Airport Capacity Management and Air Relief Operation Optimization for Disaster Response

(災害対応のための空港容量管理と救援航空機の運用最適化)

2021年12月

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Airport Capacity Management and Air Relief Operation Optimization for Disaster Response

WANG QINGQI

A dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

Department of Urban and Civil Engineering
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Japan
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by

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A dissertation submitted in partial fulfillment of the requirements for the degree of
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CERTIFICATE

The research work embodied in the present thesis entitled “**Airport Capacity Management and Air Relief Operation Optimization for Disaster Response**” has been carried out in the Graduate School of Science and Engineering, Ibaraki University in partial fulfillment of the requirements for the degree of Doctor of Philosophy (PhD). The work reported herein is original and does not from part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion or to any other scholar.

I understand the University’s policy on plagiarism and declare that the thesis and publications are my own work, except where specially acknowledged and has not been copied from other sources or been previously submitted for award or assessment.

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Abstract

Natural disasters cause severe damage to ground transportation infrastructure. When these disasters occur, air transportation generally serves as the primary transportation mode for relief efforts, with a focus on human evacuation and delivery of medical aid to the affected area. The operation strategies and execution methods in air relief activities are similar to aircraft operation strategies in normal situations. With the increasing frequency and destructiveness of disasters, the scope of relief activities and number of relief missions are also increasing, leading to an increase in the number of aircrafts operated at base airports and additional complexity in aircraft dispatchment. Thus, the traditional airport capacity assessment method and aircraft operation strategies do not satisfy the requirements for disaster relief missions. Therefore, to research airport capacity evaluation methods directed at relief base airports and to optimize aircraft dispatchment strategies in relief activities, mathematical models were developed to analyze airport capacity and aircraft dispatchment methods.

In Chapter 1, the background and purpose of this research are introduced.

In Chapter 2, related literature on airport capacity, flight plan creation, optimization model, etc. are reviewed.

In Chapter 3, to analyze airport capacity in relief activities, the concept of dynamic capacity is proposed, which can calculate the maximum number of aircrafts that can be safely operated at one time at a specific airport. An integrated simulation of the runway and apron operation was developed, to focus on airport capacity evaluation during relief activities. The simulation is used as a planning tool to analyze the maximum number of aircraft operated in different fleet-type scenarios. The results demonstrated that airports can receive more aircraft than the number of parking spots, while ensuring aircraft safety.

In Chapter 4, for when airports are threatened by a disaster, an optimal scheme is designed to plan for an aircraft evacuation prior to the disaster. First, this research establishes a model for aircraft allocation on an apron, which also considers the flexible use of airport parking spaces. Then, the optimization model is utilized to determine different aircraft evacuation schemes according to different objectives. The results illustrated that this model can provide aircraft evacuation schemes based on different conditions of evacuated aircraft, capacity of alternative airports, and model objectives.

In Chapter 5, to optimize aircraft routing planning and airport scheduling, this research referred to split delivery vehicle routing to design flight routing and establish an Airport Scheduling Model with a minimum completion time, based on the designed flight routing. To validate the proposed method, it is compared with the standard air relief method under different demand distributions.

Through numerical experiments, the proposed flight planning model has better rescue efficiency

than the common rescue method, when the distribution of demand is imbalanced.

In Chapter 6, to research the effect of the information sharing system on the efficiency of transportation, this study analyzed and defined different information sharing levels by communication devices used in air relief activities. Then, the proposed dispatch strategies corresponded to different information-sharing levels. An agent-based simulation was utilized to model the dynamic system. Finally, different dispatch strategies were compared using different indexes. The simulation results demonstrate that the efficiency of relief activities increases as the level of information sharing improves.

In Chapter 7, the conclusions of this research are summarized, and this research is expected to provide some advice and guidelines for Air Relief Coordinators.

Contents

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1 Introduction

1.1 Background

Over the past 20 years, the number of extreme weather events has increased dramatically, accompanied by heavy human and economic tolls worldwide. Specifically, from 2000 to 2019, China (577) and the United States (467) recorded the highest number of disaster events, followed by India (321), the Philippines (304), and Indonesia (278). Eight of the top 10 countries with the highest number of disaster evens are located in Asia. Over the aforementioned period, approximately 7,348 major disaster events were recorded globally; these events resulted in 1.23 million casualties, affecting 4.2 billion people and leading to economic losses amounting to $2.97 trillion (UN office for Disaster Risk Reduction). Thus, droughts, floods, earthquakes, tsunamis, wildfires, and extreme temperature events have caused severe damage.

In recent years, Japan has ranked among the countries with the most natural disasters. As Japan is situated in an area where several tectonic plates meet, the country is vulnerable to natural disasters. Notably, 23, 29, and 29 typhoons were recorded in 2020, 2019, and 2018, while 5, 6, and 3 earthquakes with magnitudes of 5 or higher were recorded in 2020, 2019, and 2017, respectively (Japan Meteorological Agency). Therefore, disaster management planning is extremely important in Japan.

With the advances in technology, additional lives have been saved; nevertheless, more people are being affected by the growing climate emergency. These disasters impact different aspects of society. In this regard, this research focused on the effect of disasters on aviation activities and analyzed the airport management and aircraft operations undertaken for disaster response.

The effects of disasters on aviation activities can be indirect. Disasters may cause casualties and property damage in the affected areas; land transportation networks may be severely damaged and require time for restoration. In such cases, aircraft would play an important role in resuming activities by overcoming various geographical barriers. For example, during the Great East Japan Earthquake, land transportation networks were disrupted almost immediately. However, airports played an important role by serving as the base of rescue operations; aircraft were employed for different types of tasks such as information gathering, emergency rescues, and personal and goods transport.

The effects of disasters on aviation activities can also be direct. Disasters can destroy aviation facilities such as the terminals in airports and airport access, resulting in suspended aviation activities; furthermore, disasters can also cause direct damage to aircraft. For instance, typhoons can directly affect aviation activities. In 2018, Typhoon 21 flooded the runway and terminal facilities of Kansai Airport, considerably impacting the normal aviation activities and stranding numerous passengers. In 2019, Typhoon 19 attacked the Tokyo metropolitan area, causing the evacuation of over 200 aircraft to other airports; this is recorded as the largest aircraft evacuation in Japan.

These events illustrate that, in the event of a disaster, aviation activities exhibit different responses such as air relief and aircraft evacuation. Therefore, it is necessary to research aircraft operations for disaster responses. Nevertheless, thus far, certain problems associated with the aircraft response to disasters remain unclear or unaddressed.

1.1.1 Airport capacity

A method for assessing the capacity of base airports during disaster relief activities has not been reported thus far. Airport congestion during relief operations is a common phenomenon. The volume of cargo and flights can temporarily overwhelm an airport's capacity, and the mix of flights further adds complexity to the airport operations (Veatch et al. 2018). For example, during the Great East Japan Earthquake, the number of aircraft operated at regional airports located in the Tohoku region was six to ten times higher than that during normal scenarios; these complicated aircraft activities due to the shortage of parking spaces and refueling (Aratani et al. 2013).

Therefore, based on such previous experiences, it is necessary to develop a method for assessing airport capacity during disaster relief operations. Currently, airport capacity is determined based on the number of parking spots; this is termed as the static capacity. However, the static capacity cannot meet the demands for flight volumes during relief activities.

1.1.2 Aircraft evacuation

In Japan, typhoons occur frequently (23 and 29 typhoons were recorded in 2020 and 2019, respectively). Typhoons can affect aviation activities owing to the heavy storm surges and rainfall. Typhoon 21, which occurred in 2018, flooded the runway and terminal facilities of Kansai Airport, thereby impacting access and stranding numerous passengers. Similar incidents occurred during typhoons 15 and 19 in 2019. This is the direct impact of typhoons on aircraft operations. Other disasters can also have direct effects on aircraft operations. For instance, the volcanic ash resulting from volcanic eruptions can damage aircraft engines, and earthquakes can damage airports and affect the normal aircraft takeoff and landing processes.

Considering the possibility of disasters directly affecting aircraft, evacuating aircraft from the affected airports to safe airports is necessary. The conventional aircraft allocation method involves parking aircraft at specific parking spots. This method, however, is not suitable during emergency evacuations, where many aircraft need to be parked in the airport apron.

1.1.3 Aircraft operation for relief activities

In the wake of a disaster, rescue operations are commenced immediately. In terms of medical rescue transportation, relief aircraft are generally assigned in response to requests through the "single-destination" method (Andreeva et al. 2015); this implies that the relief aircraft only visit one rescue center per flight mission. Although this approach enables the quick deployment of aircraft, it involves certain drawbacks such as the waste of air relief resources and airport congestion (Shinya et al. 2013).

In addition, the rescue efficiency under various relief situations has not been verified thus far.

Hence, it is necessary to verify the efficiency of this conservative method and also develop other transportation methods with higher efficiencies.

1.1.4 Communication devices in relief activities

In disaster relief organizations, apart from relief aircraft, another important piece of equipment is the communication device. With the advances in communication technology, an increasing number of communication devices have been used in air relief activities, such as telephones, satellites, and the Internet. For example, during the Great East Japan Earthquake of March 2011, communication between the disaster response headquarters and aircraft was realized through wireless communication devices. Since 2014, the Disaster Relief Aircraft Information Sharing Network (D-net), developed by the Japan Aerospace Exploration Agency (JAXA), has been applied to relief activities; this network can share the necessary information via satellites and the Internet.

The development of communication devices is expected to affect air relief strategies and the efficiency of relief activities. However, the necessary improvements in different communication devices for relief activities remain unclear. Therefore, it is necessary to verify the effects of different communication devices on air relief activities.

1.2 Research objectives

Based on the aforementioned analysis, the objectives of this research are as follows:

Airport capacity management for disaster response

1) A concept of dynamic capacity is proposed, where the number of operated aircraft is determined by considering the average delay time for landing. Subsequently, an integrated simulation model based on the dynamic capacity concept is developed to evaluate the maximum airport capacity during relief activities.

2) The characteristics of aircraft parking in airports prior to typhoons are considered; thereafter, considering the “pin packing problem,” a method to increase airport parking capacities via the flexible utilization of parking spaces is established.

Air relief routing and scheduling for disaster response

3) Existing air relief transport methods are analyzed and vehicle routing planning is considered to design new flight routing methods and optimize airport schedules, in order to improve the efficiency of relief activities.

4) The communication devices utilized for air relief activities are investigated, and different information-sharing levels are defined. Subsequently, the optimal dispatch methods are analyzed considering the different levels of sharing information and different scenarios of demand distribution.

1.3 Dissertation outline

This thesis consists of seven chapters. Chapter 1 presents the background and the introduction.

Chapter 2 provides a literature review. Chapters 3–6 present corresponding models for the method of assessing airport capacity during relief activities, the aircraft allocation method for airports during evacuation, the optimal aircraft dispatch method for air relief activities, and the effect of different levels of sharing information on transport methods. Lastly, the conclusions are presented in Chapter 7.

Chapter 1 explains the background, objectives, and outline.

Chapter 2 introduces the relevant literature pertaining to airport capacity, aircraft diversion, shelter selection, humanity logistic transport method, and dynamic routing planning, among others.

Chapter 3 explains the development of an integrated simulation of the runway and apron operation during a disaster for airport capacity evaluations using the concept of dynamic capacity. This simulation is then used as a planning tool to allocate and arrange disaster relief aircraft. This chapter describes the efforts devoted toward establishing a suitable operation strategy to efficiently utilize an airport's resources and operate rescue aircraft. These results are expected to provide useful insights into airport capacity planning for disaster relief operations.

Chapter 4 presents a model for aircraft allocation in an apron with two objectives: maximize the number of evacuated aircraft in an apron and maximize the utilization of the apron. Further, a heuristic was developed to determine the optimal aircraft evacuation schemes corresponding to different priorities. Aircraft evacuation was also simulated for the available airports during Typhoon 19 in 2019, and different aircraft allocation schemes based on different priorities were compared.

Chapter 5 describes a flight scheduling model with the minimum completion time based on the designed flight routing; different aircraft routing methods were compared under different demand distributions. Based on numerical experiments, the proposed model achieves better rescue efficiency than the conventional rescue method when the distribution of demand is imbalanced.

Chapter 6 presents different dispatch strategies corresponding to the different information-sharing levels; the agent-based simulation modeling dynamic system is employed to compare the air relief efficiency of different dispatch strategies. The simulation results demonstrate that the efficiency of relief activities increases as the level of information sharing improves and that different dispatch strategies have an impact on the effectiveness of relief activities.

Chapter 7 summarizes the conclusions of this research and provides suggestions for future research.

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2 Literature review

As this study addresses the issue of airport management and aircraft operation for disaster response, this chapter addresses detailed reviews on existing knowledge from academics and practices. Since this research includes four objectives, this chapter reviews and summaries relevant literatures for corresponding objective.

2.1 Airport capacity and operation in disaster

Airports cooperate closely with local emergency management agencies throughout the preparedness, response, and recovery phases of an emergency. Smith *et al* (2007) first discussed the cooperation, coordination, and communication roles of regional airports during disasters. Likewise, several studies have examined various aspects of airports emergency management (Barich, 2013; Minato and Morimoto, 2012; Smith, 2010, 2012 and 2014; Sampey, 2013).

As a study on airport capacity and operation in disaster, Kodato (2015) developed a simple macroscopic statistical model for runway capacity calculation while grasped the operation rules and actual conditions on air traffic control of rotary-wing aircraft with VFR and fixed-wing aircraft in local airport with restricted ATC facility (e.g. non-radar condition and/or no parallel taxiway). Choi and Hanaoka (2017) addressed the detailed phases in a diagramming for a humanitarian logistics base airport by integrating an architectural approach and airport disaster management. The results highlighted the importance of managing the flexible use of space to improve humanitarian logistics.

Kobayashi and Okuno (2010, 2011) conducted research and development on information sharing networks of disaster relief aircraft to solve problems concerning information sharing and flight management when all aircraft activities were gathered in disaster areas. Choi and Hanaoka (2016, 2017) confirmed the effect of changing queuing discipline and the significance of the runway service rate for reducing waiting time in an airport. And asserted that airport disaster response operations in the region played a vital role in reducing waiting time in airports. Finally developed a model to estimate the mean waiting time in airports through cooperative disaster response operations using an open Jackson network model.

In the past research and reports, there are few quantitative analyses about the airport capacity in a disaster including the capacity of parking spots and runways with considering the patterns of disaster relief aircrafts' activities. This research would propose a method to quantitatively evaluate the airport capacity with the runway and parking spots under the special circumstance of disaster and originally propose the new concept to plan the airport capacity to be used for disaster relief aircraft activities.

2.2 Aircraft evacuation

Actions for responding to airport outages involve predeparture actions (aircraft diverts) or routing actions (aircraft reroutes). Although this research considers the predeparture actions prior to disaster, literature on both predeparture and rerouting are reviewed. Furthermore, this research also refers to literature on the evacuation planning and shelter site selection and research on the bin packing problem for establishing the apron utilization model.

2.2.1 Aircraft divert

Various aircraft divert situations have been studied previously. Dimitris *et al.* (1998) integrated predeparture and rerouting actions in the same framework by adjusting the arrival time of aircraft in all the capacitated resources. Megan *et al.* (2013) developed a deterministic multi-resource network routing model to reroute individual aircraft to one of the several possible capacitated diversion airports. Some researchers have considered flight diversion along with passenger demand. Based on abrupt airport outages due to earthquakes, Daniel *et al*. (2017) developed a large neighborhood search heuristic to optimize the rerouting of flights bound for disrupted airports to hub airports that are not disrupted, while accommodating passengers on the existing flights departing to non-disrupted hubs. Zhang *et al*. (2008) designed an intermodal strategy where flights bound for a major hub experiencing an outage were rerouted to a nearby airport and the passengers were bussed to the hub airport. Serge *et al*. (2011) introduced a large-scale neighborhood search heuristic that defined the optimal aircraft routes and fleet assignment to these routes along with passenger itineraries, considering the operating cost as well as passenger delay. From these works, it is concluded that the existing research mainly considers passenger demand in the aircraft divert or rerouting model. There are few studies that consider the divert model based on aircraft demand. Considering the history of typhoons, this research is aimed at establishing an aircraft divert model based on aircraft demand and constraints of airport aprons.

2.2.2 Evacuation and shelter site selection

This section refers to some studies on evacuation and shelter site selection, which would provide inspiration for aircraft evacuation research framework. Chanta et al. (2012) proposed an optimization model to select temporary shelter sites for flood disasters, aiming to maximize the number of victims being moved to shelters and to minimize the total distance of all victims from their nearest shelters. Santos et al. (2013) proposed a model for flood shelter site selection, which aims to maximize the population covered by the limited number of facility locations. For flood evacuation planning research, the reader can also refer to Kongsomsaksakul *et al.* (2005) and Boonmee *et al.* (2016). With regard to cyclone, typhoon, or precipitation evacuation, Wang et al. (2015) proposed an optimization model to identify the best precipitation stations considering the associated rainfall monitoring demand. Chowdhury *et al.* (1998) proposed a multi-objective mathematical programming model and simulation model to quantify the objectives and provided decision support for cyclone shelter location. Li *et al.* (2012) developed a dynamic traffic assignment model for the selection of shelter locations with explicit consideration of a range of possible hurricane events and the evacuation needs under each of those events. With regard to earthquakes, Feng *et al.* (2005) developed a decision-making tool that could potentially be used in managing the emergency vehicles and controlling the private vehicle flows in earthquake disasters. Kulshrestha *et al.* (2011) presented a robust model for considering demand uncertainty. This model not only determines the number of shelters and their capacities, but also considers the route for access to shelters. Based on these works, it is concluded that these models focus on the procedure to evacuate personnel from affected areas to shelters with some objectives such as maximization of the number of evacuated persons, minimization of the travelling distance, or minimization of the number of shelters. The framework is similar to this research, in which aircraft are evacuated from affected airports to an alternative area with minimum number of alternative airports. However, the capacity of shelter site in these works is fixed, which is different from that in this study. This study considers flexible use of parking space in alternative airports. In other words, the core question is capacity management for temporal parking by considering the best use of parking space in an apron.

2.2.3 Bin-packing problem

To solve the question of flexible use of parking space in airport, this research refers to studies on the bin-packing problem for aircraft allocation in an apron. Klaus (1999) proposed a scheme for the bin packing problem with conflicts (BPC). To solve this problem, Khaoula *et al*. (2012) presented two heuristics and a multi-start genetic algorithm. Albert et al. (2010) provided new lower and upper bounds to solve the BPC. Khanafer *et al.* (2009, 2010) developed new lower bounds and subsequently proposed a new approach based on tree decomposition. Similar methods can also be found in Gendreau *et al.* (2004). Stoyan *et al*. (1998) proposed a hybrid method combining a branch and bound, and a reduced gradient method to solve this problem, considering cases where the items were either rectangles or circles. The problem was generalized to the three-dimensional case described by Stoyan et al. (2009). Based on the analysis of above works, these rectangular items can be regarded as parking space of aircraft in an apron and the bins can be seen as different parking spaces. Therefore, some heuristics in the bin-packaging problem could be referred here to establish the apron utilization model.

From the literature review and analysis, it is concluded that though this research is about aircraft divert, the main objective is to evacuate the aircraft to a safer place, and this research framework is similar to that of the research on evacuation and shelter site selection. The basic question and the first step of aircraft evacuation is capacity management for temporal parking. Therefore, in this study, the aim is to establish a flexible apron utilization model by referring to bin-packaging models.

2.3 Aircraft operation method

According to previous studies (Estrada el at 2019; Hanaoka et al 2013; Polater and Abdussamet 2018, Jiang, Yiping, et al 2019), the main areas in which aircraft are used in the case of natural disaster response and humanitarian relief aid include (1) post-disaster damage assessment (Oruc and Bahar 2018); (2) medical and goods transportation; and (3) post-disaster media reports (Hanaoka et al 2013). This study mainly focuses on the medical transportation, which is usually implemented by helicopters. But this research can also refer to model and algorithms in other relief activities such as the goods delivery, information collecting and media report and in other transport mode such as land transport or drone.

2.3.1 Logistics model with single objective

From the perspective of a subjective model, there are two categories: single-objective model and multiple-objective model. Regarding single-objective models, Ozdamar (2011) proposed a model for helicopter pickups for post-disaster medical care and injured evacuation, which aims at minimizing the total travel time, including that taken for the complete mission and the load/unload process. Özdamar and Onur (2012) first grouped these demand nodes into smaller clusters, and then designed the routing with the aim of minimizing the total estimated travel time. In fact, there are some other objectives similar to the total travel time; for instance, Berkoune et al (2012) minimized the total duration of all trips of a vehicle. Chiu et al (2007) minimized the objective of total travel time of all priority groups. Rabta et al (2018) minimized the total traveling distance of a drone. Meanwhile, some other researchers have added other factors with the routing time to design relief supplies. Balcik et al (2008) analyzed decisions about allocating the relief supplies and the delivery routes for each vehicle with the objective of minimizing the sum of the routing and penalty costs of the backordered and lost demand. Chowdhury et al (2017) proposed a model to design the potentiality of drones in emergency logistics. Their objectives included the cost of the locating facilities, allocating inventories, and transporting emergency supplies using trucks and drones. There are also other papers that have defined the objectives themselves. Huang et al (2012) first defined and formulated the performance metrics in relief distribution, and researched how the efficiency, efficacy, and equity influence the structure of vehicle routes and resource distribution. Liu et al (2020) considered the distance, block risk in the arc, population, the collapsed building, and the potential secondary hazard to redefine the objective of "rescue efficiency" in routing planning, to achieve the goal of maximizing the total rescue efficiency. Ferrer et al (2018) built a multi-criteria model including time, cost, coverage, equity, and security as the objectives.

2.3.2 logistics model with multiple objectives

Some studies have also considered multiple objectives. For instance, Najafi et al (2013) proposed a multi-objective model with the objectives of minimizing the total unserved injured people, total unsatisfied demands, and total vehicles in the response. Veysmoradi et al (2018) proposed a multi-objective model with the objectives of minimizing relief distribution costs and maximum traveling time of a vehicle route and maximizing the minimum route reliability. Such a multi-objective model was also established by Haghi et al (2017).

2.3.3 Logistics model with uncertainties and stochastic factors

Another stream of research considered the uncertainties and stochastic factors. Haghi et al (2017) considered the uncertainties in demand, casualty supply, and cost to determine the locations of health and distribution centers. Tofighi et al (2016) considered uncertainties in both supply and demand. Parwanto et al (2015) considered uncertainty related to each road segment's availability when designing a transshipment network. Bruni et al (2018) took the stochastic travel time into account when designing multi-vehicle routing. Rezaei-Malek et al (2016) based on the transportation mode, took the usage possibility of alternative routes into account.

2.3.4 Integrated logistics model

Some other papers have integrated the inventory location and scheduling with relief routing. Tofighi et al (2016) integrated facility location, inventory decisions, and relief distribution planning to analyze the humanitarian logistic network. Such integration of the inventory and routing was also proposed by Yi, Wei, and Linet Özdamar (2007), Mete et al (2010) and Ahmadi et al (2015), and Ahmadi (2015). Another category is combination routing and scheduling. For instance, De Angelis et al (2007) considered the airplane routing and scheduling problem for transporting food. They calculated the weekly parking schedule of planes to maximize the total satisfied demand.

According above literature review, most of the previous studies have focused on a decomposition decision or procedure, such as resource allocation and routing planning. A few recent studies have started considering an integrated model to address the entire emergency logistic process. This study plans to integrate the rescue routing planning and daily schedule to establish an entire air medical rescue model.

2.4 Information sharing levels

The fourth research purpose focuses on establishing a model that can employ different transportation strategies to dispatch aircraft based on demand requests. Hence, this section refers to research and methods for real-time dispatching and route planning or dynamic route planning.

2.4.1 Real-time dispatchment model

In dealing with real-time dispatchment questions, some researchers use Markov decision processes. To improve the computational efficiency, Goodson *et al.* (2013) improved the traditional one-step rollout policy in the Markov decision process by developing a pre- and post-decision state. Concerning the allocation question of emergency medical vehicles, Yoon *et al.* (2020) formulated a

Markov decision process model that dynamically determines the type of vehicle(s) to be dispatched. Aiming at the military medical aircraft dispatchment question, Robbins *et al.* (2020) presented a Markov decision process model to optimize sequential resource allocation decisions under demand uncertainties (severity, number, and location) and service times. Like Keneally et al. (2016), Jenkins et al. (2018) and McLay et al. (2013) presented a Markov Decision Process (MDP) model for dispatching Emergency Management System (EMS) assets to spatially distributed patients that maximizes the fraction of patients who responded within a fixed time frame.

