referring to the transition flights, in time period t. Constraint (3.5) ensured that flight i can only occupy one sector k at time period t. Flight plan of flight i is ensured by Constraint (3.6). The maximum flight time is ensured by Constraint (3.7). Paired flights are considered by Constraint (3.8), which accounts for the preparation time required for flight *j* after flight i has landed if the same aircraft is used. Constraint (3.9) determined if flight i falls within the range of punctuality for departure. Constraint (3.10) determined if whether flight i falls into the range of punctuality for arrival. Constraints (3.11) and (3.12) enforced that if flight i is punctual in its departure and arrival stages, it is regarded as punctual. Constraints (3.13) and (3.14) are the variable boundary constraints.

3.2.2.2 Second Stage Model

In this second stage of the model, the trajectories of the tropical storms are included as uncertainties, and the proposed model is presented.

$$\mathbb{E}[\gamma] = min \sum_{t \in T} \sum_{k \in K} \omega_t^k y_t^k \tag{3.15}$$

s. t. Constraints (3.5) - (3.12)

$$\sum_{i \in I} x_{i,t}^k \leq D^k (1 - \omega_t^k y_t^k), \forall k \in K, \forall t \in T, t > 0, k = orig_i \tag{3.16}$$

$$\sum_{i \in I} x_{i,t}^k \leq A^k (1 - \omega_t^k y_t^k), \forall k \in K, \forall t \in T, t > 0, k = dest_i \tag{3.17}$$

$$\sum_{i \in I} x_{i,t}^k \leq S^k (1 - \omega_t^k y_t^k), \forall k \in K, \forall t \in T, k \neq l \tag{3.18}$$

$$\sum_{k \in K} y_t^k \geq 1, \forall t \in T \tag{3.19}$$

$$\sum_{k \in K} p^k y_1^k \geq \alpha \tag{3.20}$$

$$\beta \leq \sum_{k \in K} \omega_t^k y_t^k \leq 1, \forall t \in T \tag{3.21}$$

$$y_{t-1}^k - \sum_{\substack{l \in K \\ (k,l) \in C_T}} y_t^l \leq 0, \forall k \in K, \forall t \in T \tag{3.22}$$

$$y_t^k \in \{0, 1\}, \forall k \in K, \forall\ t \in T \tag{3.23}$$

$$\omega_t^k \in [0, 1], \forall t \in T, \forall k \in K \tag{3.24}$$

Objective function (3.15) minimised the effects caused by the weather conditions. The random variable ω_t^k is included since the effect caused by a tropical storm varies, which is a random event in the model. Therefore, the impact on the sector also varies and depends on the tropical storm. If ω_t^k equals 1, it means that the sector is severely affected by the tropical storm, so no flights would be landing at the airport in sector k. Otherwise, flights would be landing. Constraint (3.19) ensured that at least one tropical storm occurs, while Constraint (3.20) ensured that the tropical storm occurring in the model has a probability of at least α in the first time period concerned. Constraint (3.21) restricted that the weather condition's effect is limited to 1, but greater than β since limited effects are caused to aircraft if the weather condition's effect is constrained. Constraint (3.22) ensured that the effect of the weather condition is centered at sector k at time period $t-1$, and would only move to neighbouring sectors in the following periods. Constraints (3.23) and (3.24) are the variable boundary constraints.

3.3 Computational Framework and Experimental Setup

3.3.1 Data generation

The occurrence of tropical storms depends on various factors, including water temperature. Therefore, they usually form at a distance of 5 degrees from the equator (Spiridonov et al., 2021). Figure 3-1 presents the locations where tropical storms typically form. Wei et al. (2023) also stated that southeastern China is one of the areas most frequently affected by tropical storms. Therefore, this paper focuses on the southeastern China. Figure *3-2* presents the concerned area in the southeastern China.

This paper adopts the geographical grid-based sectorisation method for two main reasons. First, since the trajectories of tropical storms are considered, and the grid-based method is adopted in the modern weather forecasting models, airspace sectorisation method is not adopted for the ease of computation (Bacon et al., 2000). The other reason is that in the current airspace sector system, some airspaces overlap to facilitate smooth the handover processes between airspaces (Chin & Wan-Ju, 2013). However, this overlap increases the computational difficulties in identifying the positions of tropical storms and determining which sector a tropical storm belongs to. Thus, the geographical grid-based sectorisation method is adopted.

In the selected area, a total of 15 sectors have been divided, as presented in Figure 3-3. In each sector, some major airports have been selected and identified, totalling to 45 airports in total for the entire selected area.

Data from the selected airports, including flight data, runway numbers, and capacities, have been collected through Flightradar24. Since exact data may not be available for some airports due to various reasons, including internal policies, estimations of airport and sector capacities have been performed.

Based on the regulations adopted by the ICAO (1984), the minimum separation between aircraft is 2 minutes. Due to uncertainties in the sequence and categories of aircraft size departing and arriving at airports, and to maximise the runway capacities, the minimum separation time is considered. Thus, we assume the maximum runway capacity is 30 aircraft per hour. If an airport has more than one runway, the maximum runway capacity is scaled accordingly. Table *3-2* presents the number of airports and the capacities of sectors, departures and arrivals in each sector. It is noted that since each time frame in the proposed model is 15 minutes, the capacities are based on 15-minute intervals.

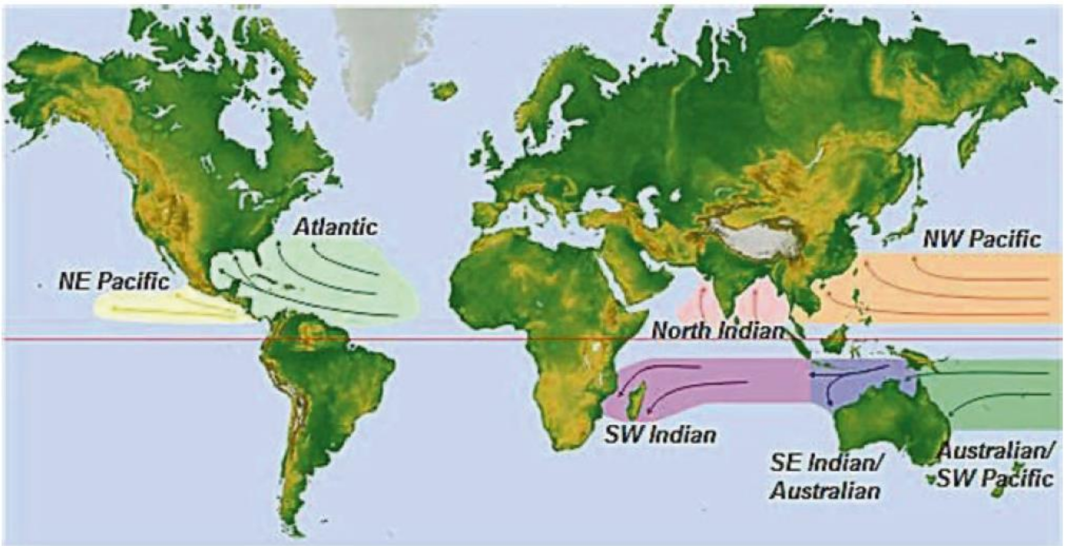

Figure 3-1: Regions where tropical storms form around the world (Spiridonov et al., 2021)

