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ORIGINAL RESEARCH

Research on the recovery method of disrupted flights considering passenger transfer and cancellation costs

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Abstract
In the face of extreme weather conditions, airport closures, or other circumstances, airlines often experience disruptions to their flight schedules, leading to the frequent operational challenge of disrupted flight recovery. The foundational model for disrupted flight recovery aims to recover as many flights as possible with minimal costs, typically encompassing aircraft re-routing and re-timing costs, aircraft maintenance costs, crew reassignment costs, and passenger transfer costs. Existing studies generally estimate these costs using fixed rates. In reality, the first three costs for airlines tend to remain relatively stable. However, different passenger transfer methods can result in significant cost variations, a focal point for ground service personnel during disrupted flight recovery. We conducted a detailed analysis of the cost combinations associated with various passenger transfer methods, including ticket refunds, overnight stays, rebooking on the same airline, and rebooking on other airlines. We established a comprehensive disrupted flight recovery model that considers the three relatively fixed costs and variations in passenger transfer costs, thereby enhancing the resilience of the traditional model based on passenger transfer methods. To solve this model, we employed an enhanced heuristic large-scale neighborhood search (LNS) algorithm. Simulation experiments on airline datasets demonstrated that recovering all disrupted flights primarily through passenger transfer is not necessarily the least costly scenario. The optimal flight recovery ratio depends on passenger refund rates and rebooking methods. By judiciously controlling passenger transfer methods and the recovery proportion of disrupted flights, comprehensive recovery costs for both flights and passengers can be reduced. The research findings not only provide theoretical support for airlines but also offer practical guidance for strategy formulation, improving passenger satisfaction, and controlling operational costs.

Keywords Flight recovery problem · Disruptions management · Large-scale neighborhood search algorithm · Passenger transfer

1 Introduction

The civil aviation industry plays a pivotal role in the global transportation system. When constructing flight schedules, airlines must consider a comprehensive range of factors, including their own interests, passenger travel demands, and relevant policies in various regions. The planning process often takes place several months in advance to ensure the punctuality and efficiency of flights (Kölker and Lütjens 2015). Despite airlines' efforts to organize flight schedules, a significant challenge faced by the aviation industry is the occurrence of unforeseeable disruptions to normal flight operations. These disruptions may stem from various unpredictable events, such as sudden weather changes, delayed arrival of flight crew, or unexpected aircraft malfunctions (Ding et al. 2023). Such issues can lead to flight delays or cancellations, passenger stranding, and even airport closures. If not handled properly, these disruptions can impact both the economic viability and reputation of airlines (Prajapati et al. 2022). Therefore, the formulation of contingency plans by airlines becomes crucial for the recovery of disrupted flights, maintaining competitiveness, and meeting passenger demands.

During disrupt flight occurrences, airlines typically employ a series of measures to adjust flight operations, encompassing aircraft delays, flight segment cancellations, route adjustments, reassignment of flight crew or the summoning of new

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crew members, and reallocation of passenger transfers (Ball et al. 2007). The objective of flight recovery is to recover as many disrupted flights as possible in the shortest time, while minimizing costs. Flight recovery costs generally consist of multiple components, including aircraft recovery costs, passenger transfer costs, crew reassignment costs, and aircraft maintenance costs (Liang et al. 2018). Aircraft recovery costs further entail cancellation costs, delay costs, aircraft swapping costs, and ferrying costs, among others. Currently, aircraft recovery costs and aircraft maintenance costs are relatively stable (Mofokeng et al. 2020), with crew reassignment costs and passenger transfer costs being key considerations in current research. Among these, passenger transfer costs are significantly impacted by flight cancellations and exert a crucial influence on the overall cost of flight recovery.