Other researchers use the framework of agent-based simulation to manage real-time dispatchment questions in different fields. This framework is widely used in researching autonomous vehicles (AVs), taxis, and rideshares. Hyland et al. (2018) utilized the framework of an agent-based simulation to model different agents, such as autonomous vehicles, travelers, and intelligent fleet operators, to compare different AV-traveler assignment strategies (control policies). Like Bischoff *et al.* (2016), Zhang *et al.* (2015) designed and applied an agent-based model to simulate the performance and estimate the potential benefits of a sharing AV (SAV) system with dynamic ridesharing. They used an agent-based simulation model to estimate different system operation scenarios to investigate the potential impact of the SAV system on urban parking demand. Fagnant *et al.* (2014) designed an agent-based simulation to investigate the effect of combing ridesharing programs and AVs on the total fleet size, travel distance, and emissions, similar to Martinez *et al.* (2017). Regarding taxi dispatchment, Grau et al. (2015) developed a tool to understand the behavior of taxi markets to policy regulations and support decision-makers using this framework. Bischoff et al. (2014) simulated the situation of electric taxicab fleets in an inner-city. Maciejewski *et al*. (2016) proposed and evaluated efficient real-time taxi dispatching strategies using an agent-based simulation. Maciejewski *et al*. (2013), Maciejewski *et al*. (2015), and Maciejewski *et al*. (2013) have similar models.

From the analysis of the literature, MDP has an advantage in the sequential resource allocation question, whereas agent-based simulation is good at comparing different strategies using different indexes. The fourth research purpose is aimed at comparing various transportation methods under different information and communication systems. Hence, this research selects the agent-based simulation framework, which can easily calculate different indexes and combine different routing planning methods that can solve the local routing problem repeatedly.

2.4.2 Dynamic routing model

To propose a dynamic flight method, this research refers to a similar model used in taxi-dispatching or ambulance fleet management in this section.

Regarding the taxi dispatchment, Ozbaygin *et al* (2019) assumed that customer itineraries may change during the execution of the planned delivery schedule and then proposed an iterative solution framework in which an active delivery schedule is re-optimized whenever a customer itinerary update is revealed. Billhardt et al. (2019) presented a new heuristic algorithm for assigning taxis to customers;

the algorithm considers taxi reassignments, which may lead to globally better solutions, and an economic compensation scheme, to incentivize private drivers to agree with the proposed modifications in their assigned clients. Liao *et al.* (2011) proposed a two-stage framework to solve the dynamic vehicle routing problem. In the second stage, the original plan was improved by considering real-time information, similar to Liao *et al.* (2007). Maciejewski *et al.* (2013) considered not only the nearest idle taxi to travelers but also idle and en route drop-off AVs in the assignment to manage dynamic planning, as did Mahmassani *et al.* (2016). Ma *et al*. (2013) designed ridesharing schedules to serve dynamic requests. Andersson *et al.* (2007) proposed a nearest-idle ambulance policy for ambulance dispatchment. Haghani *et al.* (2007) jointly considered ambulance dispatch and relocation. Schmid *et al.* (2012) employed approximate dynamic programming methods to solve ambulance dispatching and relocation.

These taxi and ambulance dispatching models are similar to real-time air-relief dispatchments. However, taxi dispatch considers the changes in demand or traffic information to make some changes to the planned routing. Moreover, ambulance dispatchers usually consider the change in the spatial distribution of the patients to re-optimize the dispatching and location of ambulances. Herein, this research focuses on the continuous effect of different transport strategies handling real-time demand requests in relief activities based on the different levels of information sharing systems.

3 Airport capacity evaluation model for disaster relief activities based on the concept of dynamic capacity

3.1 Introduction

In the Great East Japan Earthquake, compared with the land transportation network which has been disrupted and takes time to restore, airports became a rescue activity base which played an important role in the rescue operation.

However, there are challenges to aircraft operations in the event of a disaster. For example, for the regional airport in the Tohoku region during the Great East Japan Earthquake, it has been reported that 6 to 10 times as many aircraft as the usual times have been operated, and this case troubled aircraft activities due to the shortage of parking spaces and refueling (Aratani et al.2013). Based on the experience of this disaster, each prefecture constructed the revised plan to receive supports for disaster relief from the other regions (Ministry of Internal Affairs Fire and Disaster Management Agency, 2013).

In this plan, " the number of aircraft to be parked", that is how many aircraft that can be accepted by each base, is clearly stated as one item. Every airport has a maximum value of parking spots in apron area and only corresponded number of relief aircraft can be deployed. The capacity determined by the number of parking spots represents the ability of airport to accommodate aircraft simultaneously at a certain moment, and this research called it "static capacity". It needs time and cost to increase the static capacity against the problem of parking spots shortage. And there is a possibility that extra capacity may be useless in normal time. Although adding parking spots is considered as one of the measures to prepare for disasters, it is more urged to think about how to maximize the utilization of the existing resource.

Then, this study considers the possibility to apply "dynamic capacity" that how many aircraft can be handled per unit time for capacity evaluation. In other words, if a certain number of relief aircraft are always active away from the airport, additional relief aircraft can be deployed accordingly. How much is the additional capacity if the concept of dynamic capacity can be applied? Basically, through the rescue time and parking time of each rescue aircraft, the static capacity of the parking spots can be converted to a larger dynamic capacity. But the airport capacity is not determined only by parking spots, also by the runway that is usually one of the major bottlenecks. And it is also necessary to consider the activity patterns of relief aircraft specific to disasters. For the airport capacity, there are many models and mathematics theories such as queuing theory, high-speed simulation etc. But for dynamic capacity calculation with non-steady state of demand like aircraft relief operation in disaster mentioned above, queuing theory is usually difficult to apply. And there is no-existing research to develop a fast-time simulation model considering the operation in disaster and the constraints of the regional airports.

About the research of disaster respond, (Hanaoka *et al*, 2013 and Aratani *et al,* 2013) described how each airport handled aircraft and supported disaster response activities in the aftermath of the Great East Japan Earthquake and clarify the several lessons learned and future challenges that airports and airlines were faced such as parking spots and fuel shortage. And these papers introduced the actual typical operation patterns as shown in Figure 3-1. First, aircraft (mainly helicopters) came to the disaster-affected area from all over Japan sometimes via relay base (like Honda airport and Fukushima airport in Figure 3-1) and assigned those aircrafts to some airports close to the affected area like Hanamaki, Yamagata and Fukushima airport (Sendai airport was heavily damaged by tsunami) based on the airport capacity of each airport. Then, the assigned aircraft were executing disaster relief activities repeatedly from those base airports to the tsunami-affected area (east coast side area) by considering possible flight time with full fueling. In this research, these typical operation patterns are also assumed, and the main motivation of our study is the capacity problem of airport especially in the local small airport like those shown in Figure 3-1 and actually the number of assigned aircraft was significantly restricted by the airport capacity especially by parking spots. This problem is to be discussed in the next chapter.

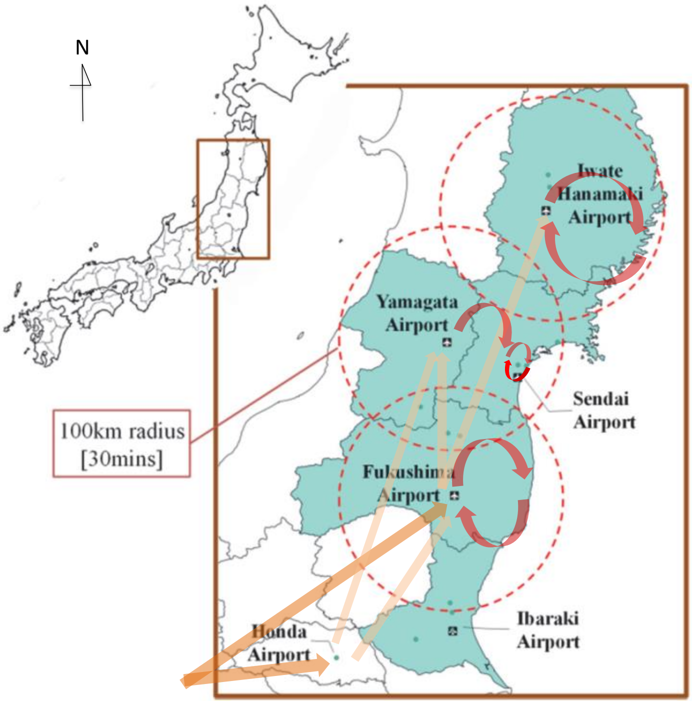


Figure 3-1 Image of the actual operation pattern of disaster relief aircraft in the aftermath of the Great East Japan Earthquake 2011 (large area in the east coast side were affected by tsunami damage)

The purposes of this study are (1) to develop an integrated simulation model considering parking spots and runway system, and also operation patterns of rescue aircrafts in disaster for evaluating dynamic capacity with delay time, and (2) to identify the bottleneck of the airport capacity and the extra capacity to be allocated with dynamic capacity concept at the time of disaster from the case study.

3.2 The concept of airport capacity at the time of disaster with dynamic capacity

The capacity of the airport depends on various elements: basic facilities for aircraft operation such as runway and parking spots, supplemental facilities such as terminal buildings and cargo handling facilities, and the airspace affecting runway operation. This research focuses on the runway, parking spots and the surrounding airspace which are directly related to the aircraft operation in runways, and then develop a simulation model to calculate the airport capacity. As for the surrounding airspace of local airports, the safety ATC separation tends to be much larger due to the lack of airport surveillance radar (ASR) than that in airspaces surrounding congested airports with ASR. This research considers such larger safety separation in a local airport with less traffic demand. In Japan, such airports without ASR are often called “Radio airport” (more specifically, airports without air traffic controller but with air traffic information assistants who provide air traffic information such as runway usage status and meteorological condition).

Parking spots (apron) can define two kinds of capacity, one is “static capacity” which is the number of aircraft that can be stationed there at any particular instant; the other is “dynamic capacity” which indicates the number of aircraft that can be served at the apron per unit of time (Richard de Neufville, 2003). Static capacity, just the number of parking spots, is used to evaluate the number of aircraft to be parked during non-activity hours such as nighttime. In this research, dynamic capacity representing the number of aircraft to be served per unit of time which depends on stand blocking time (parking time) is applied so that this research can examine the maximum utilization of airports resources. Because if a certain number of rescue aircraft are always active away from the airport, this research can consider the extra capacity to be assigned for disaster relief aircraft during airport operating time.

In order to make the concept of “dynamic capacity” clearer and easily understandable, it needs to be emphasized, this "Dynamic capacity" means the maximum number of operated aircraft per certain period under the condition of ensuring the safety of aircraft. When dynamic capacity concept is applied, it is necessary to consider delay time and safety. If it is operated in the concept of static capacity, waiting time due to the lack of parking spots capacity does not occur. However, if it is operated in the concept of dynamic capacity, there is a possibility that landing aircraft to the airport will be delayed because of the lack of parking spots capacity. While the delay time occurs probabilistically according to the conditions such as the traffic volume, it is necessary to consider the safety aspect of aircraft operation, such as avoiding excessive waiting time in the air for landing. Since the delay time is a probabilistic phenomenon, a probabilistic index is required for the evaluation of capacity, delay time and safety. In the runway capacity assessment for the congested airports, there are examples of evaluating airport capacity by setting the average delay time that can be accepted, and this kind of way of thinking is equivalent to the dynamic capacity concept. This research will evaluate airport dynamic capacity based on allowable delay time.

There are various ways of setting this allowable delay time. For example, it is possible to set the allowable time by the available flight time by using reserve fuel. Based on the reserve fuel for extra flight time defined in Article 63 of the Aviation Law, this research can set the probability of exceeding such extra flight time to be 1% or less. As an example, supposing that the flight plan time is 2 hours, the available flight time by using reserve fuel is around 30 minutes and then that can be regarded as one of the threshold value to be used for acceptable delay time when evaluating the extra capacity with dynamic capacity concept.

In addition, against waiting time exceeding such threshold value (e.g. 30 minutes) that can occur in a small probability, it is necessary to consider countermeasures for accommodating such aircraft, for example the preparation and location-database development of the land spaces for helicopters to be landed in emergency. Figure 3-2 shows the example of the registered landing/take-off spaces like an athletic field in Iwate prefecture where Hanamaki airport is located. For the extraordinary waiting time in the air can be accommodated by these spaces if this research could plan such an operation in emergency. Also the traffic flow information sharing and management system for disaster relief aircraft (helicopters) can be used for controlling the arrival time to the airport based depending on the traffic volume and capacity usage prediction by the system. The aircraft information sharing system in the event of a disaster named D-NET by currently has been developed and implemented mainly by Japan Aerospace Exploration Agency, JAXA (Kobayashi and Okuno, 2010, 2011), which can be one of the tools that make it possible to perform the traffic flow management mentioned above. Based on these capacity-related concept in disaster, this research develops the integrated simulation model for evaluating the airport capacity in disaster.

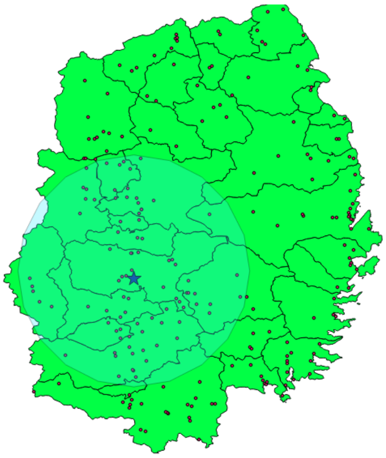


Figure 3-2 Landing/take-off spaces registered in Iwate prefecture (star-mark indicates Hanamaki airport) (source: made by GIS data of heliport from National Land Information Bureau, MLIT Japan, 2013)

3.3 Development of air traffic capacity evaluation simulation in case of disaster

The brief image and flowchart of the algorithm of the integrated simulation model for airport capacity in disaster developed in this research are shown in Figure 3-3 and Figure 3-4. In the initial state of simulation, the number of aircraft is the same as the number of parking spots (static capacity) and all are stationed in each spot. After simulation starts, all aircraft are starting to take off and then finish the mission, finally return to the airport. After parking for a certain period of time, they take off again for missions. This will be repeated from sunrise to sunset (assuming the VFR helicopters can take a mission during the sunrise time: 12 hours). As for the extra capacity over static capacity (parking spot number), after a certain period since sunrise, aircraft from other airports begin to arrive at the airport and are added to missions as disaster relief aircrafts operated based on this airport. The number of aircraft to be added is regarded as the extra capacity with the concept of dynamic capacity.

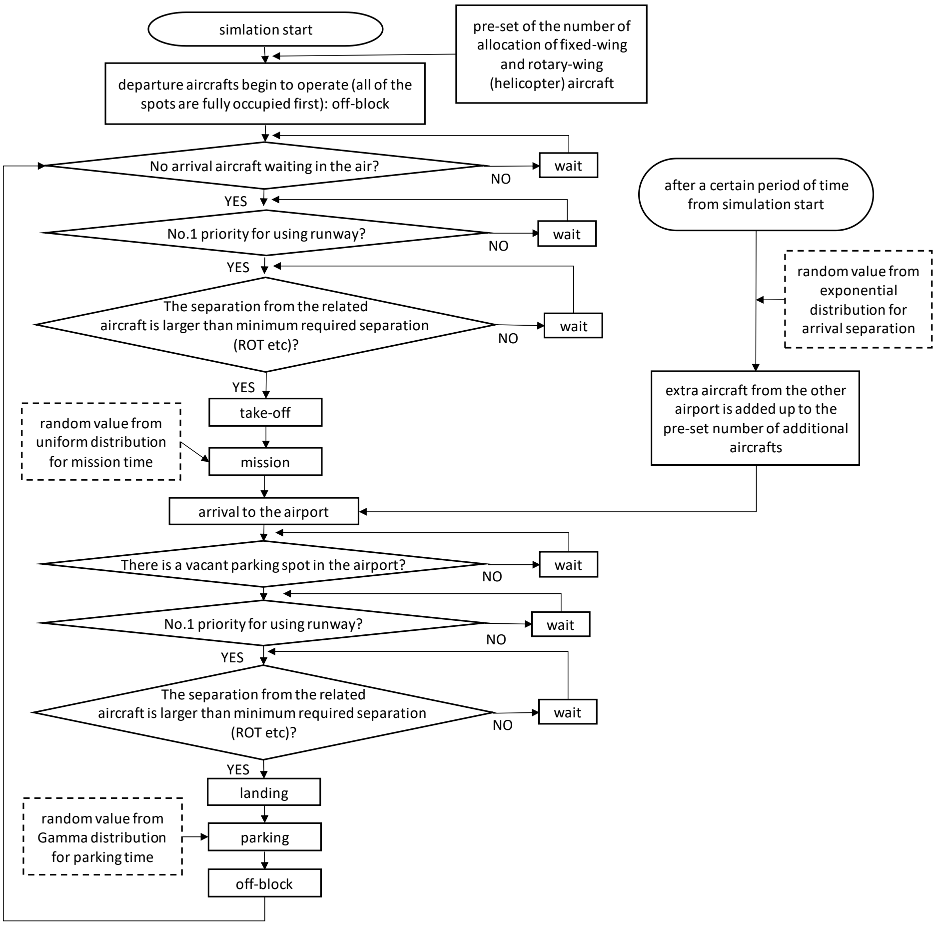


Figure 3-3 Flowchart of the simulation algorithm for airport capacity and delay analysis

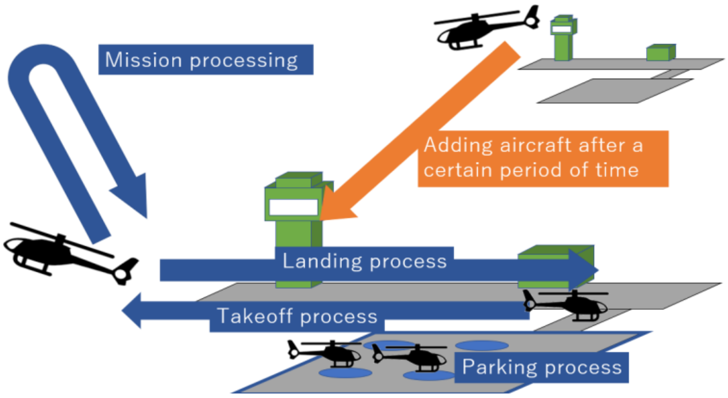


Figure 3-4 Image of integrated simulation for airport capacity in disaster

The main subsystems that constitute the simulation include the runway processing system, the parking spots (apron) processing system, the mission activities processing system, and the additional extra aircrafts generation system. Details of each subsystem will be explained in the following subsections.

3.3.1 Runway occupancy time (ROT) and required separation between consecutive aircrafts

Taking off or landing aircraft are processed according to the order in which they arrive at the runway (First Come First Served). But arrival aircraft always has a priority to use runway over departure aircraft in the simulation unless there is no parking spot vacant and First Come First Served principle is applied in the other situation. The time required for finishing the taking off or landing is the runway occupancy time (ROT), which depends on type and status (take-off or landing) of aircraft, and its combination of processed order (sequence). Therefore, it is necessary to set the runway occupation time for every combination of type and status of aircraft, and it is also needed to consider the influence of the facility constraints of the local airports and the special operation at the time of disaster. For example, at the Radio Airport without ASR, if one landing aircraft occupied the surrounding airspace from the initial arrival FIX to runway, a very large separation time (that is kind of non-radar separation) would be required in the case of consecutive arrivals since the radar separation rule (that is much shorter separation) cannot be applied. Then, runway occupancy time would be much larger in such case. Also, if there is no parallel taxiway, the time making a U-turn in the runway to leave the runway is also included in the runway occupancy time, which can be one of the factors of capacity reduction. Table 3-1 shows the runway occupancy time T_{ij}, which is calculated by the authors (Kodato, W. et al (2015)) based on the layout of the departure and arrival route, runway, and taxiway of Hanamaki Airport in Iwate prefecture, Japan. Hanamaki airport has one 2,500m runway with a parallel taxiway now (in 2011, there is no parallel taxiway, so this research assumes the runway without parallel taxiway in this study) and does not have ASR. Three types of aircraft are considered, Fixed-wing and two types of helicopters that use two different parking spot (apron) area in Hanamaki airport (different parking spot area results in different runway exit position that affects ROT). As shown in the table, much larger ROT (or time interval) is required when fixed-wing aircraft are operated successively due to IFR (Instrument Flight Rule) separation without ASR that induces larger non-radar separation. On the other hand, relatively shorter ROT is required when helicopters are operated successively due to VFR (Visual Flight Rule) separation available. There are two ROTs shown in some of the combinations in Table 3-1, one is for safety capacity; the other is for maximum capacity. The value obtained by adding a certain buffer time to the processing time is the ROT for safe capacity, and the value when assuming that aircraft are processed at the minimum separation according to the rule is the ROT for maximum capacity.

Table 3-1 Runway occupancy time (required time interval) setting in case of Hanamaki airport

T_{ij} (sec)			Successor					
			Arrival			Departure		
			Fixed-wing	Helicopter1	Helicopter2	Fixed-wing	Helicopter1	Helicopter2
Predecessor	Arrival	Fixed-wing	609	518	518	946	518	518
		Helicopter1	81/74	81/74	81/74	81/74	81/74	81/74
		Helicopter2	108/62	108/30	108/30	108/62	108/62	108/62
	Departure	Fixed-wing	290	178	178	290	178	178
		Helicopter1	141	141/30	141/30	141	141/80	141/80
		Helicopter2	113	113/30	113/30	113	113/80	113/80

– In case of two value indicated in the column, ROT for (safety capacity)/(maximum capacity) are shown.

– There are two types of parking spots position (Helicopter1/ Helicopter2) at Hanamaki Airport

3.3.2 Parking occupancy time

Parking time is required for refueling, loading/unloading freight goods and/or rescued people, maintenance of aircraft etc. Parking time is important for analyzing extra capacity with the dynamic capacity concept. Therefore, this research calculates the probability density function (distribution) of parking time for disaster relief activities from the actual parking time observed in Hanamaki airport in the aftermath of the Great East Japan Earthquake on March 12th-14th, 2011.

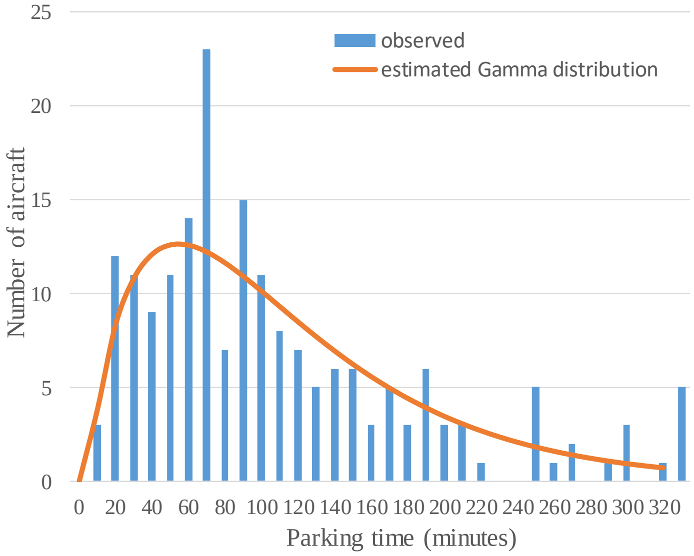


Figure 3-5 Distribution of parking time

The probability distribution function for the parking time of helicopters is assumed as Gamma distribution below.

$$f(x) = \frac{x^{\alpha-1}e^{-\frac{x}{\beta}}}{\Gamma(\alpha)\beta^{\alpha}} \tag{1}$$

$\Gamma(k)$ is the gamma function. The parameters estimated by using observed parking time samples are shown in Table 3-2, and the estimated function and observed values are shown in Figure 3-5. Then, the parking time of each aircraft are randomly generated from this distribution in the simulation.

As for the parking time of fixed-wing aircraft, since the data sample is small due to much less traffic of fixed-wing aircraft in the aftermath of Great East Japan Earthquake, it is difficult to approximate its time by a probability function. Therefore, the parking time of fixed-wing aircraft is generated randomly just from the dataset of all the observed value.

3.3.3 Mission time

Aircraft at the time of a disaster have various missions such as rescue activities, information gathering, people and goods transportation. Since the time of the mission will change due to the magnitude of the disaster, the damage situation and so on, it is inevitable to place certain assumptions on the simulation. In this simulation, it is assumed that the maximum flight time of the helicopter is about 120 minutes by considering the performance of some of the standard helicopters, and the mission time is randomly given between 30 and 90 minutes with the uniform distribution. The mission time also includes flight time between the airport and the mission sites. The longer the mission time is, the longer the aircraft is away from the airport. If considering the dynamic capacity, longer mission time can increase the number of extra aircraft in the airport. In this research, relatively shorter mission time distribution is assumed in order to avoid over-estimation of the capacity.

3.3.4 Extra aircraft to be added

In the initial state of the simulation, the additional aircraft are not deployed in the airport, so this research should set the time interval from the beginning of the simulation to the arrival of first additional aircraft at this airport. Actually, it depends on where these aircraft fly from. In this simulation, the first additional aircraft is set to arrive at the airport 30 minutes later since the simulation started. For the second and other successive aircraft are set to arrive randomly with the exponential distribution in average arrival interval of 5 minutes.