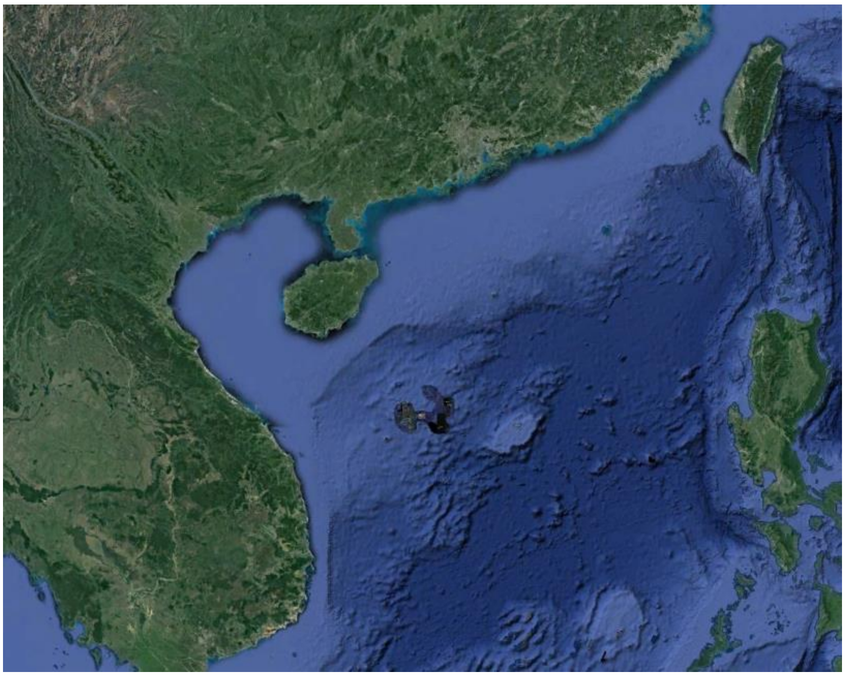

Figure 3-2: Southeastern China Region

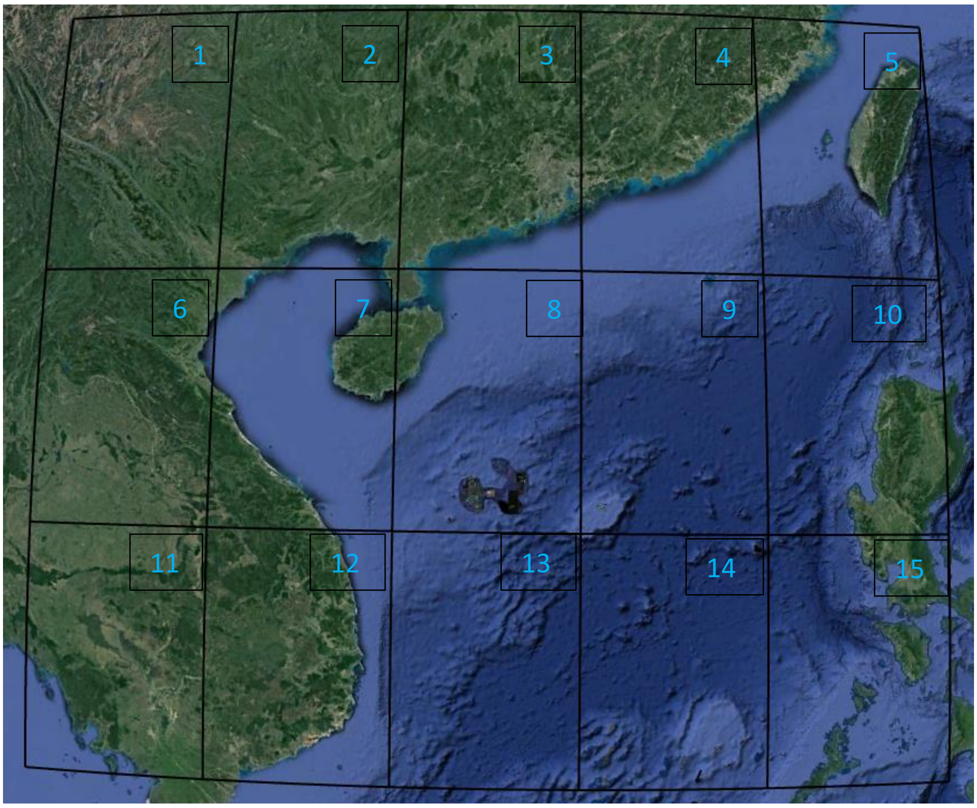

Figure 3-3: Sectorisation of the Southeastern China Region

# Sector	# Airport	Sector Capacity	Departure Capacity	Arrival Capacity	# Sector	# Airport	Sector Capacity	Departure Capacity	Arrival Capacity
1	2	106	19	13	9	0	138	0	0
2	3	115	14	9	10	2	123	9	6
3	7	46	55	37	11	5	100	23	15
4	3	115	14	9	12	3	99	23	16
5	9	54	50	34	13	0	138	0	0
6	4	108	18	12	14	0	138	0	0
7	4	99	23	16	15	2	114	14	10
8	1	121	10	7	Total	45	1614	272	184

Table 3-2: Sector Data

Regarding the tropical storms data, past tropical storm trajectories from 2010 to 2021 have been extracted from Agora (2024) and examined. In the examination, probabilities of the locations where tropical storms typically originate or enter the concerned sectors have been computed to obtain the value of p^k. The trajectories through which the tropical storms would pass have also been investigated as the set of C_T.

3.3.2 Computational Framework

The model was coded in Python 3.8.0 with IBM ILOG CPLEX Optimization Studio 20.1.0.0. The numerical analysis was conducted with Intel Core i7-10700 at 2.90 GHz with 32 GB RAM under the Windows 10 Enterprise operating environment.

In the computation, four different sets of past flight data were extracted from Flightradar24. Two of these sets were collected from days when a tropical storm was affecting the concerned region, while the other two were from normal days. To shorten the computation time, two different periods, each period containing 2 hours of flight data, were selected in each set. Five different sets of weather data, including the perfect weather scenario, were generated and computed. Figure 3-4 shows the generation process of testing flight data and Figure 3-5 shows the generation process of testing data

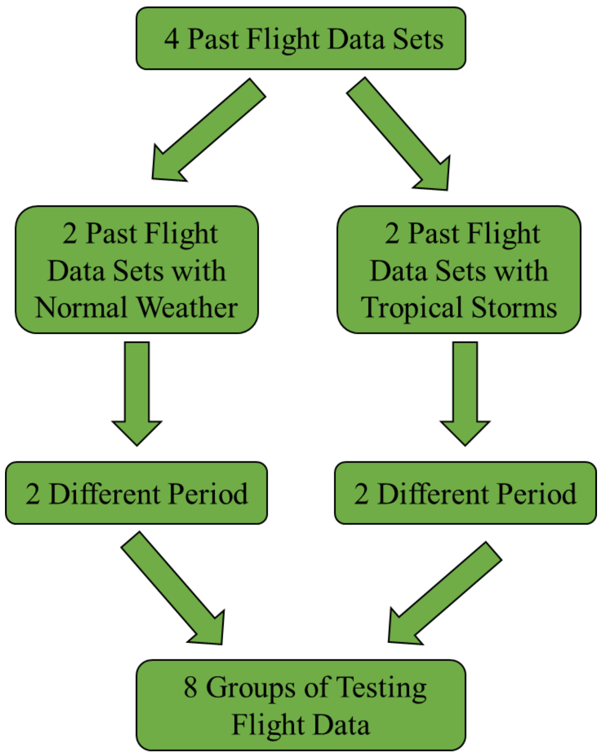

Figure 3-4: Generation process of testing flight data

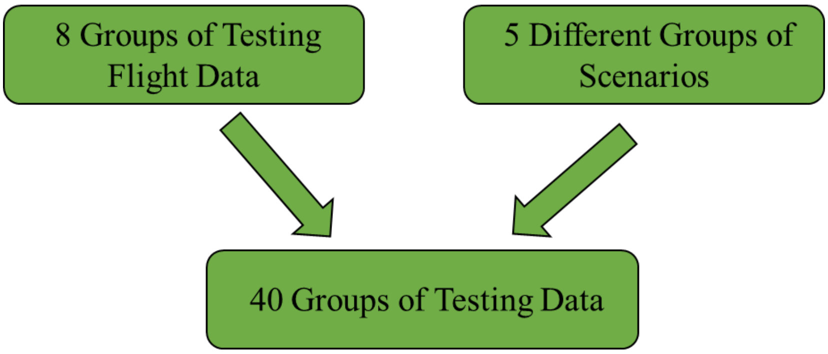

Figure 3-5: Generation process of testing flight data

3.4 Computational results and discussion

3.4.1 Computational Results

Table 3-3 shows the details and computational results, including the optimal number of the functions and time of computations, for each set under different scenarios. Table 3-4 and Table 3-5 show the percentage of the results relative to the total number of flights in each set and relative to the perfect weather scenario, respectively.