Existing methods predominantly consider aircraft recovery and maintenance costs, while passenger transfer costs are generally estimated on a per-flight basis. Moreover, there is a limited focus on the proportion of passenger transfer in current approaches. In practical scenarios, the proportion of passenger transfer in disrupted flight situations is a crucial consideration for airline personnel involved in flight recovery operations. Different passenger transfer methods and the choice of proportions for each method significantly impact passenger transfer costs, consequently influencing the total cost of flight recovery and the associated decision-making process. In light of these considerations, this study maintains alignment with existing research by incorporating crew reassignment and aircraft maintenance costs. However, it emphasizes a novel focus on the varying proportions of passenger transfer methods and their impact on passenger transfer costs. Specifically, the research investigates the effects of different passenger transfer methods and proportions in situations involving flight cancellations, delays, and aircraft swaps. The study aims to understand the changes in passenger transfer costs resulting from different transfer methods and proportions. Ultimately, the research explores flight recovery issues based on the variations in costs induced by passenger transfer methods. This research objective is instrumental in obtaining optimal proportions for recoverable flights, understanding the dynamics of changing passenger transfer methods and proportions, and providing timely decision guidance for airline personnel.

Our target of optimization is the airline route network, a complex and dynamically changing system, which has been confirmed as an NP-hard problem (Hassan et al. 2021). Due to the large number of decision variables in such problems, conventional simplex or gradient descent methods face issues such as long computation time. Therefore, heuristic algorithms are often applied to solve problems of this nature. The large-scale neighborhood search algorithm (LNS) is a commonly employed heuristic algorithm that incorporates adaptive factors such as neighborhood selection and diversification strategies (Sze et al. 2016). This algorithm demonstrates the ability to rapidly yield high-quality solutions when tackling large-scale and intricate operational optimization problems. Hence, we endeavor to employ LNS to construct a global iterative search algorithm for solving the flight recovery model we have formulated.

The contributions of this paper are as follows: (1) Within the framework of classical flight recovery models, we introduce the concept of variable passenger transfer costs, enhancing the model's resilience. (2) We establish a methodology for computing passenger transfer costs, categorizing passenger transfers into ticket refunds, rebooking on flights within the same airline, rebooking on flights of other airlines, and overnight stays. Different transfer methods incur distinct costs, and various combinations of these methods at different proportions result in diverse passenger transfer costs. (3) In the simulation and experimentation phase, an optimized LNS algorithm is employed to solve the model. We conduct a comparative analysis of the model's outcomes under different combinations of transfer proportions, providing insights for practical decision-making in the airline industry.

The structure of this paper is organized as follows. Section 2 reviews relevant literature, Section 3 provides a detailed description of the problem and introduces the disrupted flight recovery model we have constructed. Section 4 introduces a heuristic LNS algorithm. In Section 5, an analysis is conducted on data from real airlines, focusing on the impact of different forms of passenger transfer combinations on the cost of disrupted flight recovery. Section 6 concludes the work and outlines future research directions.

2 Literature review

As research on the recovery of disrupted flights progresses, researchers have considered various factors, such as aircraft maintenance (Ruan et al. 2021), airport capacity (Liang et al. 2018), crew reassignment (Lapp and Cohn 2012), passenger transfers (Bratu and Barnhart 2006), and air traffic control (Pei et al. 2021). Table 1 summarizes existing literature on airline recovery problems. The primary objective of recovering disrupted flights is to minimize the recovery cost while recovering as many flights as possible promptly. The recovery cost of disrupted flights typically includes aircraft recovery costs, aircraft maintenance costs, crew reassignment costs, and passenger transfer costs. In practice, the aircraft recovery costs, aircraft maintenance costs, and crew reassignment costs for airlines remain relatively stable. However, different aircraft recovery strategies may result in varying passenger transfer methods and associated passenger recovery costs. Therefore, addressing the recovery of disrupted flights involves two primary challenges: aircraft recovery and passenger recovery. In the following sections,