3.3.5 Simulation outputs and evaluation index

The summary of simulation parameters and inputs are shown in Table 3-2. From the simulation, this research can obtain the delay time of each aircraft (waiting time in the air for landing and waiting time beside departure runway on the ground for take-off) together with its delay causes (one is “runway” and the other is “parking spot”) as output data. By using these output data, this research can calculate the probability of delay time (waiting time) of arrival aircraft in the air more than certain minutes such as 30 minutes or 15 minutes that can be threshold value. This is the evaluation index from the aspect of “safety”. The other evaluation index can be considered from the aspect of operational “efficiency”, that are (1) the number of missions carried out in a whole day and (2) number of missions carried out per aircraft.

Since there are several parameters and values which stochastically changes according to a certain probability density function, the average index values are used for evaluation that is calculated from the results of 100 times simulation run (one simulation is 12 hours from sunrise to sunset) in the case study in the next chapter.

Table 3-2 List of simulation parameters and inputs (case of Hanamaki airport)

Parameters	Properties and details			Value
Parking time	Rotary-wing (Helicopters)	Randomly given by gamma-distribution	Parameter α	1.8193
			Parameter β	60.028
	Fixed -wing	Randomly given from observed value		
Apron ratio^{*1}	Rotary-wing	The proportion of apron 1 used		100%
		The proportion of apron 2 used		0%
Number of parking spots	Rotary-wing	The number of parking spots allowing aircraft to park (total: 24)		19-24
	Fixed -wing			5-0
Number of aircraft	Rotary-wing	The number of aircraft parked originally at the spots (total: 24)		19-24
	Fixed -wing			5-0
Runway occupancy time (sec)	Rotary-wing	The time of aircraft using runway		Table 3-1
	Fixed -wing			Table 3-1
The extra aircraft to be added	Rotary-wing	How many aircraft are to be added from other airports after simulation starts		4-10
	Fixed -wing			0
The time when the first aircraft start to be added (minutes)	Rotary-wing Fixed -wing	How many minutes after simulation start do the extra aircraft start to be added		30
The time interval of successive additional aircraft (minutes)	Rotary-wing	Randomly given by exponential distribution with the given mean time interval		5 (mean)
	Fixed -wing			5 (mean)
Mission time (minutes)	Upper limit	Randomly given by uniform distribution from lower to upper limit of time		90
	Lower limit			30

The developed simulation model is verified with simple traffic condition where the delay probability can be analytically obtained by using queuing theory and this research verified that the output from the simulation and that from queuing theory are almost same value.

3.4 Case study of extra airport capacity with dynamic capacity concept

in disaster

In this section, by using the developed integrated airport simulation model, first this research estimates the extra airport capacity with dynamic capacity concept of Hanamaki Airport which is a local airport and was used as a base for disaster relief activities at the time of the Great East Japan Earthquake, and then this research analyzes the effect of different original departure intervals on the delay and the traffic volume.

Hanamaki airport has 24 parking spots including5 spots for fixed-wing aircraft and 19 spots for rotary-wing aircraft. But according to the demand in disaster time, the fixed aircraft parking spots are often converted to rotary-wing aircraft parking spots. Also, the runway occupancy time of the fixed-wing aircraft is much larger than that of the rotary-wing aircraft, so the number of operations of the fixed-wing aircraft may be an important parameter for evaluating airport capacity, especially runway capacity. Therefore, the simulation is carried out by changing the ratio of the fixed-wing aircraft and the rotary-wing aircraft.

3.4.1 Extra capacity evaluation with dynamic capacity concept

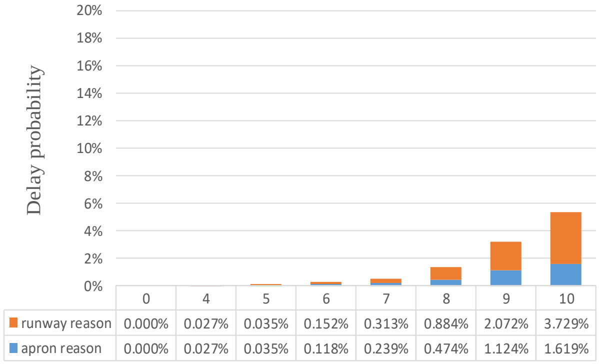
Figure 3-6 and 3-7 show the simulation results of the occurrence probability of the aircraft with the delay of (a) 15 minutes or more and (b) 30 minutes or more in case of 5 fixed-wing aircraft in Figure 3-6 and no fixed-wing aircraft in Figure 3-7. The probabilities are indicated separately depending on the delay cause (runway or parking spot). This research assumes the acceptable delay time as 15 minutes and 30 minutes for evaluating the capacity (number of extra aircraft) with the aspect of safety.

As the number of additional aircraft increases, both of the delay probability in two cases increase and the probabilities of delay with 15 minutes or more are higher than that with 30 minutes or more. Under the same number of additional aircraft, the delay possibility in case of fixed-wing aircraft operated is much higher. This is due to the large ROT of a fixed-wing aircraft in a local airport without ASR. If comparing the delay caused in the two figures, the share of the runway is higher in Figure 3-6 (fixed-wing aircrafts operated case) due to its large ROT than that in Figure 3-7 (no fixed-wing aircraft). On the other hand, the main cause of the delay when only helicopters are operated is parking spot, that means the parking spot capacity can be the bottleneck capacity rather than runway capacity due to relatively small separation minima and ROT of helicopters.

How many aircraft can be assigned to the airport with the dynamic capacity concept? This is the main question of this research. As described in section 4.5, one of the possible criteria for determining the number of aircraft assigned to an airport is the probability to exceed the acceptable delay time in the air of arrival aircraft. If assuming the probability and the acceptable delay time to be respectively 1% and 15 or 30 minutes, the acceptable extra number of aircrafts in addition to the number of parking spots can be determined as 4 aircrafts/day in case of 15 minutes of acceptable delay time and can be 7 aircrafts/day in case of 30 minutes of acceptable delay time when fixed-wing aircrafts are operated.

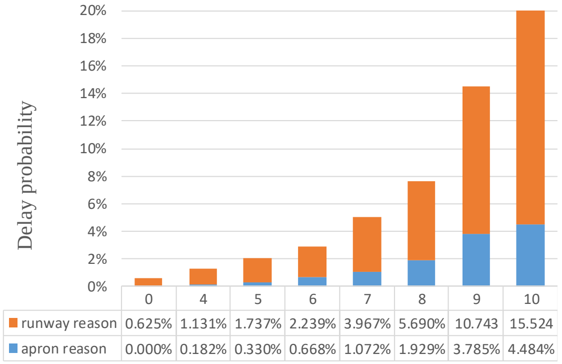
When no fixed-wing aircraft are operated, the acceptable extra number of aircraft can be determined as 8 aircraft/day in case of 15 minutes of acceptable delay time and can be 10 or more aircraft/day in case of 30 minutes of acceptable delay time. These simulation results show that the additional aircraft can be accepted to some extent from the aspect of safety if using the dynamic capacity concept, and the number of acceptable aircraft can change significantly with the condition of the number of fixed-wing aircraft which ROT is relatively large.

(a) Probability of delay 30 minutes or more
when fixed-wing aircraft operated



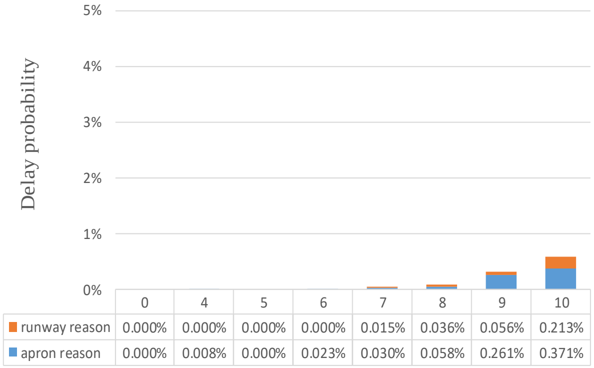
	0	4	5	6	7	8	9	10
🟧 runway reason	0.000%	0.027%	0.035%	0.152%	0.313%	0.884%	2.072%	3.729%
🟦 apron reason	0.000%	0.027%	0.035%	0.118%	0.239%	0.474%	1.124%	1.619%

(b) Probability of delay 15 minutes or more
when fixed-wing aircraft operated



	0	4	5	6	7	8	9	10
🟧 runway reason	0.625%	1.131%	1.737%	2.239%	3.967%	5.690%	10.743	15.524
🟦 apron reason	0.000%	0.182%	0.330%	0.668%	1.072%	1.929%	3.785%	4.484%

Figure 3-6 Delay probability when fixed-wing aircraft operated (5 aircraft) ((a) Probability of delay 30 minutes, (b) Probability of delay 15 minutes)


(a) Probability of delay 30 minutes or more when none fixed-wing aircraft operated

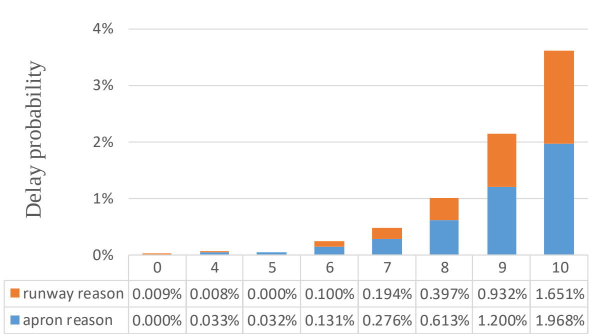
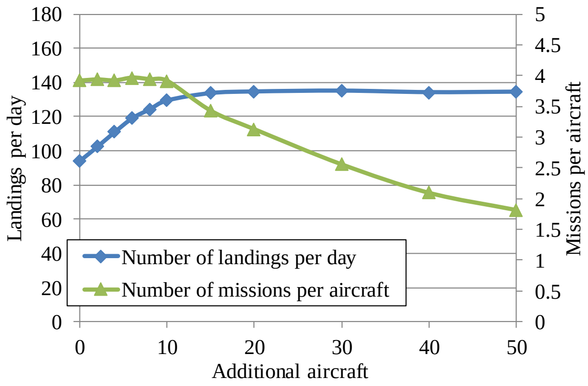

(b) Probability of delay 15 minutes or more when none fixed-wing aircraft operated

Figure 3-7 Delay probability when none fixed-wing aircraft operated ((a) Probability of delay 30 minutes, (b) Probability of delay 15 minutes)

As described in section 4.5, the extra capacity can be also evaluated from operational "efficiency" aspect. Figure 3-8 shows the total number of missions in a whole day, and the average number of missions per aircraft when changing the number of additional aircraft ((a) with and (b) without fixed-wing aircraft operated). As might be expected, the total number of missions can be increased by adding the aircraft, but too many additional aircrafts such as over 10 aircraft can have a negative impact on the operational efficiency in terms of number of missions per single aircraft in a day due to over-congestion at airport. From both of the safety and efficiency aspect, the acceptable number of extra aircraft determined by the safety aspect is reasonable. From these analyses, airport operators and governments can make a plan of airport capacity including the extra capacity with the concept of dynamic capacity for more efficient disaster relief activities with considering level of safety.

(a) When fixed-wing aircraft operated



(b) When none fixed-wing aircraft

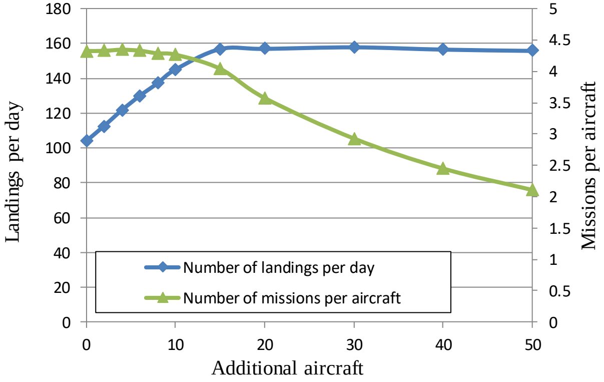


Figure 3-8 Result of landings per day and missions per aircraft((a)When the fixed-wing operated(b)When none fixed-wing operated)

3.4.2 Effect of different departure intervals on airport operation

Based on the airport operation simulation, this research can know the dynamic capacity of the airport. But how can relief operator operate the aircraft rescue activity more efficiently? The rescue activities and the flight missions are usually executed continuously and repeatedly with the same aircraft on a whole day from sunrise to sunset. And there is some possibility that the first flight of each aircraft originally assigned to the airport tends to start operation at the same time and it may result in the concentration of traffic and congestion through a whole day. Therefore, the original departure interval would affect the whole day operation. In this part, this research sets the different original departure intervals to simulate the different operation patterns, and then by analysis of traffic volume and delay of arrival and departure, try to find the relationship original departure interval and the airport operation. In order to analyze the effect of different intervals, this research sets the original departure intervals from 120 to 600 seconds and also simulate in two cases of fixed-wing operated and none fixed-wing operated.

Figure 3-9 (fixed0_heli24) shows that when fixed-wing aircraft are not operated, traffic volume and delay change as original departure intervals. The trend of the arrival and the departure is similar, both of which keep decreasing. In the original stage of the simulation, all the aircraft are already to take off, the departure is more than the arrival is in the prediction. The increase of the original departure interval will reduce the traffic volume.

For the delay, the departure delay decreases from 120 to 180 seconds and then becomes stable, while the arrival is always smooth. For the trend of departure delay, this research can analyze from runway occupancy time in Table 3-1. For this case, the runway occupancy time is 81 or 141 seconds. When the interval is smaller than 141 seconds, the departure would be affected, and the delay is high. And when the departure interval exceeds 141 seconds, the departure would not be influenced, so the departure delay is stable after that. For the perspective of delay, when the original departure interval increase, the delay will reduce, and when the original departure interval exceeds all kinds of runway occupancy, the delay will be stable.

Figure 3-9 (fixed5_heli19) shows the simulation results when fixed-wing aircraft and rotary-wing are operated together. The trend of the arrival and the departure is similar to the situation of none fixed-wing. But the numerical value is smaller, which illustrates the fixed-wing operation has a negative influence on traffic volume.

For the departure delay, during the overall declining trend, the departure delay keeps stable from 180 to 300 seconds. From the runway occupancy table 3-1, For the combined of fixed-wing and fixed-wing, the occupancy time is 290 seconds. For the pair of rotary-wing and fixed-wing, it is 178 seconds, for the rotary-wing and rotary-wing, it is 141 seconds. From the result of the simulation, this research can know when the interval is smaller than the 180 seconds, the increase of the interval has a positive effect. When the interval is from 180 to 300 seconds, the increase of the departure interval does have an obvious effect on the departure delay. After the interval is bigger than 300 seconds, the departure delay begins to decrease again, which shows the departure delay of fixed-wing and fixed-wing is reducing. For the perspective of delay, the fixed-wing, especially the pair of the fixed-wing and fixed-wing, always has a continuous influence on the departure delay throughout the different intervals.

These results show that the original (initial) departure interval can affect the delay time mainly caused by runway occupancy time restrictions at the first phase of departure operation and have a relatively smaller impact on the delay through a whole day. Therefore, it is indicated that airport operators have to just care about departure time control in the first phase of operation in a day.

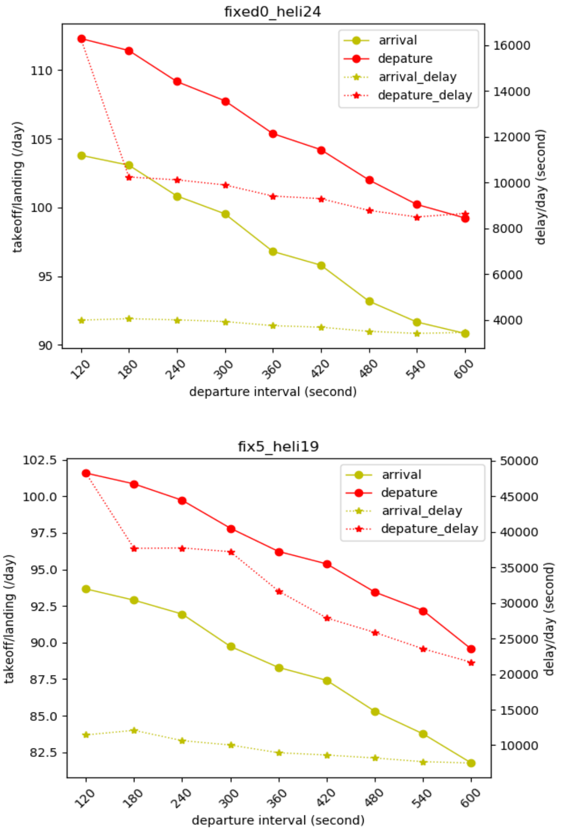


Figure 3-9 Simulation results of the different intervals

3.5 Conclusion

This research developed an integrated airport operation simulation considering runway and parking spots, as well as the special operation at the time of disaster to analyze the dynamic capacity and effect of different departure intervals on the delay time.

This research analyzed the extra capacity with the concept of dynamic capacity from the safety and efficiency perspectives. From the result of the simulation, this study can know that the longer acceptable delay time is, the larger number of acceptable extra aircraft is. The operation of fixed-wing aircraft will reduce the amount of extra capacity due to its large runway occupancy time. An appropriate number of extra aircraft will increase the number of missions per day with the acceptable level of safety. In summary, during a disease relief activity, the number of operated aircraft at each airport is determined not only simply by the number of spots (static capacity) but also by dynamic capacity introduced in this research. In the case of disaster time, airports can maximize utilization of airport facility by receiving extra aircraft from other airports to rescue more affected people.

This research also analyzed the departure interval from the aspects of traffic volume and the delay time. As the mission time of the relief aircraft is similar, the departure interval in the original phrase is important. The result of simulation shows the main determining factor of the suitable departure interval is the runway occupancy time of main operating aircraft type, and the operation of fixed-wing aircraft would have negative influence. If relief operator can consider the runway occupancy time and the mixed operation of different aircraft to set the original departure interval, the operation of rescue aircraft can be more efficient.

4 Efficient Aircraft Allocation in Airport Aprons for Aircraft Evacuation Prior to Large-scale Typhoons

4.1 Introduction

In some Asian countries including Japan, typhoon is a frequent event. In Japan, for example, from 2011 to 2020, typhoons occurred quite frequently (31 times in 2013 and 21 times in 2011). Typhoons also affect aviation activities considerably. The heavy storm surge and rain during Typhoon 21 in 2018 flooded the runway and terminal facilities of Kansai Airport, considerably impacting access and stranding numerous passengers. Similar incidents occurred during Typhoons 15 and 19 in 2019. Considering the frequency and effect of typhoons, this research has started paying attention to airport emergency management prior to typhoons. Most of the studies on airport emergency management focus on passengers and airports (Fairbanks airport, 2020; Narita Airport, 2021; Kansai Airport, 2019). The general safety measure for aircrafts prior to typhoons is to keep it in a hangar or fix it in a parking lot. This passive measure is feasible for general typhoons. However, for stronger typhoons with heavy wind and precipitation, such a passive action would lead to damage of the aircraft structure and engine, affecting the aircraft operation and increasing risk.

Therefore, to maintain aircraft safety, a more active procedure for safe evacuation of aircrafts prior to large-scale typhoon is required as weather forecast including typhoon course and intensity is improving in accuracy, even several days before the attack. In fact, during Typhoon 19, the Japan Civil Aviation Authority (JCAB) tried to centrally manage the evacuation from the affected airports in Tokyo metropolitan area to the other local airports in Japan due to the large number of aircraft evacuation demand from various airlines. Although JCAB, airlines, and airport operators could collaboratively manage to arrange the evacuation of a huge number of aircrafts to some extent, they faced some difficulties in finding and adjusting appropriate parking area in a timely manner. One of the problems is the capacity management and definition of the temporal parking capacity by considering unusual parking procedures. Another problem is making the best use of all alternative airports.

Considering that the intensity and frequency of natural disasters have gradually increased due to climate change, this study aims to propose suitable schemes for aircraft evacuation prior to the occurrence of typhoons, based on active aircraft evacuation measures.

In aircraft evacuation, parking resources are invaluable, and the efficient utilization of the airport apron is crucial. Owing to the large number of evacuated aircrafts, some of the airports were forced to accommodate the evacuated aircrafts by using their airport facilities in unusual ways such as longitudinal double parking at aprons and temporarily parking at the taxiway and runway. In fact, the New Chitose Airport closed one runway for temporary parking of evacuated aircrafts. Therefore, this study proposes a simple method to assess the maximum number of aircrafts to be parked (accepted) or the maximum utilization of apron area by considering optimal use of parking space (apron and runway/taxiway). In this case, operators can know how to use the apron and the maximum number of temporary parking aircrafts, which are the basic information of the aircraft evacuation model, for considering prior strategic plans of large-scale aircraft evacuation.

The remainder of this chapter is organized as follows. Section 2 establishes the apron utilization model with two objectives and illustrates the corresponding heuristic. Section 3 presents a case study based on the available airports during Typhoon 19 and provides an analysis and comparison of different schemes. Finally, Section 4 concludes the chapter.

4.2 Model establishment

For considering efficient aircrafts evacuation procedures prior to typhoons, one of the fundamental constraints is the capacity of temporal aircraft parking in airport facilities such as aprons, taxiways, and runways. This paper first focuses on the maximum use of apron which is used for parking usually, and secondly, this research considers the use of taxiways and runways which are not used for parking usually but can be used temporally for accommodating the overloaded evacuated aircrafts. But such use of taxiway and runway for temporal parking should be minimize for minimizing the impact on the usual airport operation. In this section, this research establishes the apron utilization model and introduce a heuristic algorithm for solving it.

4.2.1 Aircraft allocation in apron model

In aircraft allocation model, first, this study uses a heuristic algorithm to get all the possible allocation schemes for each apron. Second, for each possible allocation scheme, this study calculates two indexes: number of allocated aircraft and utilization of apron. Finally, if choose the objective of maximization of the number of aircraft, the allocation scheme with maximum number of allocated aircraft would be chosen. While there are several allocation schemes, this study chooses the scheme with better utilization. The procedure is similar when choose the objective of best utilization. Thus, this study can decide the allocation scheme according to different objectives as follows:

$$Max\{Number\}=\sum Aircraf^{small}+\sum Aircraf^{middle}+\sum Aircraf^{large} \tag{1}$$

$$Max\{Utilizaion\}=\frac{\sum Area_{Aicraft}^{small}+\sum Area_{Aicraft}^{middle}+\sum Area_{Aicraft}^{big}}{Area_{apron}} \tag{2}$$

Constraints:

$$\begin{aligned}Length^{apron} \geq {} & \sum\left(Width^{A\_small} + Interval^{Aircraft}\right) + \\ & \sum\left(Width^{A\_middle} + Interval^{Aircraft}\right) + \\ & \sum\left(Width^{A\_large} + Interval^{Aircraft}\right) + \\ & Interval^{Boundary}\end{aligned} \tag{3}$$

$$\begin{aligned}Width^{apron} \geq {} & \sum\left(Length^{A\_small} + Interval^{Aircraft}\right) + \\ & \sum\left(Length^{A\_middle} + Interval^{Aircraft}\right) + \\ & \sum\left(Length^{A\_large} + Interval^{Aircraft}\right) + \\ & Interval^{Boundary} + Interval^{Taxiway}\end{aligned} \tag{4}$$

Where:

$Width^{A\_small}, Width^{A\_middle}, Width^{A\_middle}$: width of small aircraft, middle aircraft, and large aircraft,

$Length^{A\_small}, Length^{A\_middle}, Length^{A\_large}$: length of small aircraft, middle aircraft, and large aircraft,

$Interval^{Aircraft}$: the interval between aircrafts,

$Interval^{Boundary}$: interval between aircraft and boundary of apron,

$Interval^{Taxiway}$: interval between aircraft and taxiway.

Equations 1 and 2 are objective functions, which represent the parking of as many aircraft as possible and the maximum possible utilization of the apron. Equation 3 indicates that the length of the apron ensures sufficient space for the aircraft and the interval between each aircraft as well as between the aircraft and apron boundary. Equation 4, which has the same function as equation 3, ensures that the interval is maintained in the width of the apron.

4.2.2 Heuristic algorithm

In this study, the main problem is to allocate aircraft in an apron, which is similar to the question of 2D bin packing. In summary, there are several methods such as X Fit heuristics, Knapsack-based heuristic, Clique-based heuristic, and Merging heuristic (CLAUTIAUX, 2014; GENDREAU, 2004).

Among these, the commonly used methods are bottom-left-fill and shelf fill. The bottom-left-fill method is based on placing an item at its lowest possible position. The procedure is then reiterated for each item in turn in a particular order (Khaoula, 2012; Khanafer, 2010). Shelf fill is to insert items from the left to the right side, while forming shelves. The first shelf corresponds to the rectangle bottom. The next shelf bottom is obtained with the horizontal line that coincides with the top of the highest item in the previous shelf (Khaoula, 2012; Khanafer, 2012). While Aircraft allocation in an apron involves unique characteristics. For ensuring that aircraft enter and exit the apron comfortably, operators need to allocate the same type of aircraft in one column, as shown in Figure 4-1.