Set	#	Perfect Weather		Scenario #1		Scenario #2		Scenario #3		Scenario #4	
	Flight	Optimal	Time(s)	Optimal	Time(s)	Optimal	Time(s)	Optimal	Time(s)	Optimal	Time(s)
#1	166	99	62392.83	51	4817.05	51	2332.94	51	2585.97	51	3147.63
#2	120	65	1832.36	61	888.02	65	1624.23	64	1202.31	65	1907.48
#3	128	66	3776.17	16	49.84	60	1042.48	66	592.67	66	3029.92
#4	109	72	1811.17	54	14.94	49	7.64	48	13.69	30	5.31
#5	139	68	4545.03	49	810.03	52	972.95	66	1312.06	64	1419.07
#6	101	72	1998.23	42	12.73	43	15.31	53	51.84	16	4.23
#7	122	63	6163.00	60	1743.42	63	2074.70	63	1037.44	63	1598.83
#8	115	78	128.41	60	16.58	44	16.58	55	20.48	46	20.03
Overall	1000	583	82647.2	393	8352.61	427	8079.19	466	6816.46	401	11132.5

Table 3-3: Result of computation

Set	Perfect Weather	Scenario #1	Scenario #2	Scenario #3	Scenario #4
#1	59.64	30.72	30.72	30.72	30.72
#2	54.17	50.83	54.17	53.33	54.17
#3	51.56	12.50	46.88	51.56	51.56
#4	66.06	49.54	44.95	44.04	27.52
#5	48.92	35.25	37.41	47.48	46.04
#6	71.29	41.58	42.57	52.48	15.84
#7	51.64	49.18	51.64	51.64	51.64
#8	67.83	52.17	38.26	47.83	40.00
Overall	58.30	39.30	42.70	46.60	39.80

Table 3-4: Percentage relative to the number of flights in each set

Set	Scenario #1	Scenario #2	Scenario #3	Scenario #4
#1	51.52	51.52	51.52	51.52
#2	93.85	100.00	98.46	100.00
#3	24.24	90.91	100.00	100.00
#4	75.00	68.06	66.67	41.67
#5	72.06	76.47	97.06	94.12
#6	58.33	59.72	73.61	22.22
#7	95.24	100.00	100.00	100.00
#8	76.92	56.41	70.51	58.97
Overall	67.41	73.24	79.93	68.27

Table 3-5: Percentage relative to the perfect weather scenario in each set

3.4.2 Discussion and implications

The performance of the model has been outlined in Table 3-3 and Table 3-4. When focusing on the perfect weather scenario, it is observed that the punctuality of the flights is nearly 60%. This implies that even under ideal weather conditions, no more than 60% of the flights can depart from their origin airport and arrive at their destination airport punctually. This serves as a reference when comparing the performance of the stochastic model, since the optimal values under various scenarios are not expected to exceed those of the perfect weather scenario.

Under these circumstances, Table 3-5 uses the perfect weather scenario as a reference and compares it with different weather scenarios. From the table, it is observed that the overall punctuality in each scenario reaches at least 65%. In some flight data sets, all flights can depart from their origin airport and arrive at their destination airport punctually (with a punctuality rate of 100%). Despite the effects of tropical storms, where some sectors' capacities may be severely affected, the punctuality of flights is not seriously impacted. Therefore, the performance of the model can be concluded to be satisfactory.

The translation speeds of tropical storms are relatively slow compared to the speed of a flight. Thus, the effects of tropical storms on flight operations may be limited. However, when tropical storms approach or impact a particular sector, the punctuality of flights decreases significantly. From Table 3-5, in Scenario 1, flight data set 3 achieved a punctuality rate of 24.24%. In Scenario 4, flight data sets 4 and 6 achieved the punctuality rates of 41.67% and 22.22%, respectively. In these flight data sets, since either the sector of the origin airport or the destination airport was severely affected, resulting in airports closures or extended in airport operations, leading to significant delays. Additionally, rerouting flights beforehand could not address the issue. Despite serious delays in some cases, the overall performance of the proposed model is still reasonable.

In terms of computational time, the stochastic model also performs satisfactorily. Based on Table 3-3, the total computational time in the perfect weather scenario is 82647.2 seconds, which is equivalent to around 23 hours. Particularly for flight data set 1, with a total 166 flights, the computational time reaches 62392.83 seconds, which is equivalent to around 17 hours. With a 2-hour flight data set, when the computational time is much longer than the duration of the flight data set, the results from the model cannot be used due to their outdatedness. In the other scenario-based cases, the computational time is comparably shorter than the perfect weather scenario. This result also implies that the deterministic model may not be suitable for comparing larger flight data sets. Thus, the performance of the stochastic model is determined to be better than that of the deterministic model.

One possible cause for this is the pre-processing in the computation of the programme. In the stochastic cases, some sectors are severely affected, leading to mandatory delays. In the perfect weather scenario, all the flights are evenly prioritised. Therefore, the pre-processing procedure in the stochastic model helps shorten the computational time, which can be implemented in real-world situations.

3.5 Conclusion

With the increasing number of flights and adverse weather events, the total delay time of aircraft in both departures and arrivals is expected to be rise. Thus, it is essential to reduce flight delays. To handle adverse weather events like tropical storms, it is possible to consider their routes as an uncertainty. Therefore, a two-stage stochastic optimisation model is proposed in this chapter to maximum the punctuality of the aircraft under the influence of tropical storms.

In the computations, 40 combinations of flight data and weather conditions have been examined. Although the punctuality results in some cases are poor, most cases achieve satisfactory results with punctuality of over 65% when compared to the perfect weather scenario. Additionally, the computational time of the proposed model with different scenarios is significantly shorter than that of the perfect weather scenario or the deterministic case. Therefore, the proposed stochastic model is concluded to be practical in terms of computational time.

Despite the satisfaction with the proposed model, some future approaches are suggested. In the sectorisation process, a gird-based sectorisation approach has been adopted so that each sector is in a rectangular, non-duplicated sharp. However, this may not be the best approach since the airspace division in reality is uneven. To facilitate better control, some airspace might also have overlaps to smoothen the handover process between air traffic controllers. This could be one of the approaches adopted in the sectorisation in the stochastic optimisation model in the future.

Due to insufficient knowledge of each of the airport and airspace, we assume the runway capacity and sector capacity based on past data collected. However, this cannot be regarded as the true value because the operation modes of each airport are different. If exact data can be collected and computed in the proposed optimisation model, the results would be more realistic, and this could be one of the possible future works.

Additionally, in the flight data pre-processing, only two different two-hour intervals from each flight data set have been extracted due to the computational constraints. However, some flights may require longer travel time from their origins to their destinations. Therefore, the pre-processing of data has limited the duration of aircraft movements, causing errors in the results and affecting their accuracy. By enlarging the data size, more accurate results could be achieved, which would be better suited in the real-world situations.

Chapter 4 A stochastic programming approach for joint optimization of aircraft landing and terminal traffic flow management under uncertainty

In this chapter, a stochastic programming model combining aircraft landing problem and terminal traffic flow management under uncertainty is proposed. In reality, various kinds of uncertainties, including adverse weather events, occur more frequently and disrupt air traffic operations. Some of these uncertain events can appear and disappear in a short period. Furthermore, the occurrence of these events significantly affects flights, delaying them or even compromising passenger safety. Thus, it is essential to respond to these uncertainties to ensure the level of safety during operations. Runway operations may cease due to strong wind shear, turbulence, microbursts, or other extreme weather scenarios, are limited by restricted airspace capacity. We extend the problem covering the terminal airspace. The proposed model can significantly reduce the total delay time of aircraft in the computations.

4.1 Introduction

According to EUROCONTROL (2022), the average delay per flight in Europe in 2022 was 17.3 minutes, which is the highest recorded data in the past five years. Only 64.5% of flights were recorded as arriving at their destination within 15 minutes of or earlier than their estimated time of arrival (ETA). The situation was expected to become more severe in the future due to the increase in passenger flow (IATA, 2023b). Therefore, it is necessary to address the problem of flight delays. One of the causes leading to flight delays is the previous flight sharing the same aircraft (Zámková et al., 2017). When the previous flight is delayed for any reason and a packed schedule is arranged for that aircraft, delays in the subsequent flights would usually occur. This forms a vicious circle unless the separation between flights is lengthy enough, for instance, an hour or more. However, increasing the separation time is not simple, since this affects the revenue of airlines (Desaulniers et al., 1997). Another reason causing the flight delays is the weather hazards. Lee and Zhong (2016) revealed the strong relationship between adverse weather and flight delays. Departure and arrival flights are affected under these circumstances (Borsky & Unterberger, 2019; Rodríguez-Sanz et al., 2022).

Given this context, research has concentrated on minimising delays by efficiently scheduling airport resources. The primary resources of an airport include terminal airspace, runways, taxiways, contact and remote gates, etc. These essential resources are managed collaboratively by air traffic control, airport management, and the aviation department. Most prior research has primarily focused on optimising the utilisation of airport resources individually (Daş et al., 2020; Guépet et al., 2016; Ikli et al., 2021; Ng et al., 2020). However, considering the joint scheduling of airport resources, significant benefits can be realised from both theoretical and practical perspectives (Neuman & Atkin, 2013). Consequently, recent studies have begun exploring the collaborative scheduling of these critical airport resources. For example, the joint optimisation of taxiways and runways (Benlic et al., 2016; Weiszer et al., 2020), the joint scheduling of runways, terminal gates, and aprons (Hu et al., 2024; Jiang et al., 2024; Yin et al., 2022), and the integrated optimisation of runways, taxiways, and terminal gates (Daş et al., 2020; Guépet et al., 2016; Ikli et al., 2021; Jiang et al., 2022; Ng et al., 2020).