Table 1 Summary of existing literature on airline recovery problems

Reference	Network	Multi-fleet	Cruise speed	Aircraft recovery	Passenger recovery	Crew recovery	Maintenance	Objective
Thengvall et al. (2003)	Time-space	✓		✓				Max revenue
Petersen et al. (2012)	Time-space			✓	✓	✓		Min schedule, aircraft,crew and passenger
Marla et al. (2017)	Time-space	✓	✓	✓				Min total cost and passenger delay cost
Khaled et al. (2018)	Flight connection			✓			✓	Min repair cost, max number of flights changed and max number of impacted airports
Ahmed et al. (2018)	Time-space	✓		✓		✓		Max total reward
Hu et al. (2021)	Flight connection	✓					✓	Min maintenance cost
Cadarso and Vaze (2023)	Time-space	✓	✓	✓	✓		✓	Min operation, passenger and crew recovery cost
Lee et al. (2022)	Flight connection			✓				Min total flight delay cost
Zhong et al. (2024)	Flight connection	✓		✓		✓		Min crew recovery cost
Our paper	Flight connection	✓		✓	✓	✓	✓	Min flight cancellation, passenger transfer cost, etc.

we will delve into the relevant literature and key research methodologies for each of these challenges.

2.1 Aircraft recovery

Aircraft, as a core resource for airlines, undergo aircraft recovery procedures when dealing with disrupted flights, with the initial focus on aircraft recovery strategies (Filar et al. 2001). Aircraft recovery includes re-routing, re-timing and cancellation decisions. Recovery methods primarily involve aircraft swapping (reassigning segments between different aircraft) and ferrying (repositioning an aircraft without tasks to another location, where it can be utilized)).

Foreign scholars have a relatively early history of research on aircraft recovery. Teodorović and Guberinić (1984) took the initiative in 1984 to adjust the departure and arrival times of aircraft during disrupted flights. They considered cases where a single aircraft is disrupted and used the branch-and-bound method for solving the problem. The approach involved swapping flight routes to minimize passenger delay. In Yan and Yang (1996) developed a basic schedule disruption model to address aircraft recovery problems. They employed the simplex method and subgradient Lagrangian relaxation method for solving, with the aim of reorganizing aircraft paths.

Aircraft recovery must take into account factors such as aircraft type, airport curfew, and turnaround time constraints. Sun (2020), through an analysis of flight departure times and route data, summarized the impact of nighttime curfews at airports on aircraft departure and arrival times, providing theoretical support for adjusting the times of disrupted flights. Hu et al. (2021) conducted research on the impact of changes in turnaround times on aircraft recovery, deviating from the traditional approach that only considers fixed transfer times. They developed a transfer time prediction model based on LightGBM, predicting the effective transfer time of flights and addressing aircraft recovery issues under disrupted conditions such as airport traffic reduction and closures. Wen et al. (2022) considered aircraft recovery in light of the maintenance requirements for different aircraft types. They utilized a column generation algorithm to allocate maintenance resources (such as personnel and equipment) to aircraft, addressing maintenance needs during aircraft recovery.

In recent years, the research focus on aircraft recovery has extended to the fleet level. Vink et al. (2020) established a spatiotemporal network model to solve the recovery problem for multiple fleets. Their approach is equally applicable to point-to-point and (multi) hub-and-spoke airlines. In terms of solving aircraft recovery problems, Lee et al. (2022) pioneered the application of reinforcement learning to aircraft recovery, demonstrating the effectiveness of reinforcement learning in addressing disruptions in real-world flight operations.

While aircraft recovery typically precedes passenger transfer , different methods of passenger recovery can result in varying costs and may have an overall impact on aircraft scheduling (Prajapati et al. 2022). Therefore, passenger recovery is also a crucial consideration in the context of disrupted flight recovery. The following sections will provide a detailed overview of relevant literature and research methods in this area.

2.2 Passenger recovery

Passenger recovery refers to the process of reassigning itineraries for affected passengers when disrupted flights occur. It begins at the airport where the affected passengers are located and concludes at their destination or nearby locations (Jafari and Zegordi 2010). The goal is to ensure that passengers arrive at their destination within the required time frame, meeting their itinerary requirements. Existing research on passenger recovery primarily focuses on the impact of flight delays on passengers, passenger connection times, passenger transfer willingness, and related aspects.