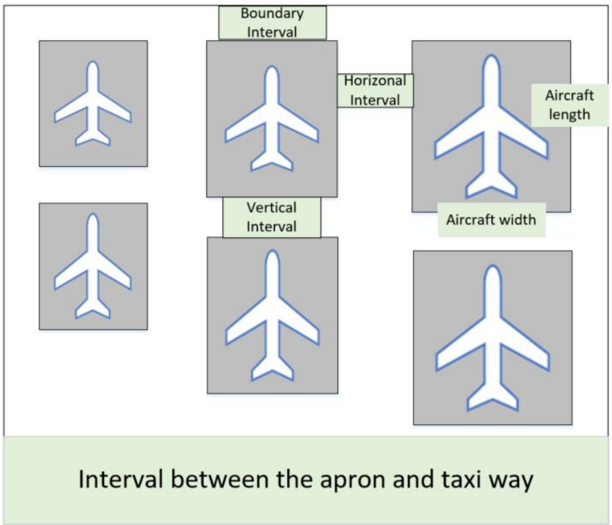


Figure 4-1 Aircraft allocation in an apron

In this heuristic, first list all the possible combinations of aircraft types corresponding to a specific apron. Further, based on the width of the apron, the aircraft type in the combinations is corrected, and the number of aircraft parked in each column is calculated, as depicted in Figure 4-2.

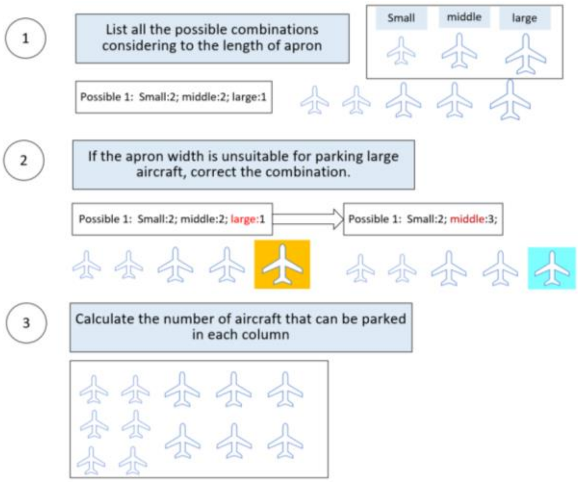


Figure 4-2 Heuristic process

```
Heuristic Algorithm
Input: maximum number of each aircraft type, considering the length of the apron.
For all the possible aircraft combinations in each column,
    consider the width of the apron for correcting the combination,
    calculate the number of aircraft that can be parked in each column,
    compare the total number of parked aircraft and apron utilization for this combination with the best one. If this is better, replace it as the best combination
End
Return the best combination.
```

4.3 Aircraft evacuation simulation

In this study, to perform a numerical experiment, Typhoon 19 is chosen in 2019, which greatly influenced the Tokyo metropolitan area due to its tremendous precipitation and wind speed and resulted in the largest aircraft evacuation exercise in the history of Japan. Thus, it is a representative of the impact of typhoons. Therefore, this research simulates this data with Typhoon 19 as an example to introduce the procedure to determine the maximum capacity of an apron through our model and analyze the suitable scheme for each apron. These results provide valuable suggestions that are helpful in improving the judgment of operators.

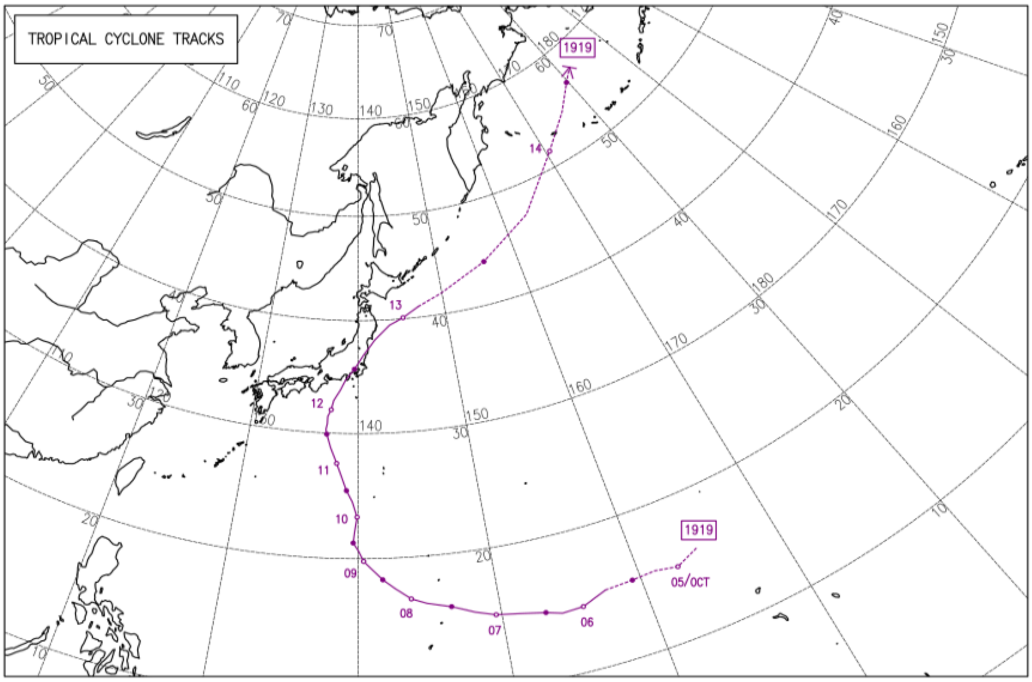


Figure 4-3 Track of Typhoon 19

(source: Japan Meteorological Agency, http://www.data.jma.go.jp/obd/stats/data/bosai/report/2019/20191012/jyun_sokuji20191010-1013.pdf)

Table 4-1 Available Airports

No	Airport	Remote apron (1)		Remote apron (2)		Remote apron (3)	
		Length (m)	Width (m)	Length (m)	Width (m)	Length (m)	Width (m)
1	*New Chitose*	987	115	514	133		
2	*Fukuoka*	113	103	1076	106		
3	*Miyazaki*			365	72		
4	*Naha*	548	125	167	184		

No	Airport	Apron in front of PTB without PBB (1)		Apron in front of PTB without PBB (2)		Apron in front of PTB without PBB (3)	
		Length (m)	Width (m)	Length (m)	Width (m)	Length (m)	Width (m)
1	*Wakkanai*	96	109	0	0		
2	*Kushiro*	111	178	66	178		
3	*Hakodate*	94	178	221	178		
4	*Sendai*	71	178	175	178		
5	*Niigata*	141	178	176	178		
6	*Hiroshima*	118	175	72	175		
7	*Takamatsu*	62	175	62	175		
8	*Matsuyama*	40	178				
9	*Kochi*	108	178	67	175		
10	*Fukuoka*	527	125				
11	*Kitakyushu*	165	174	68	174		
12	*Nagasaki*	306	178	60	178		
13	*Kumamoto*	78	178				
14	*Oita*	132	178	185	106		
15	*Miyazaki*	218	178				
16	*Kagoshima*	266	171	133	171	400	213

No	Airport (with two parallel runways)	Taxiway (m)	Runway (m)
1	*New Chitose*	3581	2418
2	*Naha*	1106	2095

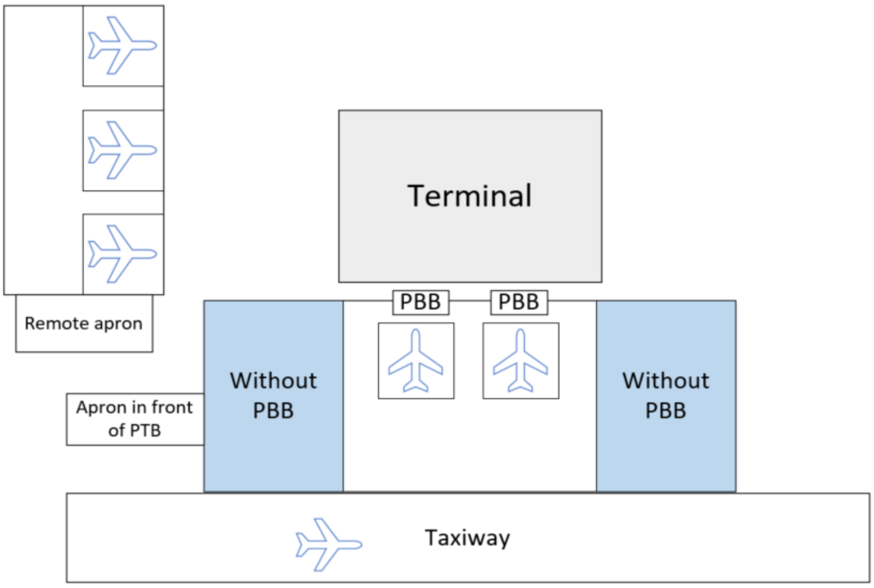


Figure 4-4 Aprons with PBB and without PBB

According to the track of Typhoon19, the main affected areas are Tokyo and the surrounding area, and the affected airports, are Haneda and Narita and Chubu airport, as depicted in Figure 4-3. Therefore, this research considers the evacuation from these three affected airports to the other local airports which are listed in Table 4-1. For airports with several aprons, the respective length and width of the apron area where evacuated aircrafts can be temporally parked are listed. There are two kinds of apron; one is "Remote apron" which is located at remote area from passenger terminal buildings (PTB), another is "Apron in front of PTB without Passenger Boarding Bridge (PBB)" (refer Figure 4-4). This research assumes that apron area with PBB cannot be used for temporally parking for minimizing usual ground operation. The final parts in the table are the taxiway and runway length of the airports which can be closed for temporally parking with keeping minimum basic airport operation efficiency.

The interval parameters used in the model according to airport operation regulations are shown in Table 4-2. These parameters are set by considering the minimum intervals described in ICAO Annex14 Volume 17th Edition 2016).

Table 4-2 Interval parameters

Parameter	Numerical value
Interval between aircraft/ horizonal in the apron	10 m
Interval between aircraft/ vertical in the apron	10 m
Interval between the aircraft and apron boundary	10 m
Interval between the apron and taxi way	40 m
Interval between aircraft/ horizonal in the runway/ taxiway	100 m

Here, this research focuses on the best possible utilization of the apron. Therefore, the number of each aircraft type is not considered, and the size of each aircraft type alone is listed in Table 4-3.

Table 4-3 Aircraft size

Type of aircraft	Model	Length (m)	Wingspan (m)
C	B737-800	40	36
D	B767-300	55	48
E	B777-300ER	74	65

Based on our model with two objectives, maximization of the number of aircraft and apron utilization, this research simulated two scenarios. The results of aircraft allocation in each apron based on the different objectives are listed in Tables 4-4 and 4-5.

Table 4-4 Number of aircraft and utilization in remote apron

NO	Airport	Size of apron (m*m)	Maximum number of parked aircraft				Best utilization of apron			
			Number of parked aircraft			Utilization	Number of parked aircraft			Utilization
			Large	Middle	Small		Large	Middle	Small	
1	*New Chitose*	**113505**	0	0	21	0.71	0	16	1	0.92
		68362	1	1	8	0.64	6	0	1	0.9
2	*Fukuoka*	11639	0	0	2	0.77	0	0	2	0.77
		114056	0	0	23	0.81	0	0	23	0.81
3	*Miyazaki*	26280	0	0	0	0	0	0	0	0
4	*Naha*	**68500**	0	2	9	0.66	0	9	0	0.79
		30728	0	2	4	0.77	0	2	4	0.77

In Table 4-4 and 4-5, these larger aprons (with a size over 50000 m^2) are marked out. For larger aprons, different objectives would affect the result of aircraft allocation. For smaller aprons, different objectives have little impact on the result. It is understandable that there are further possible allocation schemes for larger aprons, in contrast to the smaller aprons. Therefore, for these smaller aprons, the best scheme is undoubted under the condition of no restrictions on number and type of aircraft. For these larger aprons, suitability of the allocated scheme depends on the different objectives. It is suggested that the operators of larger aprons should consider practical requirement to determine the objectives of allocation.

Table 4-5 Number of aircraft and utilization in apron in front of PTB without PBB

			Maximum number of parked aircraft				Best utilization of apron			
NO	Airport	Size of apron (m*m)	Number of parked aircraft			Utilization	Number of parked aircraft			Utilization
			Large	Middle	Small		Large	Middle	Small	
1	*Wakkanai*	10464	0	0	1	0.42	0	0	1	0.42
2	*Kushiro*	19758	0	0	4	0.68	0	0	4	0.68
		11748	0	0	2	0.62	0	0	2	0.62
3	*Hakodate*	16732	0	2	0	0.67	0	2	0	0.67
		39338	0	4	4	0.87	0	4	4	0.87
4	*Sendai*	12638	0	2	0	0.93	0	2	0	0.93
		31150	0	4	2	0.9	0	4	2	0.9
5	*Niigata*	25098	0	4	0	0.87	0	4	0	0.87
		31328	0	4	2	0.89	0	4	2	0.89
6	*Hiroshima*	20650	0	2	2	0.86	0	2	2	0.86
		12600	0	2	0	0.94	0	2	0	0.94
7	*Takamatsu*	10850	0	0	2	0.68	0	0	2	0.68
		10850	0	0	2	0.68	0	0	2	0.68
8	*Matsuyama*	7120	0	0	0	0	0	0	0	0
9	*Kochi*	19224	0	0	4	0.71	0	0	4	0.71
		11725	0	0	2	0.62	0	0	2	0.62
10	*Fukuoka*	**65875**	0	0	11	0.61	0	8	1	0.78
11	*Kitakyushu*	28710	0	0	6	0.69	0	0	6	0.69
		11832	0	0	2	0.61	0	0	2	0.61
12	*Nagasaki*	**54468**	0	2	10	0.78	0	10	0	0.96
		10680	0	0	2	0.69	0	0	2	0.69
13	*Kumamoto*	13884	0	2	0	0.83	0	2	0	0.83
14	*Oita*	23496	0	4	0	0.93	0	4	0	0.93
		19610	0	0	3	0.65	0	0	3	0.65
15	*Miyazaki*	38804	0	2	6	0.81	0	6	0	0.86
16	*Kagoshima*	45486	0	0	10	0.71	0	0	10	0.71
		22743	0	0	4	0.59	1	0	2	0.7
		85200	0	0	24	0.84	10	0	0	0.96

Table 4-6 Runway and taxiway allocation

Name	Length (m)	Maximum number of aircraft				Best utilization of apron			
		Number of aircraft			Utilization	Number of aircraft			Utilization
		Large	Middle	Small		Large	Middle	Small	
New Chitose	3581	0	8	17	0.63	19	2	0	0.92
	2418	0	5	12	0.62	14	0	0	0.93
Naha	1106	0	1	7	0.59	6	0	0	0.85
	2095	0	2	13	0.6	12	0	0	0.92

Furthermore, allocations for the runway and taxiway are calculated, as shown in Table 4-6. The results indicate that although the total number of aircraft increases when choosing the objective of maximum number of parked aircraft, the improvement in the number of parked aircrafts is not obvious compared with the scheme of best utilization. However, when the objective of best utilization is chosen, utilization ratio increases significantly. It is suggested that, for runway and taxiway, the scheme of best utilization should be considered and parking of large aircraft on the runway and taxiway is feasible for better utilization of resources.

4.4 Conclusion

This study established an evacuation aircraft allocation model and analyzed different schemes based on the data of Typhoon 19. For small aprons, the scheme of maximization of the number of aircraft is usually of same output as that of the scheme of best utilization. Therefore, the difference between schemes is not significant. However, for larger aprons, the difference between the schemes is significant. It is suggested that the selection of schemes depends on the different allocation objectives. For a runway/taxiway, based on the analysis, the scheme of best utilization can improve the space usage significantly and ensure there is minimum loss in the aircraft holding capacity as well. It is better to choose the scheme of best utilization for runway/taxiway.

Current aircraft parking scheme prior to typhoon usually is same to the usual aircraft parking method. This study can provide a method to determine aircrafts allocation schemes by making the best use of parking space to improve the number of parked aircraft in apron or the utilization of apron. And findings of this study can provide guidelines for aircraft allocation in aprons for Tokyo metropolitan area in case of a typhoon attack. Though these results are calculated based on the data of typhoon 19 and aprons of airports in Japan, it is believed this model can be applied to other similar situations of aircraft evacuation. Besides, this model is also a useful basic model. In the future, based on this model, it is planned to include constraints on the number and type of aircraft and location of aprons, and consider the overall research objective, such as minimum evacuation distance or minimum alternative airports, to establish a more practical model

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5 Air Medical Rescue Model Integrating Flight Route Planning and Scheduling Considering Distribution of Demand

5.1 Introduction

In the wake of a disaster, the rescue operation begins immediately. While the land transportation system usually suffers severe damage, airports serve as the lifelines for the affected areas and humanitarian logistics. In terms of medical rescue transportation, relief aircraft are generally assigned in response to the requests. Such a feedback control is also known as pull-mode transport (Kawase et al 2019). However, because the affected local governments usually take time in obtaining accurate information at the beginning of a relief activity, owing to the suddenness of the disaster, it is challenging for this type of transport to have a global consideration and view of the situation in the entire affected region. From the perspective of aircraft arrangement, aircraft are usually assigned through the “single-destination” method, that is, from the base airport to only one rescue center, and back to the base airport. However, this method cannot fully utilize the relief resources in some cases, wherein the practical number of injuries in rescue center is lesser than the aircraft capacity. Additionally, from the viewpoint of the base airport operation, because there is no planned schedule for all relief aircraft, congestion occurs in the airside and delay occurs in the airspace around the airport, thereby reducing the rescue efficiency (Hanaoka et al 2013). This study mainly addresses the injuries transport problem that is more urgent than goods transport, which can be implemented by trucks or drones and involved with the inventory question. To address these issues, this research intends to design an air injuries rescue plan at the beginning of a relief activity, which includes flight routing designing from the viewpoints of the entire affected region and the daily schedule of the airport.

With the trend of urbanization, the population is becoming increasingly concentrated. In the event of a disaster, the cities and towns scattered throughout the affected region become the main relief locations. Due to the extent of the disaster and the distribution of the population, the distribution of injured persons is uneven. Thus, this research aims to study the problem of injuries transportation in scattered affected areas in the principle of fairness. This is performed in two steps: first, design a flight routing and schedule for an affected area, and then, apply the model to other areas and integrate them as the final solution for several affected areas.

The remainder of this paper is organized as follows. Section 2 introduces the model components, including flight routing design, optimization of the daily schedule, and extension of the model to several areas. The corresponding resolve algorithm is proposed in Section 3, which includes the tabu search for routing design and a genetic algorithm for the daily schedule. Section 4 shows a numerical experiment conducted for validating the model. Finally, the conclusion is presented in Section 5.

5.2 Air medical rescue model

5.2.1 Structure of model

The usual “single-destination” air aid transport, which means relief aircraft just visit one rescue center in one flight mission, is fast, but it has the following drawbacks. First, the number of the injured in some rescue centers maybe less than the total capacity of the aircraft, in this case the single-destination model would cause resource wastage to some extent. Second, such a transport model possibly leads to an imbalance among the centers: some centers are assigned many flights, while others just receive a few. If the amount of total aircraft is limited, some rescue centers may have to wait for a long time before obtaining the aid. Therefore, this research proposes a new flight routing design solution, with an aim that all rescue centers can receive air aid timely and these medical aid among centers are maintained fair and balance. Based on the property of the disaster area, these rescue centers are from the same area and the distances of flight routings are close to each other, which means that these aircraft possibly take off and land centrally, forming a flight wave, like Figure 5-1. In this paper, a flight routing based on the flight wave is designed. In this case, all the rescue centers can get service in one flight wave and avoid some centers waiting too long for next flight wave. The flight routing model is introduced in 5.2.2.

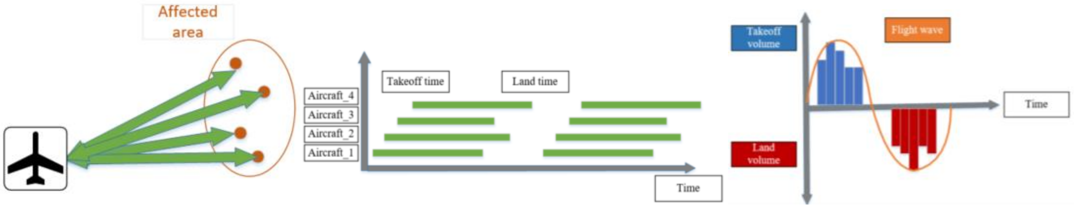


Figure 5-1 Flight wave in the disaster air relief activities

In the daily relief schedule, these relief aircraft usually take several missions. A reasonable planning of the rescue aircraft takeoff and landing times and allocation of sufficient operating time to the aircraft at the airport will make the rescue operations more orderly. Thus, a model for optimizing the airport schedule is established in this subsection.

To simplify the model, the injuries requests as inputs for flight routing design is unchanged. In other words, flight routings are designed one time by the former model, and then aircraft take different flight routings in the disaster relief activities to make the total time duration of relief activities minimum like Figure 5-2 and airport scheduling model is introduced in 5.2.3.

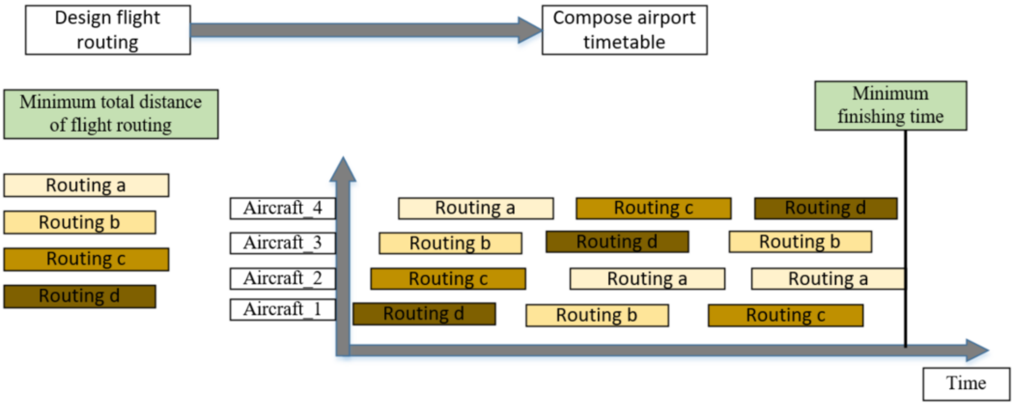


Figure 5-2 Airport scheduling

5.2.2 Routing planning

In each takeoff flight wave, the total air medical transportation ability of all aircraft is assigned to the injuries rescue centers in proportion to injuries of each center. In this case, the fairness in one flight wave can be ensured. Besides, the rescue process should be completed as soon as possible, which means that the total time of all flight routings should be kept at a minimum. This will guarantee the efficiency of flight routing.

First, the assumption of this routing model is introduced.

1. In the relief activities, the humanitarian assistance is usually executed through land and air transportation. In this paper, this research just consider the air aid, and thus, the total rescue injuries is more than the total rescue ability of all aircraft.

2. The distribution of the injured in rescue centers at the beginning of a disaster is uneven due to the damage extent and the population density: some of them are less than capacity of one aircraft, while others are more.

To formulate the flight routing model, the following sets and indices are used:

A	set of all relief aircraft
a	relief aircraft index, $a \in A$
Z	set of all rescue centers
i, j	rescue center, $i, \ j \in Z$

Following are the parameters required by the model:

Tij	flight time from center i to j
TM	max flight time constrained by fuel capacity for each flight
$\sum_{a \in A} q_i^a$	total air assistance to center i by all aircraft

Cfleet total capacity of all aircraft in one fleet

Wi weight in different center i

$$x_{ij}{}^{a} = \begin{cases} 1 & \text{if aircraft a moves from node i to node j} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{i}{}^{a} = \begin{cases} 1 & \text{if aircraft a moves via node i} \\ 0 & \text{otherwise} \end{cases}$$

$$Min \quad f = \sum_{(i,j)\in Z} T_{ij} \sum_{\forall a\in A} x_{ij}{}^{a} \tag{1}$$

Subject to

$$\sum_{a\in A} y_{i}{}^{a} \ge 1 \tag{2}$$

$$\sum_{(i,j)\in Z} x_{ij}{}^{a} \le T_M, \forall a \in A \tag{3}$$

$$\begin{cases} \sum_{a\in A} q_1{}^{a} : \cdots : \sum_{a\in A} q_Z{}^{a} = W_1 : \cdots : W_Z \\ \sum_{a\in A} q_1{}^{a} + \cdots + \sum_{a\in A} q_Z{}^{a} = C_{fleet} \end{cases} \tag{4}$$

Equation (1) minimizes the total flight time. Constraint (2) ensures that at least one airplane travels through center i. Constraint (3) restricts the flight time by total fuel. Constraint (4) illustrates that the total air medical assistance in the centers is proportional to the center weight, which can be determined by the population and extent of damage around the centers.