While the current joint scheduling of airport resources primarily focuses on runways and other airport ground activities, it is essential to recognise that terminal airspace also plays a critical role in determining the throughput and operating efficiency of the airport. Therefore, this paper proposes a joint aircraft landing and terminal traffic flow problem. The model combines two different problems: the ALP and TTFP. The rationale for combining airport and terminal airspace resources is to enhance airspace efficiency and safety. We attempt to investigate the relationship and effects between the runways and the arrival flight routes, and further optimise the airport throughput. Through the optimisation process, ATFM helps increase airport capacity and service quality, reduce operational costs and damage to the environment, and increase the satisfaction and sense of safety of the passengers.

Therefore, to incorporate ETA uncertainty into consideration, we propose an integrated ALP and TFFP stochastic model based on the two-stage stochastic programming approach. In the first stage, we focus on the aircraft landing sequence, as runway resources are limited and need to be efficiently allocated to different aircraft, which requires planning and decision-making. In the second stage, terminal controllers flexibly schedule the traffic flow in the terminal airspace according to the runway decisions.

The contributions of this paper are outlined below.

1. An integrated ALP and TFFP stochastic model is proposed to minimise the delay time.
2. The sample average approximation method is employed to transform the optimisation problem of expected value into a deterministic problem based on the empirical average of random samples, thereby solving it using standard optimisation techniques. Several computational improvement procedures are then provided.
3. A numerical study is conducted to analyse the efficiency of computational improvement procedures and the performance of the model. The stochastic model is concluded to satisfactorily reduce the delay time of aircraft.

The remaining of the work is organised as follows. A deterministic model integrating the ALP and TTFP is proposed in Section 4.2, while Section 4.3 introduces the stochastic model based on the introduced deterministic model. The computational framework and experimental setup are presented in Section 4.4. The evaluation of the impacts of computational improvements is discussed in Section 4.5. An implementation of the integrated model and a discussion of its value are included in Section 4.6. Section 4.7 provides a conclusion and outlines future work.

4.2 Deterministic Model

In this section, we first provide the problem description and the notation for the deterministic joint ALP and TTFP model in Section 4.2.1. The mathematical formulation is then provided in Section 4.2.2.

4.2.1 Problem description and notation

The joint ALP and TTFP model considers aircraft landing sequence and terminal traffic flow management simultaneously. Consider a set of arriving aircraft F, each aircraft $i \in F$ has an ETA E_i. Each arriving aircraft should land on the runway in order, with the landing sequence is determined by the decision variable y_{ij}. The landing sequence of the runway starts with a dummy starting aircraft s, and ends with a dummy ending aircraft e. A separation time R_{ij} is required when an aircraft lands on the runway. The decision-making for terminal traffic flow management is formulated using a directed graph $G = (N, A)$ with a set of waypoints N and a set of arcs A. The path of an aircraft p_i contains a set of waypoints $N = (o_i, \ldots, d)$, where o_i and d are the origin and destination of an aircraft. When aircraft i reaches waypoint $u \in p_i$, an approach time t_{iu} is associated. The delay time D_i of aircraft i is computed by difference between t_{io_i} and E_i. The travel time required for aircraft i traverse from waypoint u to waypoint v is T_{iuv}. As the speed of aircraft varies, it is a random variable (see Section 4.1 for further details). The sequence of aircraft traverse waypoint u is determined by the binary variable z_{iju}. S_{ij} is the longitudinal separation time on the path between aircraft i and j. Table 4-1 presents the definition of notations for the deterministic joint model.

Set of indices	Explanation
A	Set of arcs
F	Set of arrival aircraft
N	Set of waypoints, $N = (o_i, \ldots, d)$
Parameters	**Explanation**
d	Destination node, $d \in N$
E_i	ETA of aircraft $i \in F$
e	Dummy destination node, $e \in N$
i, j	Aircraft $i, j \in F$
o_i	Origin node for aircraft i, $i \in F$, $o_i \in N$
p_i	Path of aircraft, $i \in F$
R_{ij}	The separation time between aircraft i and j on the runway,$R_{ij} \geq 0$, $i, j \in F$, $i \neq j$
S_{ij}	The longitudinal separation time on the path between aircraft i and j, $S_{ij} \geq 0$, $i, j \in F$, $i \neq j$
s	Dummy origin node, $s \in N$
T_{iuv}	Travelling time of aircraft i from waypoint u to v, $T_{iuv} \geq 0$, $i \in F$, $u, v \in N$
t_{iu}	Time of aircraft i reaching waypoint u, $i \in F$, $u \in N$
u, v	Waypoint $u, v \in N$

Decision variables	Explanation
D_i	Delay time of aircraft $i \in F$
y_{ij}	1, if aircraft i lands on the runway before aircraft j; 0, otherwise, $i, j \in F$, $i \neq j$
z_{iju}	1, if aircraft i reaches waypoint u before aircraft j; 0, otherwise, $i, j \in F, i \neq j, u \in N$

Table 4-1: Definition of Notations for the model

4.2.2 Mathematical formulation of deterministic joint model

After the problem description and notation are provided, we present the mathematical formulation of the deterministic joint model as follows:

$$\min \sum_{i \in F} p_i D_i \tag{4.1}$$

s.t.

$$\sum_{j \in F_e} y_{sj} = 1 \tag{4.2}$$

$$\sum_{i \in F_s} y_{ie} = 1 \tag{4.3}$$

$$\sum_{j \in F_s\{i\}} y_{ji} = \sum_{j \in F_e\{i\}} y_{ij}, \quad \forall i \in F \tag{4.4}$$

$$\sum_{j \in F_e\{i\}} y_{ij} = 1, \quad \forall i \in F \tag{4.5}$$

$$t_{jd} \geq t_{id} + R_{ij} - M(1 - y_{ij}), \quad \forall i \in F, \forall j \in F, (i \neq j) \tag{4.6}$$

$$z_{iju} + z_{jiu} = 1, \quad \forall i \in F, \forall j \in F, (i \neq j), \forall u \in N_i \cap N_j \tag{4.7}$$

$$t_{io_i} \geq E_i, \quad \forall i \in F \tag{4.8}$$

$$t_{iu} + T_{iuv} = t_{iv}, \quad \forall i \in F, \forall uv \in A_i \tag{4.9}$$

$$t_{ju} \geq t_{iu} + S_{ij} - M(1 - z_{iju}), \quad \forall i \in F, \forall j \in F, (i \neq j), \forall u \in N_i \cap N_j \backslash \{d\} \tag{4.10}$$

$$D_i \geq t_{io_i} - E_i, \quad \forall i \in F \tag{4.11}$$

$$y_{ij} \in \{0,1\}, \quad \forall i \in F_s, \forall j \in F_e \tag{4.12}$$

$$z_{iju} \in \{0,1\}, \quad \forall i \in F, \forall j \in F, (i \neq j), \forall u \in N_i \cap N_j \tag{4.13}$$

$$t_{iu} \in \mathbb{R}^+, \quad \forall i \in F, \forall u \in N_i \tag{4.14}$$

$$D_i \in \mathbb{R}^+, \quad \forall i \in F \tag{4.15}$$

Objective function (4.1) minimises the total delay cost of aircraft. Constraints (4.2) and (4.3) ensured that the runway sequence started with a dummy starting aircraft s, and ended with a dummy ending aircraft e. Constraint (4.4) guaranteed the flow conservative for the runway. Constraint (4.5) ensured that every arrival aircraft must land on the runway. Constraint (4.6) guaranteed the separation time between aircraft landing on the runway. Constraint (4.7) defined the sequencing variables z_{iju}. Constraint (4.8) ensured that the arrival time of aircraft i at its entry waypoint o_i is equal to or greater than the ETA of aircraft i first appears in the TMA. Constraint (4.9) ensured that the time consistency for each waypoint on the approaching path of each aircraft. Constraint (4.10) avoided aircraft conflicts by enforcing that the arrival times at node u by aircraft i and j need to satisfy the separation time S_{ij}. Constraint (4.11) determined the delay time for each aircraft. Constraints (4.12) to (4.15) defined the domain of the decision variables.

4.3 Stochastic Programming Model

In this section, based on the model constructed in Section 4.2.2, a stochastic programming model is proposed. The problem description and notation are presented in Section 4.3.1, while the mathematical formulation of the two-stage stochastic joint aircraft landing and terminal traffic flow problem is proposed in Section 4.3.2.