Flight delays directly impact passengers' travel experiences and the reputation of airlines. Bratu and Barnhart (2006) first proposed the Disruption Passenger Method (DPM) and Passenger Delay Method (PDM) models, both based on the temporal network they studied. DPM considers approximate delay costs and passenger disruption costs, while PDM explicitly models passenger disruptions and recovery options, ultimately more accurately calculating delay costs. The experiment aims to analyze the trade-off between fuel costs and passenger recovery costs. Voltes-Dorta et al. (2017) simulated airport closure scenarios, evaluating the total delay rate and arranging disrupted passengers into itineraries with the minimum delay time. This provides a useful benchmark for formulating passenger transfer and airport closure policies, helping mitigate negative impacts on airline reputation. Evler et al. (2022) incorporated aircraft turnaround into the concepts of aircraft, crew, and passenger recovery, addressing a research gap on how to integrate delay cascades into overall modeling. Through the calculation of specific delay cost functions for flights, they found substantial correlations with the time of day, the number of subsequent flight segments, and specific subsequent destinations. This significantly reduced the number of passengers missing the next flight due to flight delays and substantially improved the recoverability of the airline network under different delay scenarios.

The balance between flight schedules and passenger connection times is also a crucial factor to consider in passenger recovery. Aloulou et al. (2013) constructed a robust aircraft routing model that is less susceptible to disruptions based on the connectivity of flights and passengers. They implicitly captured the robustness of aircraft and passenger connections, and through computational experiments based on real-world data, significantly reduced total delays, the number of delayed flights, and the number of flights missed by passengers. Additionally, Arikan et al. (2017) considered controlling cruise speeds to ensure passenger connection times. They proposed a model for the integrated recovery of aircraft and passengers, simultaneously considering the associated costs. The model overlaid aircraft and passenger itinerary networks and utilized CPLEX for solving. It demonstrated the optimal handling of simultaneous disruptions occurring in less than a minute on average in a four-hub airline network.

Hu et al. (2015) proposed a rebooking arrangement for disrupted passengers, conducted an integrated integer programming model which is based on an approximate reduced time-band network and a passenger transiting relationship to address the joint problems of aircraft and passenger recovery after a schedule disruption. In 2016, Hu et al. (2016) furthered the research on integrated recovery of aircraft routes and passengers based on the original methodology. They established a mathematical model using the flight connection network and passenger reassignment relationships. The problem was solved using the GRASP algorithm as a heuristic approach. The effectiveness of the heuristic algorithm was validated through experiments based on synthetic datasets and real-world datasets.

Subsequently, heuristic algorithms began to be applied to passenger recovery. Simultaneously, some researchers utilized heuristic algorithms based on column generation for integrated recovery of flights and passengers. Maher (2015), by establishing substitute virtual itineraries for passengers in the event of flight cancellations, successfully simulated the passenger recovery process, significantly reducing the operational costs of airlines and increasing passenger flow through the network. The use of column and row generation methods effectively addressed the comprehensive airline recovery problem of passenger redistribution, obtaining high-quality solutions in a short time. Sinclair et al. (2016) formulated a mixed-integer programming model for the combined aircraft and passenger recovery problem and proposed a column generation post-optimization heuristic algorithm to solve the problem. The resulting heuristic algorithm improved the best solutions for all instances of the 2009 ROADEF challenge within a reasonable computational time.

The above studies predominantly focus on passenger and aircraft recovery from the perspective of airlines. In these studies, the objective functions of the models are mostly formulated from the airline's standpoint rather than considering the passengers. In the current research methodologies addressing disrupted flight occurrences, many assume that passengers comply with the arrangements made by the airlines, rather than emphasizing their own preferences, thus neglecting passenger willings. To address this gap, Qiang and Wei (2018) established a discrete spatiotemporal network for disrupted flight recovery, designed a multi-level fuzzy comprehensive evaluation system for passenger satisfaction, and proposed a dual-objective flight recovery optimization model that minimizes total losses while maximizing robustness to consider passenger willings. The research by Allard and Moura (2018) is more focused on passenger choices but does not take into account the costs incurred by the airline. Cirillo et al. (2018) employed a Dynamic Discrete Choice Model (DDCM) based on passenger time constraints to predict the timing of fare changes resulting from price and itinerary uncertainties, allowing passengers a choice window. The model developed by Yan and Yang (1996) is based on passenger preferences during trip interruptions but does not consider the scenario of flight delays.