5.2.3 Airport schedule

Following parameters are used in this formulation:

$p_{\text{land}}{}^{a}$, $p_{takeoff}{}^{a}$ the priority of land or takeoff of aircraft a

$t_{takeoff\text{-}1}{}^{a}{}_{m}$ $t_{takeoff\text{-}2}{}^{a}{}_{m}$ $t_{\text{land-1}}{}^{a}{}_{m}$ $t_{\text{land-2}}{}^{a}{}_{m}$ start taking off time, finish taking off time, start landing time, and finish landing time for aircraft *a* in a flight wave *m*

$T_{\text{turnaround}}{}^{a}$ turnaround time for aircraft *a*, which is defined as the time that passes from when an aircraft lands until it takes off again for a new flight

M set of flight waves

m flight wave index

$$Min \quad f_2 = Max(T_{landtime}{}^{last\_flightwave}) - Min(T_{takeofftime}{}^{first\_flightwave}) \tag{5}$$

Subject to

$$p_{\mathrm{land}}{}^{\mathrm{a}} > p_{takeoff}{}^{\mathrm{a}}, \quad \forall a \in A \tag{6}$$

$$T_{flight}{}^{a} \le t_{land\text{-}2\ m}^{\ a} - t_{takeoff\text{-}1\ m-1}^{\ a} \le T_{M}{}^{a} \tag{7}$$

$$t_{takeoff\text{-}1\ m}^{\ a} - t_{land\text{-}2\ m-1}^{\ a} \ge T_{aroundtime} \tag{8}$$

$$[t_{takeoff\text{-}1\ m}^{\ a}, t_{takeoff\text{-}2\ m}^{\ a}] \ne [t_{\mathrm{land}\text{-}1\ m}^{\ a}, t_{\mathrm{land}\text{-}2\ m}^{\ a}], \quad \forall a \in A, \forall m \in M \tag{9}$$

Equation (5) minimizes the total scheduling time, and usually the minimum of takeoff time in the first flight wave is 0. Constraint (6) guarantees that the priority of any landing aircraft is higher than that of any ready-to-takeoff aircraft on the runway. Constraint (7) considers some delay would appear in the land phase leading to the increase of the flight time and it restricts the actual flight time between the time of designed flight routing and the max flight time by fuel capacity. Constraint (8) ensures that each aircraft has sufficient turnaround time between landing and takeoff. Constraint (9) indicates that the runway can be occupied by only one aircraft at a time, owing to the one-runway situation.

5.2.4 Several-area rescue model

During practical relief activities, airports always respond to multiple rescue areas, and the total number of injuries in an affected area is usually greater than the total capacity of the entire aircraft. To maintain fairness and efficiency in the affected areas, the entire aircraft fleet is split into smaller fleets in response to the different affected areas. The size of the fleet assigned to each area is proportional to the weight of each affected area, and the weight of each area can be determined by the average distance and number of injuries in this area. Through the constraints of operation time, the number of flight waves for each affected area can be determined. Finally, these schedules can be integrated to form the final schedule for several affected areas.

Following parameters are used in this formulation:

$Injuries_{area\_z}^{center\_i}$	the injuries of rescue center i in affected area *z*.
$Dis_{area\_z}^{center\_i}$	the distance from the rescue center *i* in affected area *z* to the airport.

$$Min \quad f_3 = T_{landtime}^{last\_flight} - T_{ltakeofftime}^{first\_fligh} \tag{10}$$

Subject to

$$W_{area\_z} = \frac{\sum_{area\_z} (Dis^{center\_i} * Injuries^{center\_j})}{\sum_{area\_z} rescue\_center} \tag{11}$$

$$\begin{cases} Fleetsize_{area\_1} : \cdots : Fleetsize_{area\_z} = W_{area\_1} : \cdots : W_{area\_z} \\ Fleetsize_{area\_1} + \cdots + Fleetsize_{area\_z} = TotalFleetsize \end{cases} \tag{12}$$

Equation (10) shows that the objective is to ensure that the transportation of injuries in all areas can be completed as soon as possible. Equation (11) represents the weight of each area, which can be determined by the average distance and number of injuries in this area. Equation (12) divides the total fleet into several branches of fleets for each affected area based on the weight of each area. Then, this research regards these branched fleets in general and analyze them individually to determine the minimum time combination of the schedule of each affected areas.

5.3 Model algorithm

5.3.1 Tabu search

The problem of flight routing planning can be regarded as the spilt delivery vehicle routing problem (SDVRP). To address this problem, the insertion algorithm is used to determine a feasible solution as an initial solution for tabu search. Then, a tabu method is implemented iteratively until the set count of iterations, and the best solution obtained thus far during the whole procedure is returned.

Following is the insertion algorithm for the initial solution:

Algorithm of insertion algorithm

```
Data: fleet size, aircraft capacity, all centers of affected area (unassigned center set), weight of each center's injuries
Result: initial flight routing
for each aircraft in fleet
    choose a center randomly form unassigned centers to add into the flight routing of this aircraft and update the aircraft transport volume and rest injuries of center
    if rest injuries of a center is zero
        remove the center from the unassigned set
    end
end
while the set of unassigned centers is not none
    choose the aircraft with rest capacity and add the center into the routing of this aircraft and update the aircraft transport volume, rest injuries of the center and unassigned set
end
```

In the tabu search, this research uses the exchange move operator to generate the neighborhood solution. The move operator can exchange the center and delivery simultaneously. Subsequently, all neighborhood solutions are evaluated and ranked according to the objective of the total flight routing time. The best neighborhood solution, which is not in the tabu list, is used as the original solution for the next iteration and added in the tabu list. When the required count of iterations is reached, the best solution obtained thus far during the whole procedure is saved.

Algorithm of tabu search

```
Data: insertion solution
Result: the best solution within the required counts of iteration
initialize the insertion solution as the original solution
while counts of iterations is less than the set count
    find all neighborhood solutions by the move operator to create the neighborhood set, evaluate the total time of solution, and rank them in ascending order
    while original solution is not updated
        search best solution from the neighborhood set which is not in the tabu list to use as original solution of the next iteration, and update the tabu list and the best solution obtained so far
    end
end
```

The move operator in this tabu search is expected to handle both centers and transport volume.

Algorithm of move operator

```
Data: a feasible solution
Result: a neighborhood solution
for center i in routing 1 from the routing set solution
    for center j in routing 2 from the routing set solution
        use the center with smaller transport volume as the exchange benchmark and spilt the larger delivery to exchange two centers and delivery simultaneously
    end
end
```

In order to exchange the center and delivery simultaneously and ensure the diversity of algorithm, this research designs this exchange move operator as Figure 5-3. For instance, there are two routings: routing 1, including two units for center A and eight units for center B, and routing 2, including six units for center C and four units for center D. The center A is made as exchange benchmark. If centers A and C are exchanged, center C would be divided into two parts; one is same to the center A, the other is the rest. Then, the part from the center C with the same transport volume to center A replaces the original center A, and the rest part of center C and original center A would form different combinations by changing the visiting turns and different combination would be compared to obtain the final neighborhood solution.

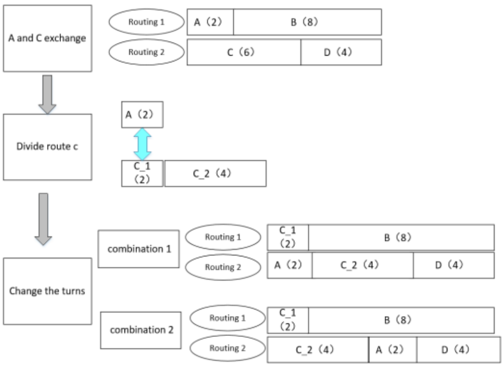


Figure 5-3 Exchange move operator

Based on Tsubakitani et al (1998), regarding the traveling salesman problem with N cities, the number of iterations is better set around the N*N term, and the size of the tabu list ranges from N/5 to 3N. In addition, to avoid falling in the local optimal area, the inset algorithm is utilized several times to generate multiple original solutions for the tabu search, and then the results of the different original inputs are compared to determine the final solution.

5.3.2 Genetic algorithm

For the flight schedule, this research can consider this problem as the resource-constraint project scheduling problem (RCPSP), with the objective of minimizing the project completion time. The genetic algorithm in conjunction with a simulation as the fitness function is used to optimize the flight schedule.

In the above sections, the flight routing based on the flight wave is designed. Relief aircraft usually take several flight missions in the rescue activity of one day; namely, there are several flight waves. In this genetic algorithm, a chromosome represents the schedule and a gene indicates one flight routing. The following five phases in the genetic algorithm is introduce.

(1) Initial population

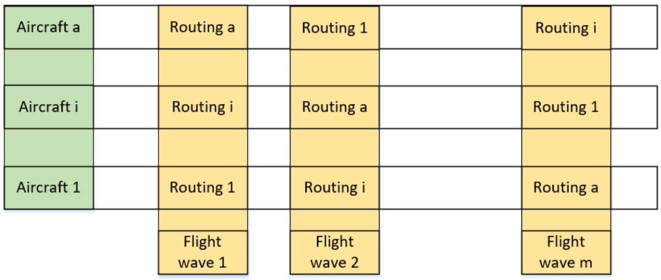


Figure 5-4 Flight schedule

Based on the above model, the flight wave composed of the flight routing can be obtained, and then, several flight waves can be combined to create an initial population, as shown in Figure 5-4.

(2) Fitness function

For this fitness, this research performs a simulation to calculate the total time of each solution and return the result. In the simulation, the input is a neighborhood solution containing several flight waves. For each flight wave, the takeoff runway occupied time, service time, and landing runway occupied time are added. Between two flight waves, the turnaround time between two flight missions for one aircraft is assigned. Throughout the process, the land priority over the takeoff is maintained. The entire scheduling process is illustrated in Figure 5-5.

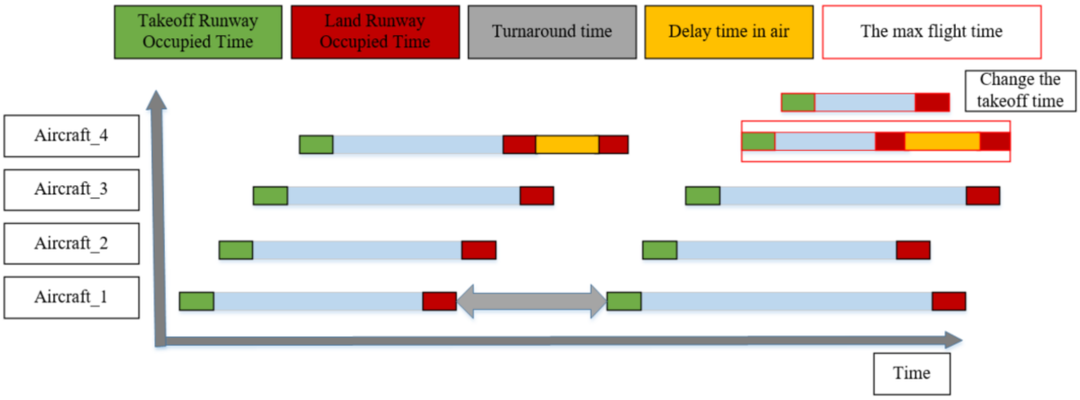


Figure 5-5 Flight scheduling

The pseudocode of scheduling simulation

```
Input: neighborhood solution including ordered flight routings
Result: total operation time and the scheduling of flight routings
For each group of flight routing from the neighborhood solution
    For each flight routing in the same group
        Fixed takeoff time and the land time of the former, the takeoff time of the latter flight just follow the former's takeoff time and verify if the land time of latter coincides with the former's, if coincides, delay the land time of the latter. And simultaneously verify if the delay time exceeds the max flight time, if so, delay the takeoff time and arrange it again
    End
    Add the turnaround time for these flight routings in former group and simulate the flight time for the next flight group
End
```

(3) Selection

For each neighborhood solution, this research uses the fitness function to achieve the total schedule time and perform sorting according to the results, and then, select a feasible solution by using the elite and random rates to create a mating pool for the mating procedure.

(4) Mating

There are two parts in the mating procedure. One is the elite solution, whose result is ranked at the top and is kept for the next procedure, and the other is used to create the crossover procedure, where a whole flight wave from two chromosomes is exchanged to obtain new schedules, as shown in Figure 5-6.

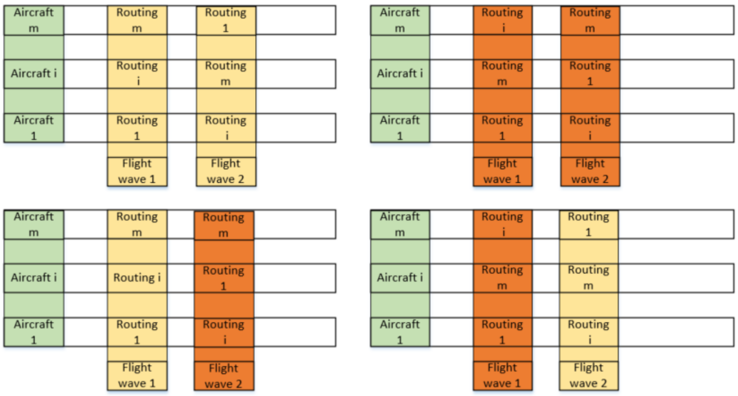


Figure 5-6 Crossover procedure

(5) Mutation

To maintain the diversity of scheduling and avoid falling into the local optimum, this research designs a mutation procedure in which two routings from the same flight wave are swapped randomly. After this, a new generation is created for the next iteration.

5.3.3 Several affected areas

This research first calculates the branch fleet for each affected area, and then applies the above model to obtain the flight routing and schedules in this area. Finally, considering the time constraint, the number of flight waves for each affected area can be determined. The different combinations of branch fleets, as shown in Figure 5-7, are calculated to obtain the best solution.

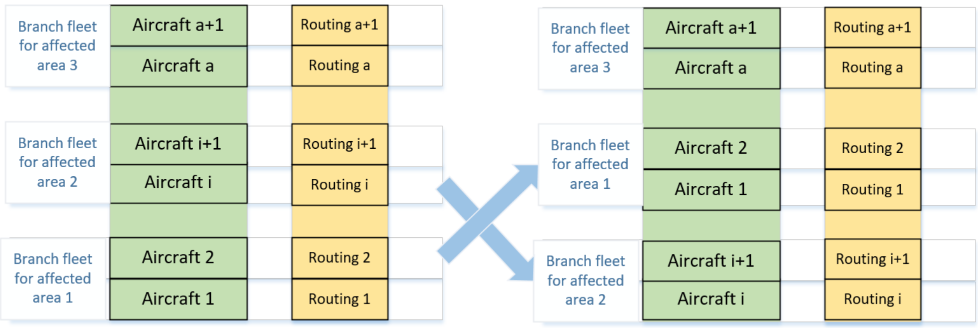


Figure 5-7 Branch fleet exchange

5.4 Numerical experiment

In this section, first, a numerical experiment is conducted on one affected area while using the "single-destination" flight routing method as a comparison. Then, the situation of several affected areas is simulated.

5.4.1 One affected area

In this section, the model is tested under different scenarios. To make numerical experiment general, the Gini coefficient is used to express the property of rescue shelters. The larger the Gini coefficient is, more uneven demands of these shelters are.

$$Gini = 1 - \frac{(0+\sum_{1}^{1} Y_i) + (\sum_{1}^{1} Y_i + \sum_{1}^{2} Y_i) + \cdots + (\sum_{1}^{n-1} Y_i + \sum_{1}^{n} Y_i)}{(0+\sum_{1}^{n} Y_i) * n}$$

The parameters and input of relief aircraft and affected centers are set as shown in Table 5-1 and Figure. 5-8.

Table 5-1 Input of this simulation

Items	Values
Runway takeoff/land occupancy time	2 min
Turnaround time between two flights using same aircraft	30 min
Speed of aircraft	200 km/h
Max flight time (in the case of holding in air)	150 min
Mission time at each center	5 min
Capacity of each aircraft	10 units
Fleet size	8
Rescue center (Polar coordinate)	(60, 30°), (60, 60°), (70, 15°), (70, 45°), (70, 75°), (80, 30°), (80, 60°), (90, 15°), (90, 45°), (90, 75°). (0,0) is the coordinate of airport.
Gini coefficient	proportion of each shelter
0.1	8: 8: 9: 9: 9: 10: 11: 12: 13: 13
0.3	1: 6: 6: 8: 9: 9: 10: 13: 16: 22
0.5	1: 1: 2: 6: 6: 6: 9: 12: 28: 29
0.7	1: 1: 2: 2: 3: 3: 4: 4: 8: 72

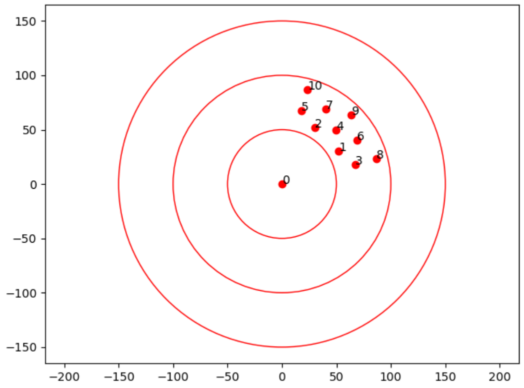


Figure 5-8 Affected centers

These results in Table 5-2,5-3,5-4,5-5 and Figure. 9,10,11,12 demonstrate that, as Gini coefficient increases, our proposed model can deliver more than the common single-destination method within the same operation time, which means that our method is more efficient.

This is reasonable. When the Gini coefficient is small, requests among affected centers are not so different. The demand at each affected center is closer to the capacity of the aircraft. These two methods “one destination” and “multiple destinations” have almost same relief efficiency. When the Gini coefficient become larger, some affected centers have very little requests while others have a lot more request. In this case, the method of “one flight one destination” could not make the best use of aircraft capacity. Therefore, the method of “multiple destinations” would have better performance over “one destination”.

Table 5-2 Result of Gini 0.1

	Fleet mission		3	4	5	6
Gini = 0.1	This paper	Time	261	355	447	541
		Volume	240	320	400	480
	One destination	Time	231	317	403	487
		Volume	220	295	372	445

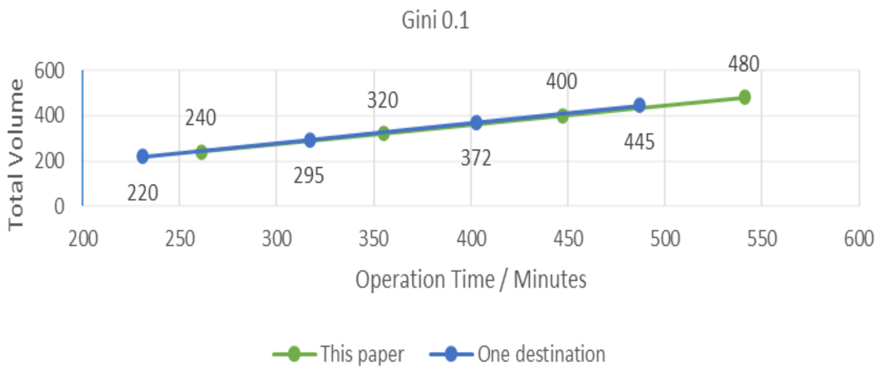


Figure 5-9 Result of Gini 0.1

Table 5-3 Result of Gini 0.3

	Fleet mission		3	4	5	6
Gini = 0.3	This paper	Time	271	367	462	559
		Volume	240	320	400	480
	One destination	Time	233	317	403	485
		Volume	179	244	316	375

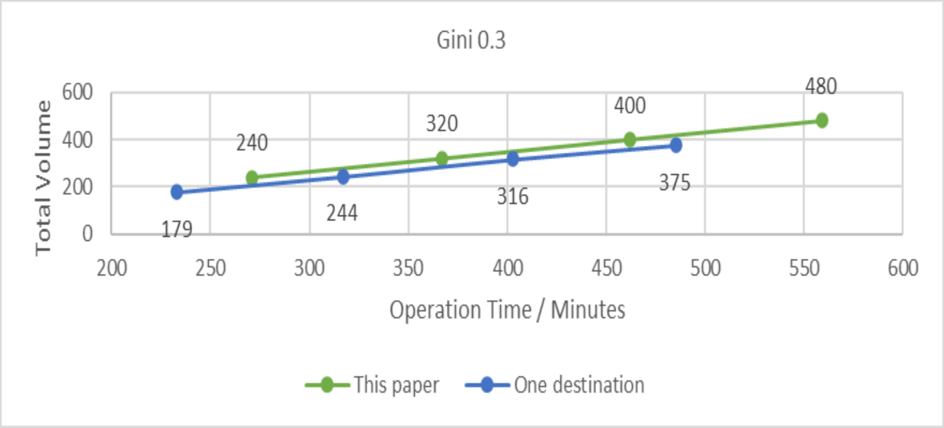


Figure 5-10 Result of Gini 0.3

Table 5-4 Result of Gini 0.5

	Fleet mission		3	4	5	6
Gini = 0.5	This paper	Time	281	377	478	579
		Volume	240	320	400	480
	One destination	Time	231	315	403	485
		Volume	132	185	244	285

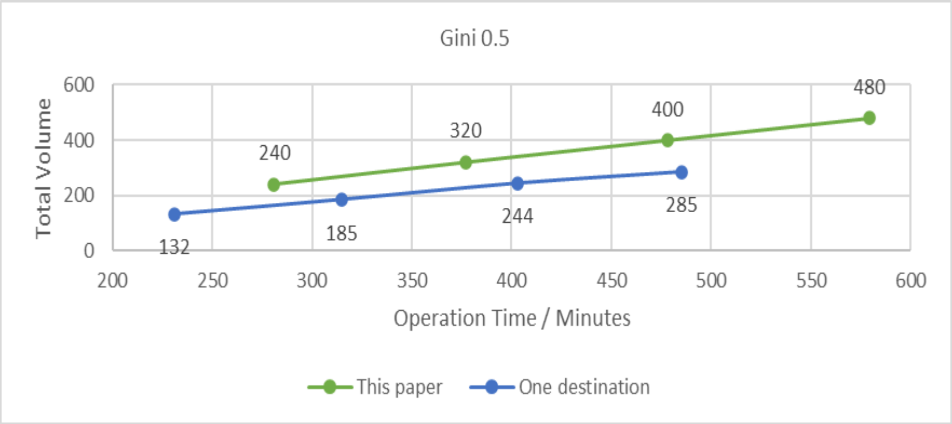


Figure 5-11 Result of Gini 0.5

Table 5-5 Result of Gini 0.7

Fleet mission			3	4	5	6
Gini = 0.7	This paper	Time	281	380	477	577
		Volume	240	320	400	480
	One destination	Time	231	317	403	485
		Volume	82	116	152	172

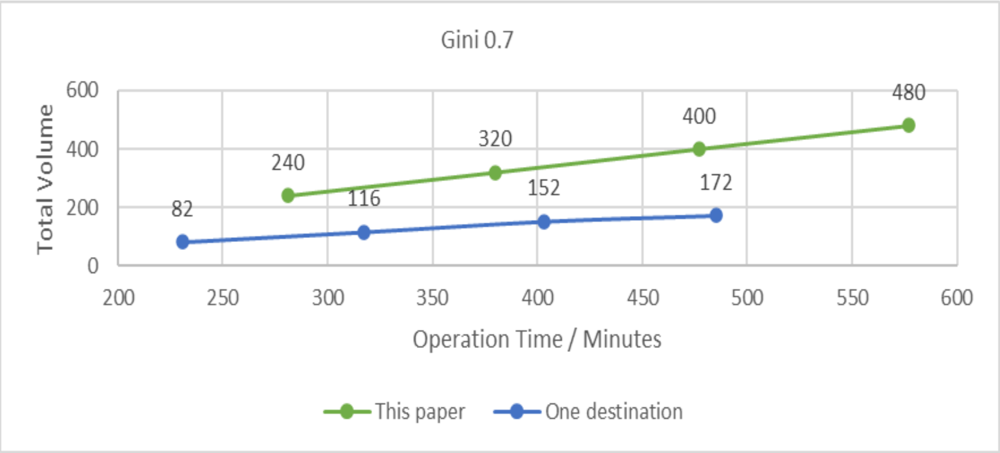


Figure 5-12 Result of Gini 0.7

In this part, this research refers to the spilt delivery vehicle routing problem (SDVRP) to design flight routing, then integrates flight route planning and scheduling to establish an air medical rescue model, finally compares relief efficiency of two transportation methods under different Gini coefficient. The results of the numerical experiments demonstrated that, when the distribution of demand is balanced, "one destination" and "multiple destinations" are not so different, while the degree of imbalance is larger (Gini coefficient is larger) "multiple destination" can improved transportation efficiency in comparison with the usual single-destination method. Hence, the distribution of demand is also an important impact when operators determine transport method in relief activities.

5.4.2 Several affected areas

For several affected areas, it is assumed that the fleet size is 20. The whole disaster area has three relief areas a, b, c, as shown in Figure 5-13, with five centers in each area, whose locations and injuries of centers are listed in Table 5-6.