4.3.1 Problem description and notation

In the stochastic model, the fundamentals are presented in Section 4.2.1. The set of scenarios Ω has been introduced in this section. Each scenario ω, such as different kinds and combinations of adverse weather conditions, has been included in the set of scenarios Ω. A weighting ρ^{ω} has been assigned to each scenario ω, with $\rho^{\omega} \in [0, 1]$, illustrating the occurrences of the weather conditions and the impact they bring to the operations. With the new problem setting, some notations from Section 4.2.1 have been revised and presented in Table 4-2 .

Parameters	Explanation
E_i^{ω}	The ETA of flight i in scenario ω, $i \in F$, $\omega \in \Omega$
ρ^{ω}	The weight assigned to the scenario ω, $\omega \in \Omega$
Decision variables	Explanation
D_i^{ω}	Delay time of flight i in scenario ω, $i \in F$, $\omega \in \Omega$
t_{iu}^{ω}	Time of flight i in waypoint d in scenario ω, $i \in F, u \in N_i, \omega \in \Omega$
z_{iju}^{ω}	1, if flight j is before flight i in waypoint u in scenario ω; 0, otherwise, $i, j \in F, u \in N_i, \omega \in \Omega$

Table 4-2: Definition of newly introduced Notations for the model

4.3.2 Mathematical formulation of two-stage stochastic joint model

After the problem description and notation are provided, we present the mathematical formulation of the two-stage stochastic joint model as follows:

$$\min \sum_{\omega \in \Omega} \left(\rho^{\omega} \sum_{i \in F} p_i D_i^{\omega} \right) \tag{4.16}$$

s.t. Constraints (4.2) - (4.5), (4.11)

$$t_{jd}^{\omega} \geq t_{id}^{\omega} + R_{ij} - M\left(1 - y_{ij}\right), \quad \forall i \in F, \forall j \in F, (i \neq j), \forall \omega \in \Omega \tag{4.17}$$

$$z_{iju}^{\omega} + z_{jiu}^{\omega} = 1, \quad \forall i \in F, \forall j \in F, (i \neq j), \forall u \in N_i \cap N_j, \forall \omega \in \Omega \tag{4.18}$$

$$t_{io_i}^{\omega} \geq E_i^{\omega}, \quad \forall i \in F, \forall \omega \in \Omega \tag{4.19}$$

$$t_{iu}^{\omega} + T_{iuv} = t_{iv}^{\omega}, \quad \forall i \in F, \forall uv \in A_i, \forall \omega \in \Omega \tag{4.20}$$

$$t_{ju}^{\omega} \geq t_{iu}^{\omega} + S_{ij} - M\left(1 - z_{iju}^{\omega}\right), \quad \forall i \in F, \forall j \in F, (i \neq j), \forall u \in N_i \cap N_j \backslash \{d\}, \forall \omega \in \Omega \tag{4.21}$$

$$D_i^{\omega} \geq t_{io_i}^{\omega} - E_i^{\omega}, \quad \forall i \in F, \forall \omega \in \Omega \tag{4.22}$$

$$z_{iju}^{\omega} \in \{0,1\}, \quad \forall i \in F, \forall j \in F, (i \neq j), \forall u \in N_i \cap N_j, \forall \omega \in \Omega \tag{4.23}$$

$$t_{iu}^{\omega} \in \mathbb{R}^{+}, \quad \forall i \in F, \forall u \in N_i, \forall \omega \in \Omega \tag{4.24}$$

$$D_i^{\omega} \in \mathbb{R}^{+}, \quad \forall i \in F, \forall \omega \in \Omega \tag{4.25}$$

Objective function (4.16) minimises the total delay cost of aircraft in each scenario ω with the weighting assigned to the scenario. Constraint (4.17) guaranteed the separation time between aircraft landing on the runway in scenario ω. Constraint (4.18) defined the sequencing variables z_{iju} in scenario ω. Constraint (4.19) ensured that the arrival time of aircraft i at its entry waypoint o_i is equal to or greater than the ETA of aircraft i first appears in the TMA in scenario ω. Constraint (4.20) ensured time consistency for each waypoint on the approaching path of each aircraft in scenario ω. Constraint (4.21) restricted conflict-free solutions by enforcing that the arrival times at node u by aircraft i and j need to satisfy the separation time S_{ij} in scenario ω. Constraint (4.22) determined the delay time for each aircraft in scenario ω. Constraints (4.23) to (4.25) defined the domains of decision variables in scenario ω.

The proposed model can be divided into two stages. In the first stage, the aircraft landing sequence is decided with constraints (4.2) to (4.5) and (4.11). After the landing sequence is determined, the scheduling of aircraft in terminal airspace is addressed in the second stage. A numerical study will further analyse the computational performance and model performance under various scenarios via sample average approximation.

4.3.3 Sample average approximation

Sample Average Approximation (SAA), which is commonly used in stochastic optimisation problems, is a Monte Carlo simulation-based sampling method developed to solve problems where the number of scenarios is significantly large (Bertsimas et al., 2018). It can also be applied to problems with continuous distributions or an infinite number of scenarios. This method has been applied in various papers to simulate uncertainty scenarios in ALP (Khassiba et al., 2022; Liu et al., 2018) and TTFP (Corolli et al., 2017; Lee et al., 2020). In the context of ALP and TTFP, SAA is typically applied to simulate arrival times or the speeds of the aircraft under different scenarios. In this chapter, SAA will be applied to simulate different arrival times caused by adverse weather conditions.

4.3.4 Computational improvement procedures

In this section, two computational improvement procedures are proposed. The purpose of including these procedures is to help obtain the optimal solutions in a shorter computational time.

4.3.4.1 Valid Inequalities

The valid inequalities are used to estimate a lower bound of the arc cost in the runway sequence. Considering aircraft $i \in F$ and aircraft $j \in F \setminus \{i\}$ landing consecutively on the runway, a lower bound of the delay costs caused by this arc (i, j) is defined as c_{ij}. To obtain c_{ij}, we solve the second-stage model (Constraints (4.16) - (4.25)) with a fixed first-stage runway sequence as (i, j), which means only aircraft i and j are considered. In this context, we relax the collision avoidance constraints of aircraft i and j with other aircraft. The optimal objective value of this model can thus be used as a lower bound of delay costs caused by this arc (i, j). The valid inequalities are formulated as follows

$$\sum_{\omega \in \Omega} \rho^{\omega} \sum_{i \in F} p_i C_i^{\omega} \geq \sum_{i \in F} \sum_{j \in F\{i\}} c_{ij} y_{ij}. \tag{4.26}$$

4.3.4.2 Knapsack Inequality

A decent initial upper bound may improve computational performance. Let UB_{start} represent a good initial upper bound of the original problem. To obtain UB_{start}, we initially solve a deterministic joint model with the expected arrival time to derive a first-stage solution. Subsequently, we fix the obtained first-stage solution and input it into the second-stage model (Constraints (4.16) to (4.25)). The resulting optimal objective value serves as the UB_{start}. The Knapsack inequality is then provided as follows

$$\sum_{\omega \in \Omega} \rho^{\omega} \sum_{i \in F} p_i C_i^{\omega} \leq UB_{start}. \tag{4.27}$$

4.4 <u>Computational framework and experimental setup</u>

In this section, the experimental setup and computational framework are presented as a preliminary for the model computations.

4.4.1 Data generation

Some datasets have been prepared for computation. Given the size of HKIA, which is a hub-and-spoke airport (Wu et al., 2018), mainly medium-sized and large-sized aircraft approach the airport. Thus, these two types of aircraft are the focus, and small-sized aircraft are not considered in this paper.

The travelling time T_{iuv} of flight i between waypoints u and v is determined as

$$T_{iuv} = \frac{d_{uv}}{s_i}, \tag{4.28}$$

where d_{uv} is distance in nautical miles between waypoint u and v and s_i is the speed of aircraft i.

The distance between waypoints can be determined through STARs published by the civil aviation department of each state. Nevertheless, the speed of the aircraft varies based on the stages and real situations. According to HKCAD (2023), the speed restriction on the approach routes is 280 knots. Therefore, we select this as the highest speed that each aircraft can travel within the TMA. Without loss of generality, we can assume the lowest speed for different sizes of aircraft by considering the highest minimum landing speed of different types of aircraft in the same category. Therefore, the range of speed s_i is defined as

$$s_i = \left[\max_{i \in Cat_i}\{\min v_i\}, 280\right], \tag{4.29}$$

where Cat_i refers to the category to which aircraft i belongs, and $\min v_i$ is the minimum landing speed of aircraft i. Table 4-3 presents the highest and lowest landing speeds for each category.