Yang and Hu (2019) conducted research on the integrated recovery of aircraft and passengers focusing on the commonly used technique in flight adjustments, namely the method of flight cancellation and consolidation. They established a mathematical programming model based on the connectivity network and passenger transfer network. Subsequently, using the GRASP algorithm, they designed a heuristic algorithm to solve the passenger transfer problem. In 2021, Hu et al. (2021) optimized this model by considering voluntary passenger recovery in various flight disruption scenarios. They defined a dual-objective problem for passengers and airlines, breaking away from the traditional assumption that passengers adhere to route assignments. This approach aimed to minimize the dual losses incurred by both airlines and passengers.

In the post-pandemic era, the recovery of flights still needs to consider passenger health. Xu et al. (2023) proposed a novel model addressing the comprehensive recovery problem for airlines under the risk of in-flight epidemic transmission risks. This model recovers the schedules of aircraft, crew, and passengers to eliminate possible epidemic dissemination while reducing airline operating costs. It enhanced airline disruption management against major public health events while minimizing economic loss.

While the aforementioned studies have considered passenger recovery from various perspectives, most have only taken into account two scenarios for passenger transfer: ticket refund and rebooking. Moreover, the cost analysis for rebooking is often rudimentary. In reality, the costs associated with different rebooking options chosen by passengers vary. These options may include rebooking on the same airline's flight on the same day, rebooking on the same airline's flight on a different day, rebooking on another airline's flight on the same day, and rebooking on another airline's flight on a different day. The proportion of passengers opting for different rebooking options also influences the overall cost of passenger recovery. Therefore, it is essential to refine the analysis of passenger transfer methods, conduct a detailed cost analysis for various rebooking proportions, and provide airlines with more direct business guidance.

2.3 Research gaps and contribution

Currently, research on passenger transfer has predominantly focused on passenger refund and rebooking requirements. There is a lack of literature investigating the impact of different proportions of passenger transfer methods on the associated costs. In practical scenarios, airlines may offer various options to passengers, such as overnight stays, rebooking, and refunds. The proportions of different refund rates and rebooking methods significantly influence the cost of passenger transfer, consequently affecting decisions related to the recovery and cancellation of disrupted flights.

Our study on passenger transfer costs is based on five different methods and their various combinations: refund, rebooking on the same airline's flight on the same day, rebooking on the same airline's flight on a different day, rebooking on another airline's flight on the same day, rebooking on another airline's flight on a different day. Each method has its own associated cost, and different proportions of passenger transfers using these methods lead to varying passenger transfer costs. This variability impacts the overall decision-making process for the recovery of disrupted flights.

Through this approach, we can make informed decisions regarding flight delays and cancellations. In situations where flights are disrupted, decisions on the proportion of flights to be recovered can be determined based on the combination of passenger transfer proportions, aiming to minimize the total recovery cost. This methodology brings the problem closer to real-world scenarios and provides airlines with direct and optimal business guidance.

3 Problem description

In the event of disrupted flight occurrences, airlines are expected to promptly recover affected flights (Prajapati et al. 2022), minimizing the impact of delays on other flights, expeditiously transferring disrupted passengers to meet their travel requirements. This paper addresses both the Aircraft Recovery Problem (ARP) and the Passenger Recovery Problem (PRP).

When defining this problem, it is essential to first elucidate the background. The cause of disrupted flight operations is the closure of a specific airport due to extreme weather conditions, rendering all aircraft at that airport unable to take off for a certain duration. The duration of extreme weather events is unpredictable, and if prolonged, it results in a significant number of aircraft being grounded. During such instances, all flights operated by these aircraft either face cancellations or need to be reassigned to other aircraft, necessitating adjustments to the flight paths.