Table 5-6 Parameters of several disaster-affected areas

Rescue center	Distance to airport	Radian	Injuries
a-1	60	30	5
a-2	60	60	5
a-3	80	15	20
a-4	80	45	30
a-5	80	75	20
b-1	120	127.5	5
b-2	120	142.5	5
b-3	140	120	20
b-4	140	135	30
b-5	140	150	20
c-1	170	215	5
c-2	170	235	5
c-3	190	205	20
c-4	190	225	30
c-5	190	245	20

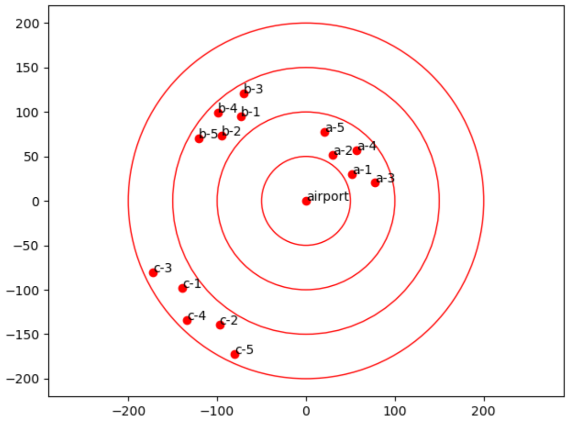


Figure 5-13 Several affected areas

Based on the injuries and distance of each center, the weight ratio of affected areas “a,” “b,” and "c" is (60*5+60*5+80*20+80*30+80*20)/5: (120*5+120*5+140*20+140*30+140*20)/5: (170*5+170*5+190*20+190*30+190*20)/5 = 0.19: 0.34: 0.46. Considering that the total size of the aircraft fleet is 20, the sizes of the 3 branched fleets are 4, 7, and 9.

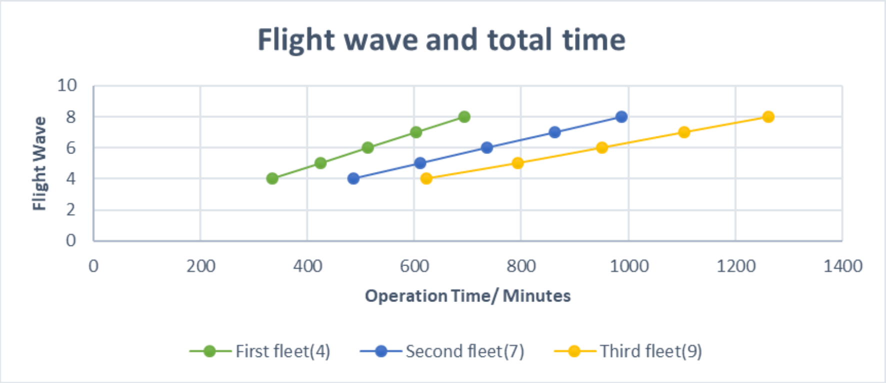
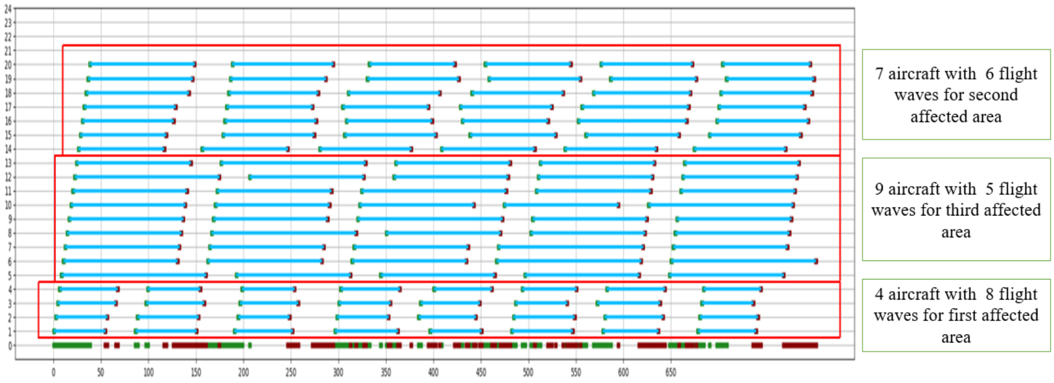


Figure 5-14 Flight wave and operation time

In Figure 5-14, the green, blue, and orange lines indicate the first, second, and third fleets, respectively. The fleet waves for each affected area can be determined by the constraints of operation time. If the operation time is restricted to around 720 min, the flight waves in the first, second, and third affected areas are 8, 6, and 5, respectively.

Finally, the turn of these schedules is changed to figure out the final schedule with minimum operation time for the several affected areas, as shown in Figure 5-15. The total time is 745 minutes and the total transport volume is 720 units.



7 aircraft with 6 flight waves for second affected area

9 aircraft with 5 flight waves for third affected area

4 aircraft with 8 flight waves for first affected area

Figure 5-15 Schedule of several affected areas

5.5 Conclusion

In this study, flight route planning and scheduling are integrated to establish an air medical rescue model. While designing the flight routing, fairness and efficiency are applied to the routing planning of one affected area, and then iterated the fleet for several flight waves to determine an optimal scheduling. Finally, this model was extended to several affected areas. The results of the numerical experiments demonstrated that the proposed model exhibited improved transportation efficiency in comparison with the usual single-destination method and could handle the complex situation of several affected areas.

This research mainly focused on uneven distribution of injured persons due to the extent of the disaster and the distribution of the population. Usually rescue aircraft perform “single-destination” flight mission which would lead to insufficient utilization of limited rescue aircraft when the injuries of some rescue centers are less than the capacity of aircraft. Therefore, in some of rescue centers it is assumed in this study the injuries are less than the capacity of aircraft while others are more. This is the main question to be resolved in this research and a strict limitation of our model too. Besides, it is assume number of injuries are unchangeable during a period time and set the fixed parameters for the turnaround time at airports and the mission time at rescue center. These assumptions limit the effectiveness of our model in more general situation. Therefore, in future research it is planned to release the assumption of injuries and research the air medical relief dispatch and scheduling question in more general situation:_dispatch the air relief aircraft when injuries are random and real time.

6 Relief Aircraft Dispatch Strategies Based on Different Levels of Information Sharing Systems

6.1 Introduction

During the Great East Japan Earthquake of March 2011, communication between the disaster response headquarters and the aircraft was through voice wireless communication devices. Then, information was collected and aggregated on the whiteboard in the disaster response headquarters. Finally, mission assignment and aircraft operation were performed based on personal judgment and experience. This kind of information sharing hinders quick and effective execution of mission assignments. Moreover, in widespread disaster areas, obstacles such as mountains could obstruct communication between the operation base and the aircraft, thus hindering relief activities. In addition, during the Sendai Airport disaster, which was at the operating base, lead response headquarters could not receive information about the affected areas; this made air relief more difficult.

Based on the experience of the 2011 earthquake in Japan, the Japan Aerospace Exploration Agency (JAXA) developed the Disaster Relief Aircraft Information Sharing Network (D-net) in 2012. This network can share necessary information between the rescue aircraft and the response headquarters during disasters to foster rescue activities via aircraft such as helicopters.

This example indicates that new communication technologies are being applied in air relief activities. However, even in Japan, not all relief helicopters can be equipped with new communication devices. Communication technologies and devices are very different over different regions and may even differ in same disaster-affected areas, according to the damages caused by different scales of the disaster level.

As communication devices are updated, relief aircraft dispatch strategies differ, and geographical factors and population distribution may affect aircraft dispatch strategies. Therefore, after the development of new communication devices, it is necessary to train new devices in different strategies and places.

There are different communication devices applied in relief activities, and dispatch strategies can be affected by both the different communication devices and demand characteristics when disaster occurs. This research plans to establish a framework for analyzing the effect of different communication devices on relief activities by combining the factor of demand distribution, as shown in Figure 6-1. The purpose of our study is to assist in determining the optimal dispatch strategy based on the different levels of communication and demand characteristics in disaster relief.

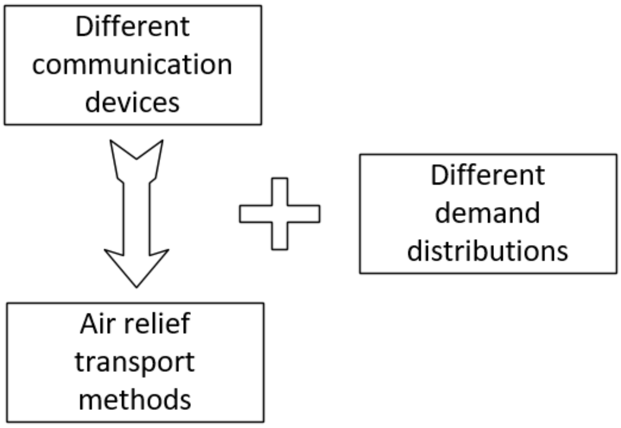


Figure 6-1 Influencing factors

Our research aims to analyze the effects of different communication methods on relief aircraft dispatch, the efficiency improvements of new communication devices for relief activities, and the effectiveness of the communication devices in dealing with different relief scenarios. This research first defines different information sharing levels in air relief activities and then propose aircraft dispatch methods based on these sharing levels. Finally, the effect of different transport methods in different disaster relief scenarios is analyzed.

The application of communication technology has a role in all four distinct phases of disaster management: mitigation, preparedness, response, and recovery. However, this research focuses specifically on the response phase, which has a direct relationship with aircraft operations and is also the most critical phase for rescue activities.

This research defines the information sharing levels based on three main types of information used in air relief activities, as shown in Figure 6-2.

Information about injuries from shelters: the information about injuries in shelter sites should be sent to response headquarters in a timely manner.

Information about injuries and corresponding flight routing before takeoff (at the airport): this information is the flight routing plan that response headquarters design for aircraft, based on received information regarding injuries.

Information about injuries and dynamic routing (in the air): this information is the dynamic flight plan that response headquarters design for aircraft, based on updated information regarding injuries.

Three typical information sharing levels were used in our research, the criterion for which are outlined in Table 6-1.

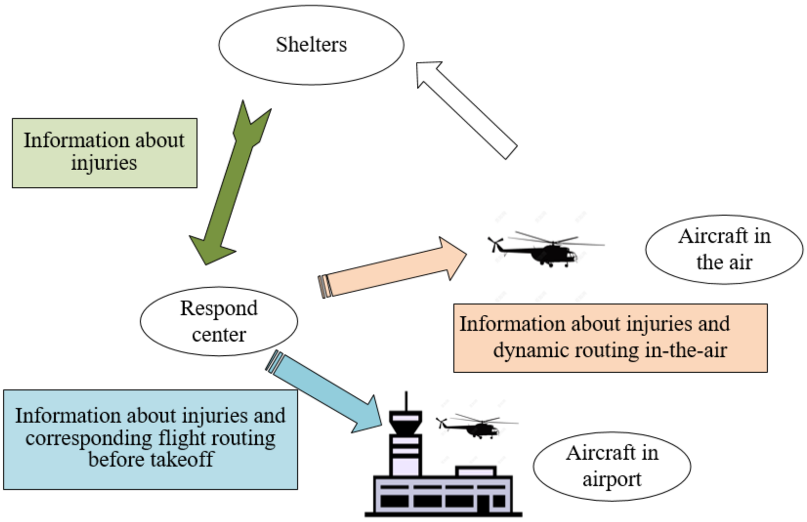


Figure 6-2 Information used in air relief activities

Table 6-1 Different levels of information sharing systems

	Information about Injuries from Shelters	Information about Injuries and Corresponding Flight Routing before Takeoff (at the Airport)	Information about Injuries and Dynamic Routing (in the Air)
Level one	No	No	No
Level two	Yes	Yes	No
Level three	Yes	Yes	Yes

If devices for the different relief agents are unavailable or damaged by a disaster, communication among different entities such as aircraft dispatchers, shelter sites, and aircraft pilots is hindered. Consequently, aircraft dispatchers will be unaware of the extent of the damage in the disaster-affected area or the number of injured persons in shelters. In such cases, relief aircraft dispatchers must send aircraft to collect information on the shelter site. Flight missions would therefore include reconnaissance missions and transportation of injured persons. this research refers to the information and communication level in this kind of air rescue activity as “Level one”.

“Point to point” communication can be established and ensured through means such as equipping shelter sites and response centers with satellite telephones. In this case, when a disaster (earthquake) occurs, communication between the shelter site and relief response center can be established; thus, information on the rescue shelters can be reported rapidly to relieve the response center. Based on this information, aircraft dispatchments can be performed with more explicit destinations, that is, pilots are informed about the centers before they take off. This research refers to this stage of information and communication as “Level two”.

If real-time communication among different agents can be established, such as using satellite broadcasting to develop an integrated disaster information service platform, real-time connections among relief agents such as aircraft dispatchment centers, shelters, and pilots can be made available to support real-time rescue activities. In this case, the pilot will be aware of the destination before takeoff and can also make dynamic routing during the flight mission. This research refers to this phase of information sharing as “Level three”.

Most of the demands from the affected area include food, medical aid, and injury transportation. According to Hanaoka et al 2013, aircraft usually embark on injury transportation missions by considering the advantages of speed and the ability to easily overcome ground obstacles. Therefore, the flight mission in our model aimed at injury transportation or personnel evacuation.

The remainder of this paper is organized as follows. Section 2 formally defines and presents a mathematical formulation of the aircraft dispatch problem. Section 3 describes three information-sharing systems and their corresponding assignment strategies. Section 4 briefly describes the agent-based simulation framework employed to model the dynamic system of injury centers, aircraft, and dispatch centers in airports. Section 5 lists the experiments designed to compare different dispatch strategies and presents the computational results. Finally, Section 6 presents the conclusion.

6.2 Model establishment

In this research, our main aim is to compare the efficiency of different information sharing levels in air relief activities. To facilitate the modeling, this research analyzes the efficiency of different dispatch strategies, based on the different information sharing levels. This is a sequential optimization problem, which includes demand inputs to inform aircraft dispatchment decisions based on received information in real-time. An iterative approach is taken to optimization, incorporating new information to obtain the optimal result. In this section, the characteristics of our aims are analyzed and an overall model is proposed. Different transport strategies for iterative optimization are proposed based on different information sharing levels in Section 4. Section 5 introduces the simulation structure used in this research.

Based on past relief activities, the demand requests from affected areas are generally reported to local authorities or relief response centers. Then, the authorities or centers transfer these requests to aircraft dispatchment centers in the airport to arrange relief aircraft transportation of persons to hospitals or designated locations. This research simplifies this process as follows: demand requests (injuries or personnel) can be reported from the shelter sites to aircraft dispatchment centers in airports; then, aircraft dispatchers can send aircrafts to these shelter sites and transport the injured to the airport. Besides, in actual air relief activities, the demand is usually greater than the actual transportation capacity. Thus, prediction of future demand is not usually considered.

Therefore, this study considers an aircraft fleet transporting the injured back to the airport based on the requests from rescue centers that are updated throughout a finite horizon. Moreover, aircraft dispatchers cannot determine or forecast future requests.

Figure 6-3 shows an overview of the temporal nature of the problem. At the instance “now,” the fleet operator has complete information about past injury requests, and the dispatchment center could assign the aircraft based on the injury requests and available aircraft. However, they have no information about future injury requests.

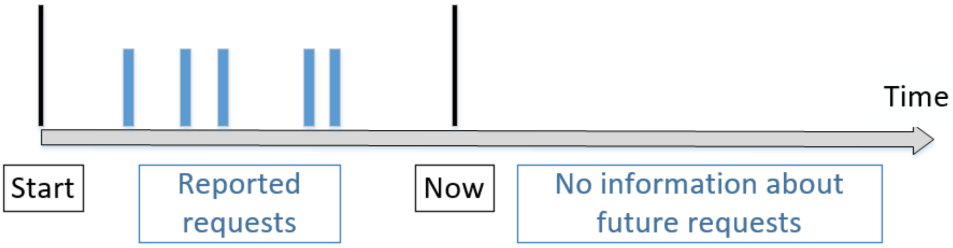


Figure 6-3 Overview of the temporal aspect of relief aircraft dispatch

Our model is a type of sequential optimization problem. Here, this study uses the Bellman equation to provide a solution approach:

$$Min\sum_{t}\left\{C(S_t,x_t)+\sum_{s^*\in S}V_{t+1}(s^*)\right\} \tag{1}$$

where St is the state of the system at time t, which contains the states of all the agents such as demand reports, aircraft, and dispatch centers, xt is the decision variable, which denotes the assignment of the aircraft to the demand request, C(St, xt) is the summary objective value of the system in state S at time t, Vt(s) represents the objective value of the system in state S at time t and s* is the state of a part of the system at time t + 1.

Based on this, this research can compare several policies that differ in their method used in solving the local optimization problem $\mathrm{Min}\{\mathrm{C(St,xt)}\}$. These different policies are implemented when the system finds unprocessed reported requests and available aircraft simultaneously:

$$\underset{t}{Min}\sum_{a\in A^t}(Dis(\sum_{i\in R^t}x_i^{\,a})) \tag{2}$$

$$\sum x_i^{\,a}\geq 1 \quad \forall\, a\in A^t \tag{3}$$

$$\sum x_i^{\,a}\geq 1 \quad \forall\, i\in R^t \tag{4}$$

where x is the decision variable at time t, At is the set of available aircraft at time t and Rt is the set of requests at time t.

Equation (2) minimizes the overall distance covered in transporting the injured, which is the objective whenever the policy is implemented. Equation (3) indicates that any chosen aircraft can be assigned to one shelter. Equation (4) indicates that any chosen shelter can be dispatched to one aircraft.

6.3 Dispatch strategy based on the information sharing system

This section introduces different information-sharing systems and the corresponding dispatching strategies. In our model, the information sharing system includes three main agents: rescue shelters, aircraft, and aircraft dispatchment centers. Different information-sharing systems mean different information structures among different agents. This section introduces the mutual reaction of agents in different information-sharing systems and proposes corresponding transported strategies. These strategies are embedded in the simulation.

6.3.1 Level one and corresponding transportation method

In Level one, there is no information sharing among aircraft dispatchers, shelters, and aircraft pilots. This means that aircraft dispatchers and pilots do not know any information beforehand. Moreover, the shelters have no device to report the number of injuries to the aircraft dispatchment centers. In this case, the information about injuries can be obtained if the dispatchment center sends aircraft to a random rescue shelter to conduct “reconnaissance and rescue”, as shown in Figure 6-4.

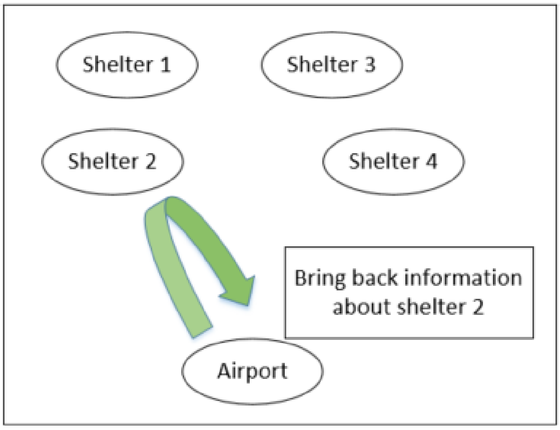


Figure 6-4 Information flow in Level one

Under this condition, the dispatch center could dispatch the aircraft to perform two kinds of missions: First, the center could assign all the available aircraft to obtain information about the rescue shelters, and if any injuries are present, the aircraft could transport the injured back to the airport. The second is that the dispatch center could dispatch aircraft to undertake rescue missions.

6.3.2 Level two and corresponding transportation method

In Level two, there is communication between the shelters and airports. In this case, the shelters could report the number of injuries to the airport operation center, as shown in Figure 6-5. Then, dispatchers could assign the aircraft based on the reported request from the rescue shelters.

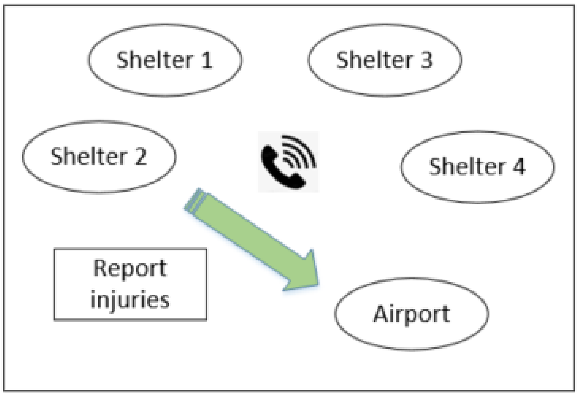


Figure 6-5 Information flow in Level two

In this case, the dispatchment center has information on the number and location of injuries. The dispatchment center can design a flight route before take-off. Hence, this research proposes two dispatch methods: “one-destination” and “multiple-destinations”.

1. One-Destination Strategy

Here, one flight has only one destination (one rescue shelter). It is a common dispatch method for disaster relief activities. According to the reported injury request, the dispatchment center assigns one aircraft to one rescue shelter. Upon arrival at the rescue center, the aircraft collects as many injured persons as possible and returns to the airport directly. This method is a traditional and conservative dispatchment method. It is easy and quick to assign and recycle aircraft.

However, each aircraft has only one destination, and the aircraft capacity might not be utilized fully if the number of injuries in some rescue centers is less than the aircraft capacity. Therefore, a multiple-destination strategy is proposed.

2. Multiple-Destination Strategies

Considering the shortcomings of the one-destination strategy, one flight can be assigned with several rescue shelters. Each time requests are received from the disaster area, all the available aircraft are identified, and then a flight route is designed considering all of them. This method can be referred to as a split delivery vehicle routing problem.

For this local objective, it is necessary to determine the number of aircraft At and number of requests Rt of the local optimization through the reported requests and available aircraft. If the reported requests are larger than the total capacity of the available aircraft, requests are selected by the principle of first-come and first-serve. The remaining requests are not assigned until there are available aircraft. If the total capacity of the aircraft is larger than the reported requests, the number of aircraft could be the rounded-up value of (total requests/capacity of a single aircraft):

$$\begin{cases} R^* = \underset{=Capacity_A}{\{ri, ri+1, \cdots\}} & Capacity_A < sum(R_{report}) \\ N_{aircraft} = RoundUp(\dfrac{R_{report}}{Capacity_S}) & Capacity_A > sum(R_{report}) \end{cases} \tag{5}$$

where CapacityA is the capacity of all the available aircraft, CapacityS is the capacity of a single aircraft, Rreport denotes the set of all the unprocessed reported requests and R*denotes the set of requests that would be considered as local question.

To solve this optimization model, simulated annealing is utilized. For details, please refer to Appendix A.

6.3.3 Level three and corresponding transportation method

In Level three, not only can the shelters report the number of injuries to the airport, but pilots can also access real-time information about the rescue shelters, as shown in Figure 6-6. In this case, the aircraft can perform dynamic routing based on real-time demand information. This means that the aircraft could be assigned to another shelter if it still has sufficient capacity left after severing the first shelter.

In the dynamic routing planning strategy, first, aircraft are assigned to a shelter based on requests, similar to the "one-destination" method. Then, after severing the planned shelter, the aircraft pilot determines whether there is any remaining capacity. If so, the pilot connects to the dispatch center and identifies another shelter. Considering the fuel and injured already on board, dynamic routing in this study is performed only once in one flight mission.

From the description, it is considerred that this method is more flexible than the "one-destination" and "multiple-destination" strategies. If there is remaining capacity after servicing one shelter, the pilot can report to the headquarters to take-off to another shelter, which is better than the "one destination" method. If the aircraft arrives at one shelter and finds that the injured are more than the reported request, it serves to full capacity at that location. However, in the same situation, the "multiple-destination" method would have to collect persons and travel to the next planned shelter. Thus, this is better than the "multiple-destinations" strategy. Although numerical experiments were not conducted, from the analysis above it can be concluded that the "dynamic routing" is more flexible and effective in managing the uncertainty between the reported requests before takeoff and the actual mission at the shelter.

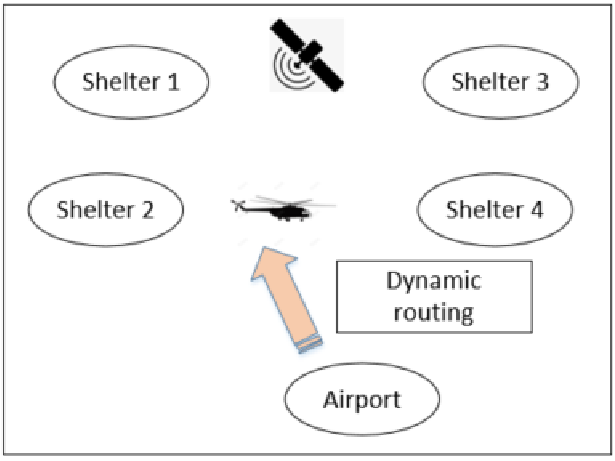


Figure 6-6 Information flow in Level three

In fact, this research proposed transport methods based on the characteristic of corresponding level of information sharing. Some methods are being used in relief activities, such as "reconnaissance and rescue" and "one flight one destination". Others, such as "multiple destinations" and "dynamic", have been used in practice in ground transport or discussed in literature. Further, the reason this research chooses these methods is that they represent the characteristics of different levels of sharing information. This study wants to compare different information systems by comparing different transport methods, which is the main purpose of this research.