	Category of aircraft	
	Large	Medium
Highest Speed s_i (in knots)	280	280
Lowest Speed s_i (in knots)	185	160

Table 4-3: Speed of aircraft in each category (HKCAD, 2023; ICAO, 2018b)

Based on the table, the range of travelling time between each pair of waypoints can be computed by equation (4.28). However, since the actual speed of an aircraft depends on the decisions of ATCOs, a fixed aircraft speed is assumed in this paper, where the travelling time lies within the computed range.

The determination of the longitudinal separation time S_{ij} is also required. According to Doc 9426-AN/924 (ICAO, 1984), wake turbulence separation has been established to reduce potential hazards caused by wake turbulence. Therefore, separations between flights have been initiated and presented in Table 4-4. Conversion is conducted based on the speed obtained from (4.29) and the separation time S_{ij} is obtained.

		Trailing Flight	
		Large	Medium
Leading Flight	Large	4	5
	Medium	3	3

Table 4-4: Longitudinal separation distance (in nautical miles)

According to ICAO (2016), the runway separation minima when the surveillance systems are used is 5 NM for two consecutive flights. Though reductions can be applied under different circumstances, including perfect weather for flying and the aid of advanced technology such as ADS-B, the runway separation distance remains at 5 NM under adverse weather conditions. Conversion is conducted based on the speed obtained from Figure 4-1 and the runway separation time R_{ij} is obtained.

The entry time E_i and origin node o_i of aircraft i are determined from the collected data. Deviations may occur in the dataset, so data pre-processing is performed to align them with the experimental setup.

Ten paths have been introduced based on the TMA of Hong Kong, and each path consists of several waypoints listed in Table 4-5. The locations of the waypoints can be referenced in Figure 4-1.

4.4.2 Computational framework

The model was coded in Python 3.8.0 with Gurobi Optimizer 11.0.0. The numerical analysis was conducted with Intel Core i7-10700 at 2.90 GHz with 32 GB RAM under Windows 10 Enterprise operating environment.

Path Number	Path	Path Number	Path
1	1, 11, 15, 27, 30, 31	6	6, 13, 14, 19, 25, 27, 30, 31
2	2, 11, 15, 27, 30, 31	7	7, 13, 14, 19, 25, 27, 30, 31
3	3, 11, 15, 27, 30, 31	8	8, 21, 26, 28, 30, 31
4	4, 12, 17, 25, 27, 30, 31	9	9, 21, 26, 28, 30, 31
5	5, 12, 17, 25, 27, 30, 31	10	10, 28, 30, 31

Table 4-5: List of Paths

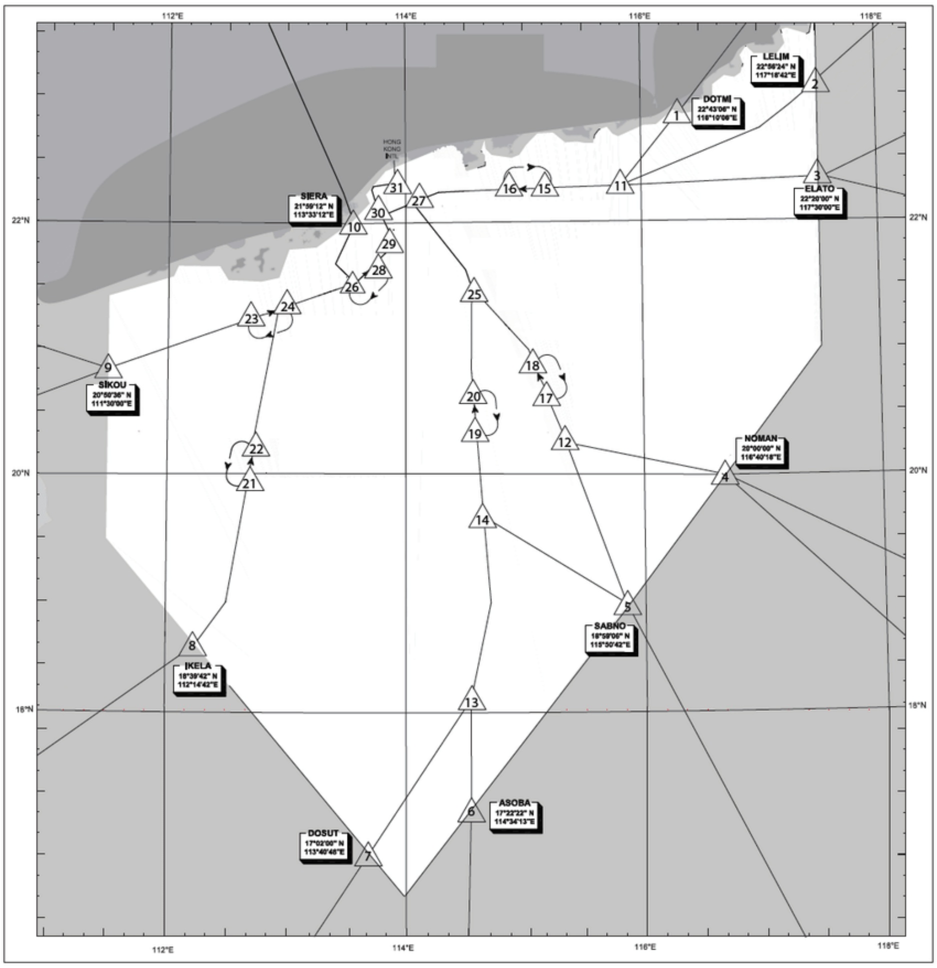

Figure 4-1: The approach path of the Hong Kong TMA (Ng et al., 2020).

A total of six groups have been generated for the computation. In each computation, the number of flights and their distribution among different sizes of aircraft vary. The number of flights in each group illustrates different capacities at the airport, while the ratios of larger-sized aircraft to medium-sized aircraft are generated based on historical data from HKIA. In each group, data have been computed through 10, 25, 50, 75, and 100 different scenarios to simulate the effects caused by adverse weather conditions, such as delays due to rerouting, leading to variations in the arrival times of flights. Each group is tested using four different methods, as shown in Figure 4-2.

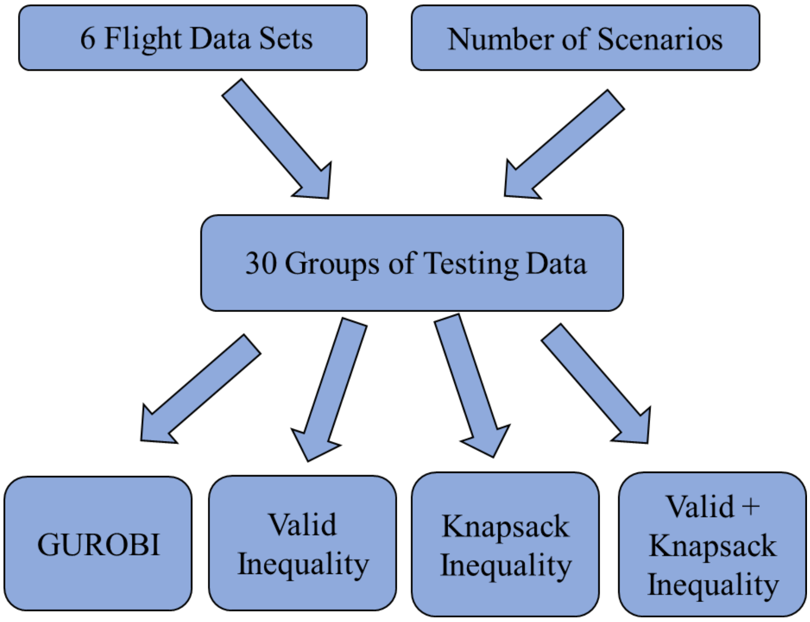

Figure 4-2: Computational Framework

4.5 Impact of computational improvement procedures

In this section, the original results are presented. Results computed using the GUROBI optimizer, only valid inequalities, only the Knapsack inequality, and both methods as the computational improvement procedures are introduced. The impacts caused by each procedure are also discussed.

4.5.1 Results

Table 4-6 shows the details and computational results, including the gap and time of computations, in each group. The gap in the results is computed by

$$Gap(\%) = \frac{UB - LB}{UB}, \tag{4.30}$$

where UB refers to the upper bound and LB refers to the lower bound.

Based on Table 4-6, the number of optimal solutions and best solutions can be obtained, as shown in Table 4-7. If the gap is reached in the computation within the time limit, both the optimal solution and the best solution are counted. If the gap is not reached for all computations, a comparison is performed among the four methods, and the best solution is counted for the lowest gap value obtained among the methods.