When undertaking the adjustment and recovery of aircraft paths, the following constraints must be followed when adjusting aircraft paths for recovery:

(1) Each flight can only be executed once at most, and each flight is either executed or cancelled.
(2) When adding additional flights for an aircraft, only additional flight circles are allowed.
(3) When there is an additional flight for a single aircraft, the supplemental flight needs to be scheduled at a time that does not conflict with the original scheduled flights.
(4) The delay times for each flight cannot exceed the maximum delay time limit.
(5) The new flight path generated after adjustment must meet the minimum turnaround time limit between the flight executed by each aircraft and its subsequent flights.
(6) When rebooking passengers, the new flight they are reassigned must meet their connection time limit.
(7) The curfew time requirements of the airport must be met.

3.1 Passenger transfer cost

The primary methods of passenger transfer involve ticket refunds and rebooking. To overcome the issue of imprecise cost estimation in existing research methods for passenger transfer, we have meticulously categorized the rebooking methods into four distinct types: rebooking on the same airline's flight on the same day, rebooking on the same airline's flight on a different day, rebooking on the different airline's flight on the same day, and rebooking on the different airline's flight on a different day, as illustrated in Fig. 1.

The primary determinant for selecting the mode of passenger transfer is passenger preference. In the event of flight cancellations, the majority of passengers tend to favor ticket refunds, with a minority opting for rebooking. Among those choosing rebooking, a significant portion prefers flights on the same day with the current airline. However, this option is subject to seat availability constraints, and if the remaining seats on the rebooked flight are insufficient, the passenger's preference cannot be accommodated. In such cases, we offer an alternative solution of rebooking on the same day with a different airline, meeting the demands of passengers with this preference. For passengers willing to accept an overnight stay, arrangements can be made for rebooking on different days with the current airline and on different days with a different airline, with accommodation provided. In the event of flight delays, some passengers may opt to wait for the original flight, while others may choose ticket refunds or rebooking, following the same rebooking options outlined above.

3.2 Model formulation

3.2.1 Parameter and decision variable

Index :

p	Aircraft index
f	Flight index
a	Airport index
r	Aircraft path index

Set :

P	Set of aircraft, $p \in P$
A	Set of airport, $i, j \in A$
R	Set of feasible path for aircraft $r \in R$
F	Set of flight, $f \in F$
$RA(a)$	Set of flight paths for aircraft arriving at airport a for the last flight, $a \in A$
$RP(p)$	Set of feasible paths for aircraft P, $p \in P$
$H(f)$	Set of flights that can accept the transferring passengers from flight f, $f \in F$

Parameters:

$norm_f$	The operating cost of flight f , $f \in F$;
can_f	Costs spent when flight f is cancelled, $f \in F$;
CD_f	Costs spent of a one-minute delay for flight f, $f \in F$;
k_{fr}	If flight f is included in the aircraft path r, it is denoted as 1; otherwise 0. $f \in F, r \in R$;
plf_f	The passenger load factor of flight f, $f \in F$;
$TAT(p)$	The minimum turnaround time for aircraft p, $p \in P$;
$TPT(p)$	The minimum connection time for passengers in aircraft$p$, $p \in P$;
τ_f	The flight duration of flight f, $f \in F$;
AT_f	The actual arrival time of flight f, $AT_f = DT_f + \tau_f$, $f \in F$;
DTO_f	Scheduled departure time of flight f, $f \in F$;
$nump_f$	Number of passengers on flight f, $f \in F$;
D_f	The maximum allowable delay time for flight f, $f \in F$;
pn_a	Number of aircrafts that need to be landed at airport a at the end of the recovery period, $a \in A$;
$n(p)$	The number of flights executed by aircraft p, $p \in P$;
$f_m(p)$	The m-th flight f executed by aircraft p, $m \le n(p)$, $f \in F, p \in P$;
σ	The refund cost for one passenger when a flight is disrupted;
α	The cost for a passenger rebooking on the same airline's flight on the same day;
β	The cost for a passenger rebooking on the different airline's flight on the same day;
γ	The cost for a passenger rebooking on the same airline's flight on a different day;
θ	The cost for a passenger rebooking on the different airline's flight on a different day.