6.4 Simulation

In this study, different strategies are compared by utilizing an agent-based simulation framework. In agent-based modeling, this study can identify individual active components of a system, define their behaviors, and establish connections between them. The global dynamics of the system can emerge from the interactions of the many individual behaviors. Besides, it is also convenient to obtain various indicators for analysis.

Therefore, an agent-based simulation tool is adopted to model the dynamic system of relief aircraft, rescue shelters, and dispatchment centers. The different strategies are embedded in the simulation to compare the effect of the relief activities using different indexes.

This simulation has several components, as shown in Figure 6-7: injury data, airport operation, and dispatch strategies. The injury data are the input requests from the shelter, which are introduced in the numerical section. The dispatch strategies, which were embedded in this simulation, have been explained in the previous section. This section focuses on the aircraft operation process.

In this simulation, each aircraft has four states: take-off, updating the injuries, landing, and dispatching. Hence, four corresponding aircraft groups are setted and place the aircraft with similar states in the same group. This simulation determines the state of the aircraft in each group and updates these groups every minute. The following is a description of the different aircraft groups:

Takeoff group:

The simulation first updates the takeoff group. In this group, the aircraft have been assigned both the planned flight routing and time from the dispatch group (which is explained later). Each minute, the simulation simultaneously checks the planned takeoff time and the runway slot. If the aircraft's planned takeoff time is appropriate with any vacant runway slot, then the aircraft enters the next aircraft group, collecting group, and is removed from the takeoff group. If the aircraft's planned takeoff time is not appropriate in the runway slot, its planned time could be delayed to wait for the next check.

Collecting group:

In this group, each aircraft takes off and travels to the planned rescue center according to the planned routing. Upon arrival at a rescue shelter, the aircraft collects the injured. When it completes the various planned destinations, it enters the landing group and is removed from the collecting group.

Landing group:

The simulation checks the planned landing time and runway slot. If the planned landing time is suitable in the runway slot, the aircraft is removed from the landing group and enters the dispatching group. If there is no suitable runway slot for the landing time, it is delayed until the next check.

Dispatching group:

This part embeds different modules according to the different strategies. Each aircraft in this group is waiting to be assigned a planned routing and flight time. When a new injury request comes into the simulation system, the system checks the available aircraft and then employs different strategies to arrange a planned routing and flight time to the aircraft. After this, the aircraft is removed from this group into the takeoff group.

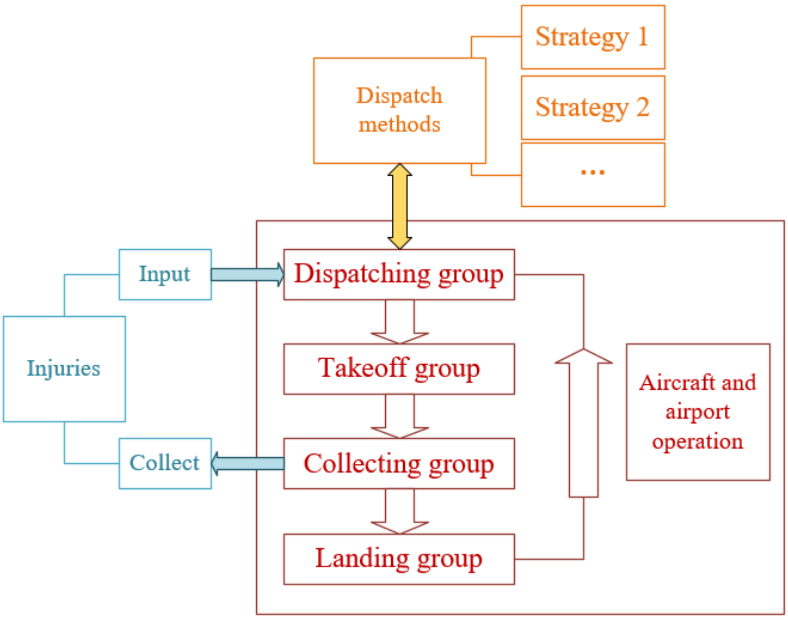


Figure 6-7 Framework of simulation

6.5 Numerical experiments

This section presents a numerical experiment to compare different transportation strategies based on the metrics. This research used three metrics: total flight time, finished time, and average waiting time. The total flight time is the total time of all flight missions in the relief activities. The finished time is the landing time of the last relief flight in the relief activities. The average waiting time is the average duration time from arrival at the shelter to the injured boarding.

6.5.1 Artificial designed demand

From past relief activities, all data on transportation injury constituted the number of total rescued injuries in all relief activities or on some days. Most of the relief data are confidential and unavailable to the public. It is, thus, difficult to access the injury information. Hence, this study used more general artificial data.

This research updates the injured every time interval, and each time the inputs in each shelter are determined by the demand/capacity (D/C) and the Gini coefficient, as shown in Figure 6-8. D/C is the proportion of the total number of injured (demand) in all shelters and the capacity of all the aircraft that can satisfy the total demands of all shelters for each time input. The Gini coefficient indicates the degree of imbalance among shelters, which can determine the proportion of each shelter. The demand of each shelter for each time input can be determined based on the total demand of all shelters and the proportion of each shelter. The Gini coefficient is defined as follows:

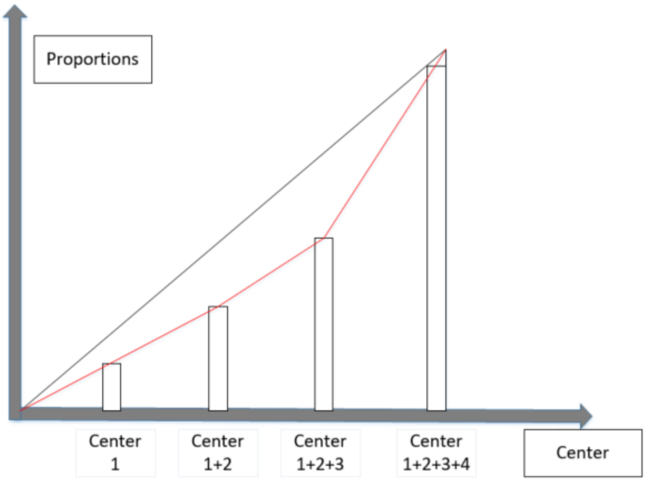


Figure 6-8 Gini coefficient of all shelters

In Figure 6-8, there are four shelters. I1, I2, I3, and I4 (in ascending order) that indicate the number of injured in each shelter. The Gini coefficient can be calculated as follows:

$$P_1 = I_1,\ P_2 = I_1 + I_2,\ P_3 = I_1 + I_2 + I_3,\ P_4 = I_1 + I_2 + I_3 + I_4 \tag{6}$$

$$S_1 = \frac{0 + P_1}{2} * L + \frac{P_1 + P_2}{2} * L + \frac{P_2 + P_3}{2} * L + \frac{P_3 + P_4}{2} * L \tag{7}$$

$$S_2 = \frac{0+P_4}{2} * 4L \tag{8}$$

$$Gini = \frac{S_2 - S_1}{S_2} \tag{9}$$

A larger Gini coefficient indicates a significant unbalanced demand distribution among these shelters. By setting different D/C and Gini coefficients, this study can simulate different general situations to test the model as Figure 6-9.

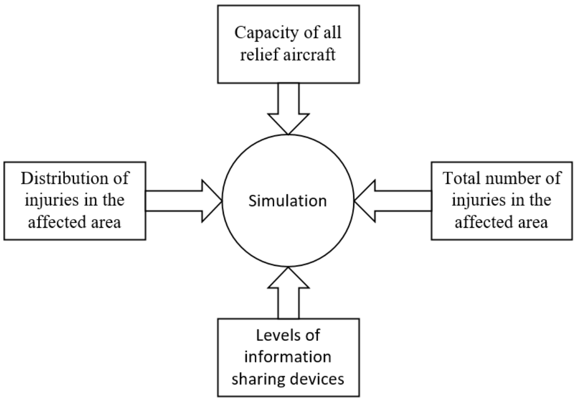


Figure 6-9 Input parameters in the simulation

6.5.2 Result of numerical experiment

This section performed simulations using different Gini coefficients and D/C ratios. To make experiment more representative, 20 cases are designed, including different demand imbalance degrees and different demand/capacity ratios, as shown in Table 6-2. For each case, this research simulated four transport methods (three different information sharing levels) and analyzed the result using three indicators (total flight time, relief activities finishing time, and waiting time per injury). In this simulation, the injuries in each case are listed in Appendix B. For each case, the input was unchanged. From the beginning of the simulation, the increase in injuries for each shelter was input at 60-min intervals until the simulation had run for 5 h. At this point, the injuries stopped updating, but the simulation did not stop until all the injured persons were transported. The parameters used in the simulation are listed in Table 6-3. The results of the simulation are summarized in Table 6-4.

Table 6-2 Different simulation scenarios

20 Cases	Gini = 0.1	Gini = 0.3	Gini = 0.5	Gini = 0.7
D/C ratio 0.6	Case 1	Case 2	Case 3	Case 4
D/C ratio 0.8	Case 5	Case 6	Case 7	Case 8
D/C ratio 1.0	Case 9	Case 10	Case 11	Case 12
D/C ratio 1.2	Case 13	Case 14	Case 15	Case 16
D/C ratio 1.4	Case 17	Case 18	Case 19	Case 20

As the Gini coefficient increases, the injury distribution becomes more unbalanced. As the D/C ratio increases, the demand increases, and the transport capacity decreases. Four transport methods were simulated for each case.

Table 6-3 Parameters in the simulation

Parameters	Value
Scope of disaster (km × km)	100 × 100
Airport	(0.0)
Location of rescue shelters (km, km)	(30,30), (70,30), (30,70), (70,70), (50,50)
Fleet size	5
Capacity of aircraft	10 unit
Minimum takeoff/landing interval (min)	4
Stop time at each shelter for loading (min)	20
Speed of aircraft (km/h)	200

Table 6-4 Result of simulation

Time (min)		Gini = 0.1			Gini = 0.3			Gini = 0.5			Gini = 0.7		
D/C	Dispatch Method	Total Time	Finish Time	Waiting Time	Total Time	Finish Time	Waiting Time	Total Time	Finish Time	Waiting Time	Total Time	Finish Time	Waiting Time
0.6	One	2332	743	115	1626	513	162	2381	795	173	4448	1480	220
	Two-I	1223	450	86	1289	446	94	1404	506	113	1668	560	199
	Two-II	1171	483	107	1419	570	138	1340	495	117	1429	634	168
	Three	1136	446	82.6	1179	446	84	1183	422	86	1351	495	121
0.8	One	1945	632	125	2621	847	256	2599	808	322	2531	797	423
	Two-I	1683	544	142	1662	534	133	1803	611	187	1924	639	221
	Two-II	1684	567	135	1753	565	138	1760	288	148	1707	698	205
	Three	1502	521	116	1418	506	108	1575	518	123	1644	554	150
1.0	One	2148	687	175	3149	1020	259	5465	1820	321	11,613	4033	499
	Two-I	1903	621	155	1861	627	166	2042	653	211	2114	705	235
	Two-II	2068	647	169	2003	634	164	2004	648	173	2066	724	216
	Three	1700	562	134	1688	533	143	1703	550	141	1919	618	180
1.2	One	3462	1096	273	3273	1057	297	6830	2289	435	13,173	4583	592
	Two-I	2305	722	228	2324	726	215	2415	758	247	2388	776	262
	Two-II	2363	730	221	2388	698	229	2349	778	258	2326	780	260
	Three	2126	698	192	2143	687	192	2198	712	213	2323	758	234
1.4	One	4572	1465	408	5804	1897	484	9679	3263	513	21,888	7652	580
	Two-I	2572	814	270	2605	823	273	2627	820	278	2586	812	311
	Two-II	2753	877	292	2666	845	289	2719	851	280	2697	875	309
	Three	2488	790	236	2406	792	234	2530	798	260	2578	826	296

“One” indicates “reconnaissance and evacuation” in Level one; “Two-I” indicates “one-destination” in Level two; “Two-II” indicates “multiple-destination” in Level two; and “Three” indicates “dynamic routing” in Level three.

To simplify the interpretation of the results, this research converted the data from a tabular form into the charts shown in Figure 6-10. The left column indicates the total time (in minutes) of the different methods using different D/Cs and Gini coefficients, the middle column shows the finishing time (in minutes), and the right column shows the waiting time (in minutes). Each row represents a different D/C ratio. In each figure, there are four categories representing different Gini coefficients. In each Gini histogram, different shades of green bars represent different transport methods. Based on Table 6-4 and Figure 6-10, alongside previous analysis, now the questions posed in Section 1 can be answered.

1. Effects of different communication methods on relief aircraft dispatch

In Section 4, this research proposed corresponding transport methods based on different information sharing levels. The dispatchment methods are based on the characteristics of different information sharing levels.

Based on the simulation result, this research can further analyze the most suitable scenario for each transport method. From Figure 6-10, it can be observed that the “reconnaissance and rescue” method is better when the Gini coefficient is 0.1 or 0.3. In this case, almost all the shelters have injuries to be evacuated. Even if there is no information from the shelter sites, as long as aircraft are dispatched to a shelter, they can bring some injuries back.

The “one destination” method in level two is more suitable to scenarios where D/C is smaller than 1 and the Gini coefficient is 0.1 or 0.3. In these cases, the available aircraft exceed the demand, and the distribution of injuries is even. Although this is a simple method, it remains efficient.

The “multiple destinations” method in level two is more suitable to scenarios where D/C is smaller than 1 and the Gini coefficient is 0.5 or 0.7. Due to the extremely uneven distribution of injuries, some shelters may have more injuries than the capacity of the aircraft, while others may have few injuries. Therefore the “multiple destinations” method is more suitable for this extreme distribution.

The “dynamic transport” method is best in every scenario. In fact, this method combines the advantages of the two methods in level two. In particular, it has the best performance for waiting times.

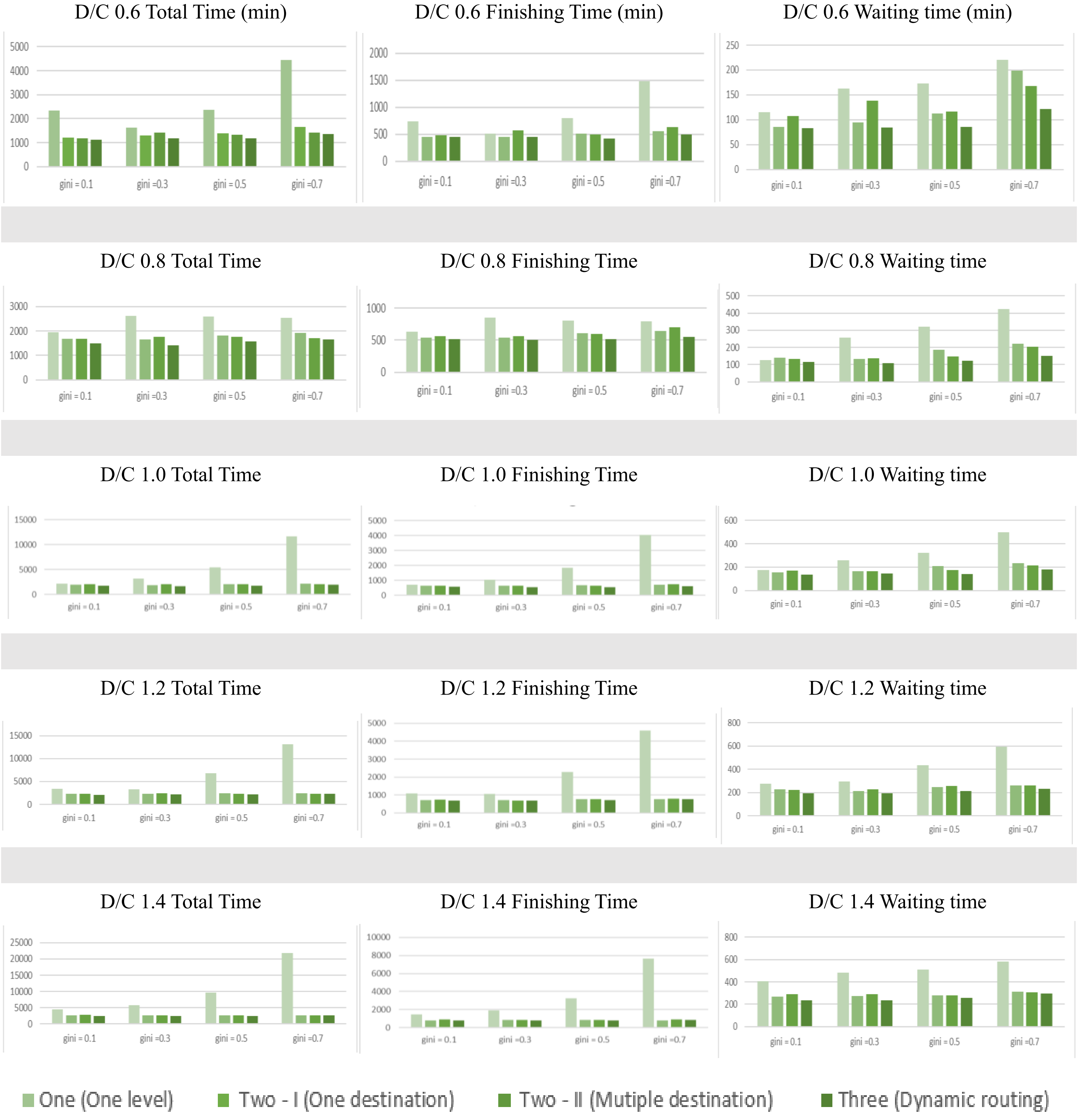


Figure 6-10 Simulation results

2. Improvements in information sharing for the efficiency of relief activities

1) “Reconnaissance and rescue” (the one-level method) always has the worst transportation

efficiency in the total flight time, finishing time, and waiting time, especially when the Gini coefficient is large. This is because in “reconnaissance and rescue,” there is no information communication between the aircraft dispatchers and shelters. In this case, aircraft dispatchers need to keep sending aircraft to collect information. There are some cases where the aircraft travels without any injured persons, which leads to worse total flight time, finishing time, and waiting time. When the Gini coefficient is large enough, although there may be very few injured in some shelters, dispatchers still need to keep sending aircraft for further updates on the situation in the shelter. This results in a greater waste in the flight resources.

2) Dynamic routing (Level three) is better than both methods in Level two, especially when the D/C is smaller and the Gini coefficient is larger. This is because, in this case, a single flight to a destination cannot make the best use of the aircraft capacity, and the total number of injured does not match the total capacity of the aircraft fleet. Moreover, the multiple-destination method is not very flexible. Thus, dynamic routing is the best option.

3. effectiveness of different levels of information for dealing with different relief Scenarios

1) The Gini coefficient and D/C affect the effectiveness of the transport methods. Table 6-4 and Figure 6-10 show that a larger Gini coefficient in the same D/C or larger D/C in the same Gini coefficient could increase the flight time, finishing time, and waiting time.

2) When D/C is larger than 1 (such as 1.2 or 1.4), the methods in Level two and three mostly have the same performance. In this case, when the Gini coefficient is smaller, the demand in each shelter is often larger than the aircraft capacity; thus, the injured in one shelter can be transported by a single aircraft. When the Gini coefficient is larger, most demand is focused on one or two shelters, and thus, other shelters do not consume as much flight resources. Hence, when D/C is larger than 1, regardless of the Gini coefficient, the methods in Level two and Level three have the same performance.

3) When D/C is smaller than 1, the difference between the two methods can be seen at Level two. One destination (two-I) is better than multiple destinations when the Gini coefficient is smaller (such as 0.1 or 0.3), whereas multiple destinations are better when the Gini coefficient is larger (such as 0.5 or 0.7). This is because when D/C is smaller than 1 and the Gini coefficient is small, there are sufficient flight resources and the injured in each shelter may be less than the capacity of the aircraft. Under these conditions, the one-destination method is fast and efficient. When D/C is smaller than 1 and the Gini coefficient is large, more flight resources are available, but the distribution of the demand is imbalanced. In some shelters, the injured might exceed the capacity of the aircraft. In this condition, multiple destinations could be better.

4. Implications for air rescue operations

From the results of the numerical experiment, the following implications can be provided for achieving more efficient operations on air rescue:

1) The information-sharing level or communication system in air relief activities is extremely

important, and the level of the information-sharing system determines the optimal aircraft dispatch strategies. Based on this numerical experiment, different agents (aircraft, airports, and shelters) and involved organizations (medical teams, fire departments, response headquarters, etc.) could be connected by an integrated information-sharing system that could improve relief efficiency.

2) To determine which strategies must be implemented, it is necessary to consider the information sharing level, demand distribution, and disaster level. Our simulation has proved that the total amount and distribution of demands could affect the result of dispatch strategies. Therefore, a suitable strategy must be employed according to different scenarios.

3) In a single relief activity, the demand distributions and communication systems could vary with the relief phases. For example, at the beginning of the relief, the information system used is "Level one". After communication devices recovering, the information sharing level is improved.

6.6 Conclusion

In air rescue activities during a large-scale disaster, different communication devices among the different stakeholders, such as whiteboard, satellite telephone, and real-time devices (D-net), are utilized for sharing information. This study aimed to quantify the effect of the different information-sharing systems on the efficiency of air relief activities.

First, this research defined an information-sharing system in three levels: no communication among different entities; part of the entities could be in contact (usually rescue shelters and rescue centers), and real-time communication among all entities. Second, based on the properties of different information-sharing levels, different transportation methods are proposed. Third, an agent-based simulation is utilized to embed different aircraft dispatchment methods into air relief activities. Finally, by comparing different methods under different scenarios of the D/C ratio and Gini coefficient (demand imbalance), this research analyzed the influence of the different communication systems on relief activities.

The key findings of this study are:

The higher the level of the information-sharing system, the better the efficiency of relief activities. This is proved by quantitative analysis.

Even if the total distribution of demand affects the effectiveness of transportation methods, when handling an imbalanced distribution of demand, the more flexible methods, such as multiple destinations or dynamic routing, have a higher performance, especially for the indicator of waiting time.

The total demand number can also affect the effectiveness of transportation methods. For example, when the D/C ratio is larger than 1, the methods in levels two and three have an almost identical performance. In this case, the simple and commonly used method "one flight one destination" is sufficient.

All three findings are demonstrated for the first time in published scientific literature.

Hence, it is suggested:

To improve the preparedness for disaster response, advanced communication devices should be used in relief activities as much as possible, especially in some areas where the population distribution is uneven.

Considering the possibility of an uneven injury distribution, a disaster relief authority or local government can design optimal transport methods in advance to make the best use of relief resources.

Our results show that when the number of injuries is evenly distributed and either equal to slightly more than the total injuries, the basic and commonly used method “one destination” is also effective. Therefore, to reduce the complexity of rescue whilst maintaining efficiency, it is recommended that the location distribution of rescue shelters should be designed considering the population distribution.

In this study, for the overall model, the process of air rescue was simplified, and the flight routing only included airport and rescue shelters, without considering aircraft refueling in the airport and other missions. Only one transport method was called for each simulation, without considering the combination of different transport methods; For the input data, although this research used different coefficients to simulate the different scenarios of demands in the affected area; in each scenario the input of demand was uncharged for several hours. These constitute the limitations of our research. In our future work, it is planed to introduce practical disaster data and demand variations with time to analyze the optimal air transport method in more complex practical situations.

Appendix A

In this paper, simulated annealing is used in multiple destinations, which is introduced as follows:

Algorithm 1 simulated annealing

```
while counts of iterations is less than the set count
    let S = S0
    for (original temperature; end temperature; cooling factor)
        pick a random neighbor, S new = neighbor (S)
        if P (E (S), E(S new), T) ≥ random (0,1)
            S = S new
output: the final state S
```

Goal function:

Herein, this research sets the function as the minimum total traveling distance.

Neighbor function:

The move operator is expected to handle both nodes and transport volume. To exchange the node and delivery simultaneously and ensure the diversity of the algorithm, this exchange move operator is designed, as shown in Figure 6-11.

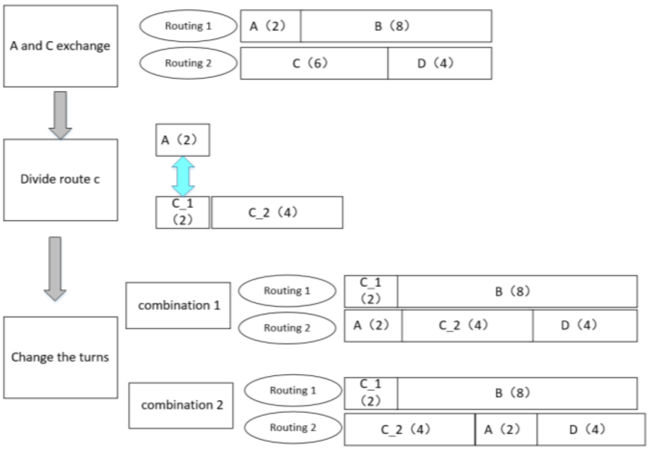


Figure 6-11 Exchange operator

Acceptance probability function:

$$P\left(E(S),E(S_{new}),T\right)=\exp(\frac{E(S)-E(S_{new})}{T})$$

Annealing schedule temperature: to maintain the quality of the solution and the speed of calculation, the original temperature is selected as 100, the final temperature as 1, and the cooling factor as 0.9.