Group	# flight	Size of flight	# Scenario	GUROBI		Valid Inequality		Knapsack Inequality		Valid + Knapsack	
				Gap (%)	Time(s)	Gap (%)	Time(s)	Gap (%)	Time (s)	Gap (%)	Time (s)
1	5	M: 2 L: 3	10	0.00	0.01	0.00	0.01	0.00	0.03	0.00	0.03
			25	0.00	0.03	0.00	0.03	0.00	0.10	0.00	0.08
			50	0.00	0.07	0.00	0.05	0.00	0.21	0.00	0.23
			75	0.00	0.11	0.00	0.07	0.00	0.01	0.00	0.01
			100	0.00	0.14	0.00	0.10	0.00	0.01	0.00	0.01
2	10	M: 2 L: 8	10	0.00	0.20	0.00	0.12	0.00	0.32	0.00	0.20
			25	0.00	0.72	0.00	0.37	0.00	1.83	0.00	0.73
			50	0.00	1.74	0.00	0.96	0.00	2.75	0.00	3.88
			75	0.00	5.68	0.00	1.80	0.00	3.94	0.00	3.30
			100	0.00	9.22	0.00	2.13	0.00	4.92	0.00	6.39
3	15	M: 12 L: 3	10	0.00	2.94	0.00	2.55	0.00	3.16	0.00	2.99
			25	0.00	110.82	0.00	14.68	0.00	21.85	0.00	14.88
			50	0.00	89.80	0.00	53.11	0.00	50.53	0.00	58.14
			75	0.00	193.42	0.00	112.81	0.00	115.94	0.00	125.13
			100	0.00	299.38	0.00	212.44	0.00	129.41	0.00	168.90
4	15	M: 4 L: 11	10	0.00	3.45	0.00	2.73	0.00	14.26	0.00	10.90
			25	0.00	66.80	0.00	32.86	0.00	51.59	0.00	10.30
			50	0.00	203.12	0.00	1593.87	0.00	1339.52	0.00	177.40
			75	16.96	1800.00	0.52	1800.00	0.39	1800.00	0.23	1800.00
			100	97.93	1800.00	98.25	1800.00	--- (100)	1800.00	--- (100)	1800.00
5	20	M: 5 L: 15	10	0.00	618.26	0.00	175.62	0.00	235.50	0.00	172.94
			25	30.04	1800.00	27.90	1800.00	0.00	596.45	0.00	729.59
			50	73.23	1800.00	98.80	1800.00	30.96	1800.00	0.00	690.74
			75	98.80	1800.00	98.82	1800.00	--- (100)	1800.00	--- (100)	1800.00
			100	98.78	1800.00	98.81	1800.00	--- (100)	1800.00	--- (100)	1800.00
6	25	M: 20 L: 5	10	28.42	1800.00	30.21	1800.00	27.72	1800.00	--- (100)	1800.00
			25	43.68	1800.00	47.34	1800.00	42.74	1800.00	48.43	1800.00
			50	47.61	1800.00	53.62	1800.00	47.72	1800.00	57.02	1800.00
			75	70.21	1800.00	89.79	1800.00	55.73	1800.00	--- (100)	1800.00
			100	98.45	1800.00	--- (100)	1800.00	--- (100)	1800.00	--- (100)	1800.00
Overall				23.47	713.53	24.80	733.54	20.18	685.74	23.52	612.56

Table 4-6: Comparison of the optimality gap and CPU time indicators.

Group	GUROBI		Valid Inequality		Knapsack Inequality		Valid + Knapsack	
	#Opt	#Best	#Opt	#Best	#Opt	#Best	#Opt	#Best
1	5	5	5	5	5	5	5	5
2	5	5	5	5	5	5	5	5
3	5	5	5	5	5	5	5	5
4	3	4	3	3	3	3	3	4
5	1	3	1	1	2	2	3	3
6	0	2	0	0	0	3	0	0
Overall (30)	19	24	19	19	19	23	19	22

Table 4-7: Comparison of the number of optimal and best solutions found by algorithms.

4.5.2 Impact of the computational improvement procedures

The purpose of proposing computational improvement procedures is to reduce the computational time for optimisation, especially for stochastic scheduling problems. The reason is that for these kinds of problems, uncertainties may vary, causing the results of the optimisation model to be inaccurate. To best illustrate the environment, it is essential to compute the model regularly until the problem is solved. Therefore, the shorter the computational time for the model, the better its practical usage. This explains why computational improvement procedures are considered in the problem.

The average gap values and computational time for each method are calculated for comparison Table **4-6**. From the table, the Knapsack inequality provides the best average result across all groups in terms of average gap value, while the combination of valid inequality and Knapsack inequality has the lowest computational time among all methods. However, the concerned computational improvement procedures may not be able to obtain all results in the groups.

Out of 30 combinations of groups and scenarios, results for only 23 combinations can be obtained (where the results are the best results) through the Knapsack inequality. Especially when the number of scenarios is large, the chances of not obtaining the results using the concerned computational improvement procedures are higher. This may imply that if the discussed method is selected as a computational improvement procedure, either the computational time has to be increased, or the optimal solutions cannot be obtained within the set time limits. Thus, the selected procedure may not be the best for improving the results of the stochastic programming model.

For the second-best procedure, which is the combination of the valid inequality and Knapsack inequality, the same problem is observed, as shown in Table 4-6. Therefore, a better choice for the selection of computational improvement procedures would be using GUROBI only. From Table 4-7, the number of best solutions is the highest. Also, from Table 4-6, it can be observed that all results from each group can be obtained. Thus, it can be concluded that not using any computational improvement procedures in the stochastic programme would be the most suitable method for computing the results, and this method will be used in Section 4.6 for further computations.

4.6 Practical implementation and value of stochastic joint model

In this section, several comparisons between different models have been conducted and discussed.

4.6.1 Joint optimization model versus first come first serve strategy

The FCFS strategy is a commonly and currently used method by ATCOs for landing sequencing. The delay time was computed and compared with the deterministic model. For both models, the first scenario from each group is used for the computations. Table 4-8 shows the delay times of FCFS and deterministic models in each group.

It is common practice that when an aircraft approaches the airport, it has the priority to land on the runway. Nevertheless, since the separation minima between aircraft must be maintained, this method often results in a large delay time for each flight. When one flight is delayed, subsequent flights may also be affected to ensure safety. The proposed deterministic model, however, aims to minimise the delay time of the system by rearranging the sequence of flights beforehand to optimise the delay time. From Table 4-8, it is observed that the delay time of the FCFS strategy is significantly larger than that of the proposed deterministic model. Thus, it is sufficient to conclude that the proposed deterministic model performs better than the FCFS strategy in terms of minimising of total delay time costs.

Group	FCFS	Deterministic
1	346.0000	0.0000
2	4108.0000	600.2225
3	3712.0000	1695.0069
4	10338.0000	411.6031
5	25554.0000	2171.3415
6	39296.0000	3503.7781
Total delay time (s)	13892.3333	1396.9920

Table 4-8: Comparison of the delay times between FCFS and deterministic model.

4.6.2 Performance of the stochastic joint model - Value of the Stochastic Solution

The value of the stochastic solution (VSS) is the difference between the expected value of the expected value solution (EEV) and the optimal objective value of the stochastic programming (SP) model (Birge & Louveaux, 2011). The expected value solution $\widehat{\boldsymbol{Y}}_{\boldsymbol{EV}}$ is the optimal solution of the deterministic model with expected aircraft arrival times. After the solution $\widehat{\boldsymbol{Y}}_{\boldsymbol{EV}}$ is obtained, it is fixed, and the EEV is obtained by solving the model (4.31). The formulations of VSS are presented in equations (4.32) and (4.33).

$$EEV = \min \mathbb{E}\left[f\left(\widehat{\boldsymbol{Y}}_{\boldsymbol{EV}}, \omega\right)\right]. \tag{4.31}$$

$$VSS = EEV - SP, \tag{4.32}$$

$$VSS(\%) = \frac{(EEV - SP)}{SP}, \tag{4.33}$$

The VSS is an indicator used to determine whether the sequence obtained by the deterministic model fits that of the stochastic model. If $VSS = 0$, it indicates that the results obtained from the stochastic model match those of the deterministic model, meaning that the optimal solution is reached. If $VSS > 0$, it means that the optimal solution obtained by the proposed stochastic model is better than that of the deterministic model.