Decision variables :

x_{rp}	1 is aircraft p executes path r , 0 otherwise, $r \in R$, $p \in P$;
y_f	1 if flight f is cancelled, 0 otherwise; $f \in F$;
DT_f	The actual departure time of flight f, $f \in F$;
η_f	The refunding rate for flight f, $f \in F$;
t_f^g	The proportion of passengers rebooking from flight f to flight g, $f \in F, g \in H(f)$;
ta_f^g	The proportion of passengers rebooking from flight f to another flight (flight g) operated by the same airline on the same day, $f \in F, g \in H(f)$;
tb_f^g	The proportion of passengers rebooking from flight f to another flight (flight g) operated by the same airline on the other day, $f \in F, g \in H(f)$;
tc_f^g	The proportion of passengers rebooking from flight f to another flight (flight g) operated by the different airline on the same day, $f \in F, g \in H(f)$;
td_f^g	The proportion of passengers rebooking from flight f to another flight (flight g) operated by the different airline on the other day, $f \in F, g \in H(f)$.

3.2.2 Objectives

One of the longstanding goals of airlines is to efficiently recover disrupted flights at minimal cost. We have defined both aircraft recovery costs and passenger transfer costs separately. Equation 1 represents aircraft recovery costs, which encompass the delay costs, cancellation costs, and operational costs incurred by flights executed by the aircraft. Operational costs include aircraft maintenance and crew reassignment costs, and their calculation aligns with prior research (Mofokeng et al. 2020; Zhang et al. 2015). Equation 2 signifies passenger transfer costs, encompassing ticket refund costs and rebooking costs. The rebooking costs are further detailed into costs for rebooking on the same airline's flight on the same day, rebooking on the same airline's flight on a different day, rebooking on the different airline's flight on the same day, and rebooking on the different airline's flight on a different day. Lastly, Equation 3 defines the objective function for disrupted flight recovery as the minimization of the sum of aircraft recovery costs and passenger transfer costs.

$$C_1 = \sum_{f \in F} y_f can_f + \sum_{p \in P} \sum_{r \in RP(p)} \sum_{f \in F} norm_f k_{fr} x_{rp}; \tag{1}$$

$$C_2 = \sum_{p \in P} \sum_{r \in RP(p)} \sum_{f \in F} k_{fr} x_{rp} (DT_f - DTO_f) CD_f + \sum_{f \in F} \sum_{g \in H(f)} (\alpha ta_f^g + \beta tb_f^g + \gamma tc_f^g + \theta td_f^g) nump_f + \sum_{f \in F} \sigma \eta_f nump_f; \tag{2}$$