Appendix B

The inputs of injuries in shelters for the numerical experiment.

Table 6-5 Inputs for the simulation when the total demand is 30

Gini	Shelter 1	Shelter 2	Shelter 3	Shelter 4	Shelter 5	Gini
0.1	5	5	5	7	8	0.11
0.3	2	4	5	7	12	0.31
0.5	1	1	5	5	18	0.51
0.7	1	1	1	1	26	0.67

Table 6-6 Inputs for the simulation when the total demand is 40

Gini	Shelter 1	Shelter 2	Shelter 3	Shelter 4	Shelter 5	Gini
0.1	6	7	8	9	10	0.10
0.3	2	5	8	11	14	0.30
0.5	1	2	3	14	20	0.50
0.7	1	1	1	2	35	0.69

Table 6-7 Inputs for the simulation when the total demand is 50

Gini	Shelter 1	Shelter 2	Shelter 3	Shelter 4	Shelter 5	Gini
0.1	8	8	10	11	13	0.10
0.3	4	5	10	11	20	0.30
0.5	2	2	7	9	30	0.50
0.7	1	1	2	3	43	0.67

Table 6-8 Inputs for the simulation when the total demand is 60

Gini	Shelter 1	Shelter 2	Shelter 3	Shelter 4	Shelter 5	Gini
0.1	9	11	11	12	17	0.11
0.3	4	8	10	15	23	0.30
0.5	1	3	9	13	34	0.51
0.7	1	1	2	4	52	0.70

Table 6-9 Inputs for the simulation when the total demand is 70

Gini	Shelter 1	Shelter 2	Shelter 3	Shelter 4	Shelter 5	Gini
0.1	11	12	13	16	18	0.10
0.3	7	8	12	13	30	0.30
0.5	3	5	5	15	42	0.50
0.7	1	2	2	3	62	0.70

7 Conclusion

7.1 Summary of findings

In this work, several models and analyses were employed for evaluating the research objectives related to the disaster response of aircraft operations.

1) To assess airport capacity during disaster relief, this study developed an integrated airport operation simulation considering the runway and parking spots, in order to analyze the dynamic capacity. Based on the results of the simulation, during disaster events, airports can maximize the utilization of airport facilities by receiving more aircraft than the number of spots (static capacity), thereby rescuing more affected people.

2) To determine the optimal aircraft allocation schemes, this research established an evacuation aircraft allocation model and analyzed different schemes based on data pertaining to Typhoon 19. The results demonstrate that the proposed approach can offer different aircraft allocation schemes according to different objectives.

3) To improve the efficiency of air relief transport, this research referred to the SDVRP for designing flight routing and then integrated the flight route planning and scheduling to establish an air medical rescue model. The results of the numerical experiments demonstrated that, while the degree of imbalance is larger (i.e., the Gini coefficient is larger), the “multiple-destination method” can improve transportation efficiency, as compared with the conventional single-destination method. The distribution of demand is also an important factor when determining the transport method for relief activities.

4) Furthermore, the influence of different communication systems on relief activities was analyzed. This research defined different levels of information sharing and established a simulation for comparing the effects of different levels of sharing information and different injury distributions. The results demonstrated that the level of the information-sharing system, distribution of demand, and total amount of demand have notable impacts on the transport methods.

7.2 Future research

This research established several models to analyze airport capacity, aircraft allocation, aircraft transport methods, and different levels of information sharing during air relief activities. However, certain areas warrant further improvements in the future.

7.2.1 Utilizing more practical data

The most challenging factor in this dissertation is data. It is difficult to obtain accurate and adequate data regarding airport operations and aircraft dispatch during disaster responses. For example, in the injury transport model, this study used the Gini coefficient to generate a random input. Most relief data are confidential and unavailable to the public. Hence, in the future, more practical data should be investigated to improve the accuracy of the model.

7.2.2 Making models closer to reality

To facilitate modeling, the process of air relief activities was simplified. For example, in this research, flight routing only included airport and rescue shelters, without considering the aircraft refueling in airports and other such missions. In the future, it is necessary to introduce hospitals and temporal rescue centers into the models and make the models closer to reality.

7.2.3 Developing more dynamic model

In this study, the input of demand remained unchanged during each simulation. However, in practical relief activities, the demands, including goods and personnel transport, are dynamic. Therefore, in future research, it is planed to introduce practical disaster data and demand variations with respect to time to analyze the optimal air transport method under more complex practical situations.

References

Aviation Law, Article 63, Rule 153

Airport Emergency plan, Fairbanks International Airport, Alaska, February 2020

Aratani, T., Hirata, T., Osada, T., Hanaoka, S., Todoroki, T., & Indo, Y. (2013). Aircraft activities and airport operations in the aftermath of the Great East Japan Earthquake-—case of Iwate Hanamaki, Yamagata and Fukushima Airport. Civil Engineering Association Proceedings D3, Vol.69, No. 5, 229-246. (in Japanese)

Ahmadi, Morteza, Abbas Seifi, and Behnam Tootooni. "A humanitarian logistics model for disaster relief operation considering network failure and standard relief time: A case study on San Francisco district." Transportation Research Part E: Logistics and Transportation Review 75 (2015): 145-163.

Alinaghian, Mahdi, Mohammad Aghaie, and Mohammad S. Sabbagh. "A mathematical model for location of temporary relief centers and dynamic routing of aerial rescue vehicles." Computers & Industrial Engineering 131 (2019): 227-241.

Andersson, Tobias, and Peter Värbrand. "Decision support tools for ambulance dispatch and relocation." Operational Research for Emergency Planning in Healthcare: Volume 1. Palgrave Macmillan, London, 2016. 36-51.

Andreeva-Mori, Adriana, Keiji Kobayashi, and Masato Shindo. "Particle swarm optimization/greedy-search algorithm for helicopter mission assignment in disaster relief." Journal of Aerospace Information Systems 12.10 (2015): 646-660.

Barich, F. (2013). ACRP Report 88: Guidebook on integrating GIS in emergency management at airports. Transportation Research Board of the National Academics, Washington, DC, 134.

BERTSIMAS, Dimitris; PATTERSON, Sarah Stock. The air traffic flow management problem with enroute capacities. Operations research, 1998, 46.3: 406-422.

BISAILLON, Serge, et al. A large neighbourhood search heuristic for the aircraft and passenger recovery problem. 4OR, 2011, 9.2: 139-157.

BOONMEE, Chawis, et al. Multi-model optimization for shelter-site selection: A case study in Banta municipality, Thailand. Proc. of Infrastructure Planning in Japan Society of Civil Engineers, 2016, 53: 2175-2181.

BILLHARDT, Holger, et al. Taxi dispatching strategies with compensations. Expert Systems with Applications, 2019, 122: 173-182.

Bischoff, Joschka, and Michal Maciejewski. "Agent-based simulation of electric taxicab fleets." Transportation Research Procedia 4 (2014): 191-198.

Bischoff, Joschka, and Michal Maciejewski. "Simulation of city-wide replacement of private cars with autonomous taxis in Berlin." Procedia computer science 83 (2016): 237-244.

Balcik, Burcu, Benita M. Beamon, and Karen Smilowitz. "Last mile distribution in humanitarian relief." Journal of Intelligent Transportation Systems 12.2 (2008): 51-63.

Berkoune, Djamel, Jacques Renaud, Monia Rekik, and Angel Ruiz. "Transportation in disaster response operations." Socio-Economic Planning Sciences 46.1 (2012): 23-32.

Bruni ME, Beraldi P, Khodaparasti S. "A fast heuristic for routing in post-disaster humanitarian relief logistics." Transportation Research Procedia 30 (2018): 304-313.

Chiu, Yi-Chang, and Hong Zheng. "Real-time mobilization decisions for multi-priority emergency response resources and evacuation groups: model formulation and solution." Transportation Research Part E: Logistics and Transportation Review 43.6 (2007): 710-736.

Chowdhury, Sudipta, et al. "Drones for disaster response and relief operations: A continuous approximation model." International Journal of Production Economics 188 (2017): 167-184.

Choi, S., Hanaoka, S. (2016). Managing waiting time for different aircraft operators in immediate disaster response. In Proceedings of 14th World Conference on Transport Research, Shanghai.

Choi, S., Hanaoka, S. (2017) Estimating the mean waiting time in airports through cooperative disaster response operations, Journal of Air Transport Management, Volume 65, October, Pages 11-17.

Choi, S., Hanaoka, S., (2017) Diagramming development for a base camp and staging area in a humanitarian logistics base airport, Journal of Humanitarian Logistics and Supply Chain Management, Vol. 7 Issue: 2, pp.152-171.

CLAUTIAUX, François, et al. Lower and upper bounds for the Bin Packing Problem with Fragile Objects. Discrete Applied Mathematics, 2014, 163: 73-86.

CHANTA, Sunarin; SANGSAWANG, Ornurai. Shelter-site selection during flood disaster. Lect. Notes Manag. Sci, 2012, 4: 282-288.

CHOWDHURY, Jahir U., et al. Models for cyclone shelter planning in Bangladesh. Water International, 1998, 23.3: 155-163.

De Angelis, Vanda, et al. "Multiperiod integrated routing and scheduling of World Food Programme cargo planes in Angola." Computers & Operations Research 34.6 (2007): 1601-1615.

Estrada, Mario Arturo Ruiz, and Abrahim Ndoma. "The uses of unmanned aerial vehicles–UAV's-(or drones) in social logistic: Natural disasters response and humanitarian relief aid." Procedia Computer Science 149 (2019): 375-383.

Ferrer, José M., F. Javier Martín-Campo, M. Teresa Ortuño, Alfonso J. Pedraza-Martínez, Gregorio Tirado, and Begoña Vitoriano. "Multi-criteria optimization for last mile distribution of disaster relief aid: Test cases and applications." European Journal of Operational Research 269.2 (2018): 501-515.

FENG, ChM, et al. A bi-level programming model for allocating private and emergency vehicle flows in seismic disaster areas. In: Proceedings of the Eastern Asia Society for Transportation Studies, Vol 5. 2005. p. 1408-1423.

Fagnant, Daniel J., and Kara M. Kockelman. "The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios." Transportation Research Part C: Emerging Technologies 40 (2014): 1-13.

GENDREAU, Michel; LAPORTE, Gilbert; SEMET, Frédéric. Heuristics and lower bounds for the bin packing problem with conflicts. Computers & Operations Research, 2004, 31.3: 347-358.

GOODSON, Justin C.; OHLMANN, Jeffrey W.; THOMAS, Barrett W. Rollout policies for dynamic solutions to the multivehicle routing problem with stochastic demand and duration limits. Operations Research, 2013, 61.1: 138-154.

Hanaoka, Shinya, Yuichi Indo, Terumitsu Hirata, Tomoyuki Todoroki, Taro Aratani, and Teppei Osada. Lessons and challenges in airports operation during a disaster case studies on Iwate Hanamki airport Yamagata airport and Fukushima airport during the great east Japan earthquake. Journal of JSCE 1(1) (2013): 286-297.

HYLAND, Michael; MAHMASSANI, Hani S. Dynamic autonomous vehicle fleet operations: Optimization-based strategies to assign AVs to immediate traveler demand requests. Transportation Research Part C: Emerging Technologies, 2018, 92: 278-297.

Homola, Jeffrey, et al. "UTM and D-NET: NASA and JAXA's collaborative research on integrating small uas with disaster response efforts." 2018 Aviation Technology, Integration, and Operations Conference. 2018.

Haghani, Ali, and Saini Yang. "Real-time emergency response fleet deployment: Concepts, systems, simulation & case studies." Dynamic fleet management. Springer, Boston, MA, 2007. 133-162.

Huang, Michael, Karen Smilowitz, and Burcu Balcik. "Models for relief routing: Equity, efficiency and efficacy." Transportation Research Part E: Logistics and Transportation Review 48.1 (2012): 2-18.

Haghi, Mahbubeh, Seyed Mohammad Taghi Fatemi Ghomi, and Fariborz Jolai. "Developing a robust multi-objective model for pre/post disaster times under uncertainty in demand and resource." Journal of Cleaner Production 154 (2017): 188-202.

HAMDI-DHAOUI, Khaoula; LABADIE, Nacima; YALAOUI, Alice. Algorithms for the two dimensional bin packing problem with partial conflicts. RAIRO-Operations Research, 2012, 46.1: 41-62.

Jenkins, Phillip R., Matthew J. Robbins, and Brian J. Lunday. "Examining military medical evacuation dispatching policies utilizing a Markov decision process model of a controlled queueing system." Annals of Operations Research 271.2 (2018): 641-678.

Jiang, Yiping, et al. "Emergency logistics in a large-scale disaster context: Achievements and challenges." International Journal of Environmental Research and Public Health 16 (2019): 779.

JANSEN, Klaus. An approximation scheme for bin packing with conflicts. Journal of combinatorial optimization, 1999, 3.4: 363-377.

Japan Meteorological Agency, website: https://www.jma.go.jp/jma/indexe.html.

Keneally, Sean K., Matthew J. Robbins, and Brian J. Lunday. "A markov decision process model for the optimal dispatch of military medical evacuation assets." Health care management science 19.2 (2016): 111-129.

Kawase, Riki, Junji Urata, and Takamasa Iryo. "Optimal control strategy for relief supply considering information and demand uncertainty after a major disaster." IFAC-PapersOnLine 52.6 (2019): 31-38.

KULSHRESTHA, Ashish, et al. Robust shelter locations for evacuation planning with demand uncertainty. Journal of Transportation Safety & Security, 2011, 3.4: 272-288.

KONGSOMSAKSAKUL, Sirisak; YANG, Chao; CHEN, Anthony. Shelter location-allocation model for flood evacuation planning. Journal of the Eastern Asia Society for Transportation Studies, 2005, 6: 4237-4252.

KHANAFER, A.; CLAUTIAUX, F.; TALBI, E. G. Tree-decomposition based tabu search for the bin packing problems with conflicts. In: Metaheuristics International Conference, MIC09. Hamburg, Germany. 2009.

KHANAFER, Ali; CLAUTIAUX, François; TALBI, El-Ghazali. New lower bounds for bin packing problems with conflicts. European journal of operational research, 2010, 206.2: 281-288.

Kansai Airport BCP (Business Continuity Plan), Kansai Airport, June, 2019.

Kobayashi, K. and Okuno, Y. (2010) Research and development of disaster relief aircraft information sharing network (D-net). The 49th Japan Aviation Society Aircraft Symposium, 388-393. (in Japanese)

Kodato, W. and Hirata, T. (2015) Fundamental analysis of airport operation and capacity in disaster, Proceedings of 51th Conference of Infrastructure Planning, JSCE. (in Japanese)

LI, Anna CY, et al. Shelter location and transportation planning under hurricane conditions. Transportation Research Part E: Logistics and Transportation Review, 2012, 48.4: 715-729.

Liu, Bingsheng, et al. "Decision making on post-disaster rescue routing problems from the rescue efficiency perspective." European Journal of Operational Research (2020).

LIAO, Tsai-Yun; HU, Ta-Yin. An object-oriented evaluation framework for dynamic vehicle routing problems under real-time information. Expert Systems with Applications, 2011, 38.10: 12548-12558.

LIAO, Tsai-Yun; HU, Ta-Yin; KUO, Hsin-Hwa. Dynamic fleet management under real-time information. In: Proceedings of the Eastern Asia Society for Transportation Studies Vol. 6 (The

7th International Conference of Eastern Asia Society for Transportation Studies, 2007). Eastern Asia Society for Transportation Studies, 2007. p. 145-145.

Lee, Yong-Min, Bon-Jun Ku, and Do-Seob Ahn. "A satellite core network system for emergency management and disaster recovery." 2010 International conference on information and communication technology convergence (ICTC). IEEE, 2010.

Mete, Huseyin Onur, and Zelda B. Zabinsky. "Stochastic optimization of medical supply location and distribution in disaster management." International Journal of Production Economics 126.1 (2010): 76-84.

MURITIBA, Albert E. Fernandes, et al. Algorithms for the bin packing problem with conflicts. Informs Journal on computing, 2010, 22.3: 401-415.

Ministry of Internal Affairs Fire and Disaster Management Agency. (2013) Fire protection promotion No. 162 preparation or review of a support plan for emergency fire assistance aircraft unit. (in Japanese)

McLay, Laura A., and Maria E. Mayorga. "A model for optimally dispatching ambulances to emergency calls with classification errors in patient priorities." IIE Transactions 45.1 (2013): 1-24.

Martinez, Luis M., and José Manuel Viegas. "Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal." International Journal of Transportation Science and Technology 6.1 (2017): 13-27.

Maciejewski, Michal, and Kai Nagel. "Simulation and dynamic optimization of taxi services in MATSim." Transportation Science (2013): 000-000.

Maciejewski, Michał, and Kai Nagel. A microscopic simulation approach for optimization of taxi services. 2013.

Maciejewski, Michal, and Joschka Bischoff. "Large-scale microscopic simulation of taxi services." Procedia Computer Science 52 (2015): 358-364.

Mahmassani, Hani S. "50th anniversary invited article—Autonomous vehicles and connected vehicle systems: Flow and operations considerations." Transportation Science 50.4 (2016): 1140-1162.

Maciejewski, Michal, Joschka Bischoff, and Kai Nagel. "An assignment-based approach to efficient real-time city-scale taxi dispatching." IEEE Intelligent Systems 31.1 (2016): 68-77.

Ma, Shuo, Yu Zheng, and Ouri Wolfson. "T-share: A large-scale dynamic taxi ridesharing service." 2013 IEEE 29th International Conference on Data Engineering (ICDE). IEEE, 2013.

Minato, N., Morimoto, R. (2012). Collaborative management of regional air transport during natural disasters: Case of the 2011 East Japan earthquake and tsunami. Research in Transportation Business & Management, 4, 13-21.

Najafi, Mehdi, Kourosh Eshghi, and Wout Dullaert. "A multi-objective robust optimization model for logistics planning in the earthquake response phase." Transportation Research Part E: Logistics and Transportation Review 49.1 (2013): 217-249.

Narita International Airport BCP (Business Continuity Plan), Narita Airport, April,2021

Ozdamar, Linet. "Planning helicopter logistics in disaster relief." OR spectrum 33.3 (2011): 655-672.

Özdamar, Linet, and Onur Demir. "A hierarchical clustering and routing procedure for large scale disaster relief logistics planning." Transportation Research Part E: Logistics and Transportation Review 48.3 (2012): 591-602.

Oruc, Buse Eylul, and Bahar Yetis Kara. "Post-disaster assessment routing problem." Transportation Research Part B: Methodological 116 (2018): 76-102.

OZBAYGIN, Gizem; SAVELSBERGH, Martin. An iterative re-optimization framework for the dynamic vehicle routing problem with roaming delivery locations. Transportation Research Part B: Methodological, 2019, 128: 207-235.

POWELL, Warren B.; SIMAO, Hugo P.; BOUZAIENE-AYARI, Belgacem. Approximate dynamic programming in transportation and logistics: a unified framework. EURO Journal on Transportation and Logistics, 2012, 1.3: 237-284.

Parwanto, Novia Budi, Hozumi Morohosi, and Tatsuo Oyama. “Applying network flow optimization techniques to improve relief goods transport strategies under emergency situation.” American Journal of Operations Research 5 (2015): 95-111

Polater, Abdussamet. "Managing airports in non-aviation related disasters: A systematic literature review." International Journal of Disaster Risk Reduction 31 (2018): 367-380.

Rezaei-Malek, Mohammad, et al. "An approximation approach to a trade-off among efficiency, efficacy, and balance for relief pre-positioning in disaster management." Transportation Research Part E: Logistics and Transportation Review 93 (2016): 485-509.

Rabta, Boualem, Christian Wankmüller, and Gerald Reiner. "A drone fleet model for last-mile distribution in disaster relief operations." International Journal of Disaster Risk Reduction 28 (2018): 107-112.

RYERSON, Megan S.; CHURCHILL, Andrew M. Aircraft Rerouting due to Abrupt Facility Outages: Case Study of the 2011 Great Tωhoku Earthquake, Japan. Transportation research record, 2013, 2336.1: 27-35.

ROBBINS, Matthew J., et al. Approximate dynamic programming for the aeromedical evacuation dispatching problem: Value function approximation utilizing multiple level aggregation. Omega, 2020, 91: 102020.

Richard De Neufville, Amedeo R. Odoni (2003) Airport Systems: Planning, Design, and Management, McGraw-Hill.

Salanova Grau, Josep Maria, and Miguel Ángel Estrada Romeu. "Agent based modeling for simulating taxi services [: case study in Barcelona]." Procedia Computer Science, Volume 52, 2015. Elsevier, 2015.

Schmid, Verena. "Solving the dynamic ambulance relocation and dispatching problem using approximate dynamic programming." European journal of operational research 219.3 (2012): 611-621.

Smith, J. F., Waggoner, S. S., Hall, G. (2007). Building sound emergency management into airports. In Aviation: A World of Growth (pp. 47-60).

Smith, J. F. (2010). Regional Cooperation, Coordination, and Communication Between Airports During Disasters. Transportation Research Record, 2177(1), 132-140.

Smith, J. F. (2012). The roles of general aviation airports in disaster response. Journal of Homeland Security and Emergency Management, 9(2).

Sampey, T. (2013). Preparing for large scale emergency events at airports. Airport Magazine, 25(5).

Smith, J. F. (2014). ACRP Synthesis 50: Effective cooperation among airports and local and regional emergency management agencies for disaster preparedness and response: a synthesis of airport practice. Transportation Research Board of the National Academies, Washington, DC.

STOYAN, Yu G.; YASKOV, G. N. Mathematical model and solution method of optimization problem of placement of rectangles and circles taking into account special constraints. International Transactions in Operational Research, 1998, 5.1: 45-57.

STOYAN, Yu; CHUGAY, A. Packing cylinders and rectangular parallelepipeds with distances between them into a given region. European Journal of Operational Research, 2009, 197.2: 446-455.

SUH, Daniel; RYERSON, Megan S. A large neighborhood search heuristic to establish an optimal ad-hoc hubbing strategy in the wake of a large-scale airport outage. Journal of Air Transport Management, 2017, 65: 156-165.

SANTOS, M. G., et al. Flood facility location-allocation in Marikina City using MCLP with Lagrange. In: Proc. of 14th Asia Pacific Industrial Engineering and Management Systems Conference. 2013.

Tofighi S, Torabi SA, Mansouri SA. "Humanitarian logistics network design under mixed uncertainty." European Journal of Operational Research 250.1 (2016): 239-250.

UN office for Disaster Risk Reduction, An overview of the last 20 years 2000 – 2019: Human cost of disasters. Online: file:///C:/Users/keikaku_2017_3/AppData/Local/Temp/Human%20Cost%20of%20Disasters%202000-2019%20Report%20-%20UN%20Office%20for%20Disaster%20Risk%20Reduction.pdf. (Assess *on October 18, 2021)*

Veysmoradi D, Vahdani B, Farhadi Sartangi M, Mousavi SM. "Multi-objective open location-routing model for relief distribution networks with split delivery and multi-mode transportation under uncertainty." Scientia Iranica 25.6 (2018): 3635-3653.

Veatch M, Goentzel J. Feeding the bottleneck: airport congestion during relief operations[J]. Journal of Humanitarian Logistics and Supply Chain Management, 2018.

WANG, Ke, et al. Optimizing precipitation station location: a case study of the Jinsha River Basin. International Journal of Geographical Information Science, 2016, 30.6: 1207-1227.

Wilkinson, P. J., and D. G. Cole. "The role of radio science in disaster management." URSI Radio Science Bulletin 2010.335 (2010): 45-51.

YOON, Soovin; ALBERT, Laura A. A dynamic ambulance routing model with multiple response. Transportation Research Part E: Logistics and Transportation Review, 2020, 133: 101807.

Yi, Wei, and Linet Özdamar. "A dynamic logistics coordination model for evacuation and support in disaster response activities." European Journal of Operational Research 179.3 (2007): 1177-1193.

ZHANG, Yu; HANSEN, Mark. Real-time intermodal substitution: strategy for airline recovery from schedule perturbation and for mitigation of airport congestion. Transportation research record, 2008, 2052.1: 90-99.

ZHANG, Wenwen, et al. The performance and benefits of a shared autonomous vehicles based dynamic ridesharing system: An agent-based simulation approach. In: Transportation Research Board 94th Annual Meeting. 2015.

ZHANG, Wenwen, et al. Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. Sustainable Cities and Society, 2015, 19: 34-45.

Zheng, Jun, et al. "Design of Integrated Service Platform Based on Satellite Mobile Communication System." 2019 IEEE 2nd International Conference on Electronics and Communication Engineering (ICECE). IEEE, 2019.