Group	# Scenario	EEV	SP	VSS (%)
	10	12.7493	12.7493	0.00
	25	9.1723	9.1723	0.00
1	50	5.7842	5.7842	0.00
	75	5.4290	5.4290	0.00
	100	5.1960	5.1960	0.00
	10	629.8270	632.3435	-0.40
	25	645.3056	646.8099	-0.23
2	50	629.5969	630.3491	-0.12
	75	591.0320	591.7840	-0.13
	100	643.4060	644.2449	-0.13
	10	5063.7921	2130.0778	137.73
	25	5115.1086	2235.7881	128.78
3	50	5094.4670	2258.7938	125.54
	75	5072.4830	2179.7100	132.71
	100	5061.8477	2209.2042	129.13
	10	3100.6649	2651.2128	16.95
	25	3302.3410	2424.0386	36.23
4	50	3318.2686	2640.3603	25.67
	75	3324.3214	2689.6911	23.59
	100	3347.8241	107783.9035	---
	10	3850.7956	3850.7956	0.00
	25	3652.0445	3652.0445	0.00
5	50	4058.0890	3652.0445	11.12
	75	4101.7540	220452.0779	---
	100	4127.1243	220756.4081	---
	10	7810.5786	6702.9876	16.52
	25	7548.2435	7213.9194	4.63
6	50	7286.7389	7055.3430	3.28
	75	7396.7726	8121.3198	---
	100	7405.3165	223571.4123	---

--- : the gap of the computational results is significantly large (gap ≥ 50%), VSS would not be computed.

Table 4-9: Computations of EEV and VSS.

From Table 4-9, only Group 1 has all VSS values of the sub-groups being 0.00, indicating that there is no difference between the deterministic and stochastic programming models. In this group, the number of flights considered is the smallest, and it is relatively small compared to reality. Therefore, the sequence of the aircraft would be easily determined manually.

Except for Groups 1 and 2, some sub-groups in the other groups have obtained positive VSS values. This implies that the stochastic programming models are performing better than the deterministic programming models. It is believed that in the computations of stochastic models, different scenarios have already been considered, leading to more accurate results. For the EEV, the results are computed through the expected values of the deterministic model, where the sequence of the model is based on the first scenarios of the group. When the first scenario of the group is a “good” datum, meaning that the delay time obtained from the scenario is low, this implies that the scenario in the simulation may not be a comparatively worse case. This explains why the VSS values in some groups may be positive and why the stochastic model is needed when uncertainties are considered in optimisation models.

For Groups 4, 5, and 6, due to the inability to obtain the global optimal solutions of the stochastic models, the values in the table are the local optimal values after 30 minutes of computations. The VSS values with a computational gap larger than 50% are be computed. However, for the other sub-groups in Groups 4, 5, and 6, a significant value of the stochastic solution can be observed. As the number of aircraft considered in the model increases, the computational time required also increases. Thus, when a large number of scenarios is considered, it requires more than 30 minutes to obtain the global optimum. Yet, it is impractical to perform the analysis with results requiring more than 30 minutes since the environment under adverse weather conditions may have already changed. Therefore, one of the limitations is the inaccuracy due to the size of the model. Nevertheless, when the number of scenarios considered is limited to 50, even if the global optimum is not attained, the value of the stochastic model can be observed from the analysis in Table 4-9.

As for Group 2, most of the sub-groups have negative VSS values larger than -0.2. This indicates that the performance of the deterministic model with this group of data is better than that of the stochastic model. One possible factor leading to this result is the computational methods of EEV and SP. In the computation of SP, the uncertainty sets are inserted into the programme for computations. Therefore, the solutions obtained from the computations have considered all the scenarios and attained the best solutions. However, EEV is the expected value when different scenarios are inserted into the deterministic solutions. By fitting the sequence of the deterministic model, a slightly better expectation may be obtained, leading to $\text{EEV} < \text{SP}$. As observed from the values in Group 2, the difference between EEV and SP are near with $|\text{VSS}| < 0.2$. Therefore, it is acceptable in this case.

Thus, it is concluded that the stochastic programming model generally performs better than the deterministic programming model.

4.7 Conclusion

With the increasing number of adverse weather conditions and flights, the total delay time is expected to rise. This directly affects aircraft operations and passenger planning. Therefore, a two-stage joint aircraft landing and terminal traffic flow optimisation model is proposed in this paper to jointly consider the terminal traffic flow problem and aircraft landing issues. Through the proposed model, we aim to minimise the delay time cost of aircraft while considering various extreme weather events.

In the proposed stochastic model, a computational improvement procedure is included to reduce the computational time of the model, and computations show that direct computation is the best improvement procedure among the chosen methods. The sample average approximation is used in this chapter to simulate a large number of weather scenarios. A comparison between the FCFS strategy, the proposed deterministic model, and the proposed stochastic model is conducted. Through this comparison, the proposed stochastic model performs the best among the three methods in reducing total delay time cost of aircraft.

At the time of writing, the Hong Kong International Airport has completed the construction of third runway, while one of the existing runways is under reconfiguration. The runway configuration in Hong Kong is such that the north runway is mainly used for arrival flights and the south runway is mainly used for departure flights. Thus, in this paper, a single runway system is adopted for the simulation, which may increase the delay time of the aircraft. Further research can be conducted to investigate models adopted for multiple runway systems.

Assumptions are also established in the model to simplify the computation procedures. One possible relaxation in future studies can be the aircraft speed. In this paper, we assume the speed of arriving aircraft to be fixed. Yet, the speed can be more dynamic to match with the scenarios. Therefore, the dynamic speed of aircraft can be considered in the optimisation model in future studies.

Due to the size of the model, a long computation time is required. In some groups under certain scenarios, optimal values cannot be obtained for this reason. Besides developing a new optimisation model, investigation computational improvement procedures could be a possible approach in future work. It is believed that with suitable computational improvement procedures, the computational results can be improved, which would further suit the real-world situations and could be implemented.

Multiple airport regions (MARs) can also be a promising approach for future research in extending the proposed model. By considering the flight routes of different airports within a given region, the model could become more practical. However, the size of the currently proposed model is relatively large, leading to a long computational time for result simulations. Therefore, this concept is not considered in the current paper, but future research might extend the model to incorporate MARs.

Chapter 5 Conclusion and Future Works

In this chapter, a conclusion to the thesis and future works are included.

5.1 Conclusion

Due to the increasing number of adverse weather events and flights, flight delays have become a significant problem in aviation, and this phenomenon is expected to worsen. Therefore, the ultimate goal of this thesis is to reduce flight delays so that the likelihood of aircraft being affected can be minimised. A two-stage stochastic approach is adopted in this thesis to formulate two mathematical programming models aimed at either maximising the punctuality of flights or minimising total flight delays.

The first research question addresses predictable weather events, with tropical storms selected as the focal events. A two-stage stochastic mixed-integer optimisation model, which considers the effects of tropical storms, is proposed. In this model, the occurrence and effects of tropical storms are treated as uncertainties. Under these circumstances, the punctuality of flights is maximised. The performance of the proposed stochastic model is satisfactory in terms of optimality and computational time. Therefore, it can be concluded that the proposed stochastic model can effectively reschedule flights to minimise the number of delays.

Rainfall is chosen as the unpredictable weather event to be discussed in response to the second research question. A two-stage stochastic mathematical programming model is proposed to reduce the total flight delays of aircraft. In the proposed model, the ALP and TTFP models are considered simultaneously, allowing for the prior rearrangement of landing sequences. Due to the unpredictability of rainfall, a sample average approximation approach has been adopted to simulate the results. A comparison between various methods, including the FCFS strategy, the proposed deterministic model, and the proposed stochastic model, is performed to assess performance. Computational results indicate that the proposed stochastic model performs better than the other methods in minimising total flight delays. Therefore, it can be determined that the proposed joint stochastic model could effectively reduce flight delays. By integrating the ALP and TTFP models, ATCOs could anticipate the effects of adverse weather events and rearrange flight sequences accordingly.

Despite the advanced technology available today, it remains challenging to accurately forecast weather changes. Therefore, it is impossible to completely avoid flight delays caused by adverse weather events. However, by considering various uncertainties in the developed models, it is believed that the number of flight delays can be significantly reduced through the proposed two-stage stochastic models.

5.2 Future Works

The conditions of weather events, including their strength and affected locations, may change significantly within a short period of time. Therefore, a real-time approach could be a realistic and practical area for future investigation. With the implementation of a real-time optimisation model, flight delays could be further reduced. This could enhance passenger satisfaction and also benefit airlines and airports as aircraft operations could continue more smoothly.

To better align with the real-world environment, some assumptions or restrictions may need to be relaxed. For instance, in the proposed models, emergency flights have not been considered, since these flights must be handled with the highest priority. However, this implies that the proposed model would not be fully implemented, since other flights would have lower priority, which could significantly increase flight delays. Therefore, the consideration of emergency flights in models concerning weather events would be a possible research approach for the future.

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