$$\min C = C_1 + C_2; \tag{3}$$

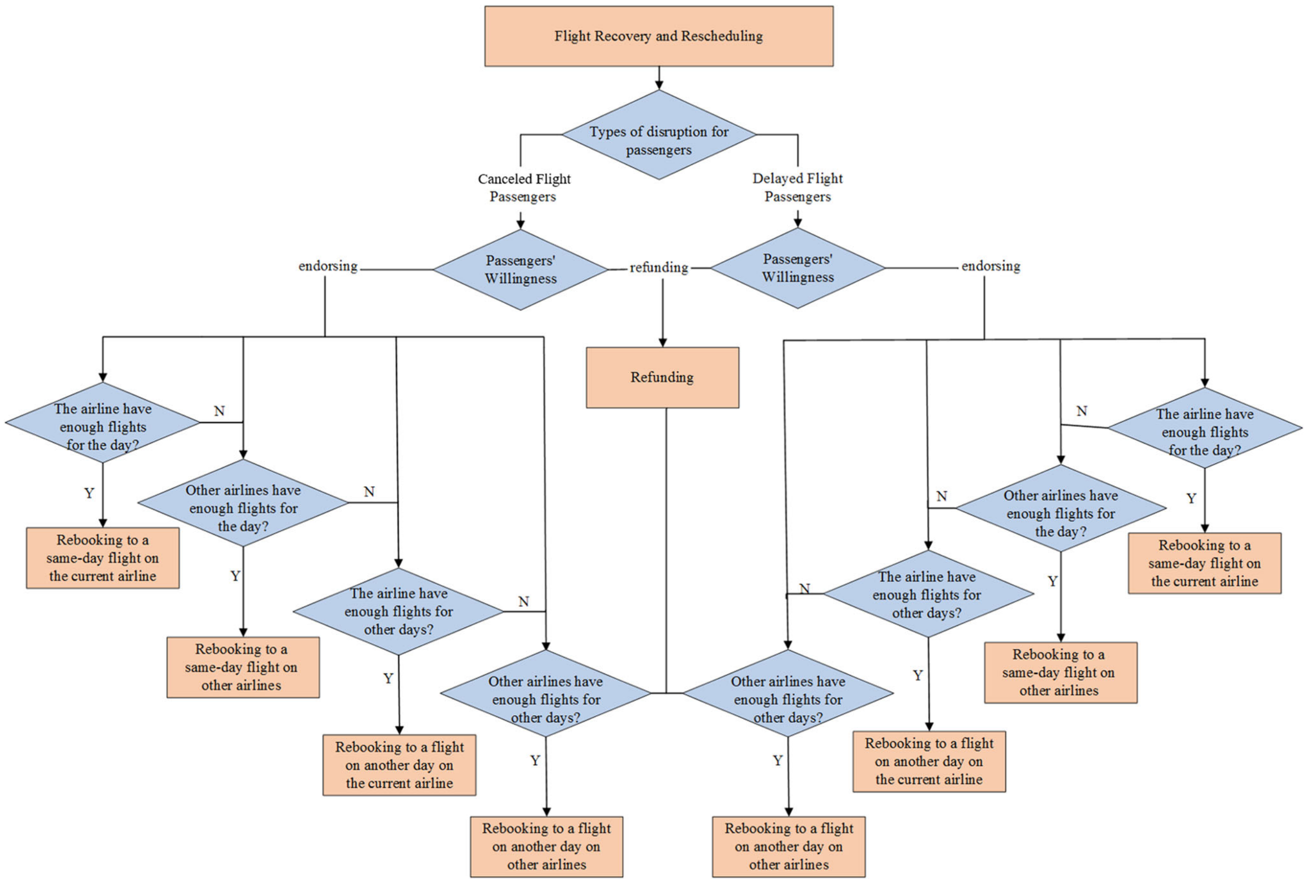


Fig. 1 Passenger transfer process by airlines according to the different willingness of passengers

3.2.3 Constraints

$$\sum_{p \in P} \sum_{r \in PR(p)} k_{fr} x_{rp} + y_f = 1, \forall f \in F. \tag{4}$$

$$\sum_{r \in RP(p)} x_{rp} \leq 1, \forall p \in P. \tag{5}$$

$$\sum_{r \in RA(a)} x_{rp} = pn_a \forall p \in P. \tag{6}$$

$$(1 - y_f)(DT_f - DTO_f) \leq D_f, \forall f \in F. \tag{7}$$

$$(1-y_{f_{m+1}(p)})DT_{f_{m+1}(p)} - (1-y_{f_m(p)})AT_{f_m(p)} \leq TAT(p), \forall p \in P, m < n(p). \tag{8}$$

$$(1-y_{f_{m+1}(p)})DT_{f_{m+1}(p)} - (1-y_{f_m(p)})AT_{f_m(p)} \leq TPT(p), \forall p \in P, m < n(p). \tag{9}$$

$$\sum_{g \in H(f)} t_f^g + \eta_f = y_f, \forall f \in F. \tag{10}$$

$$\sum_{g \in H(f)} t_f^g \leq (1 - plf_g) \sum_{r \in RF(g) \cap RP(p)} x_{rp}, \forall f \in F. \tag{11}$$

$$\sum_{g \in H(f)} (ta_f^g + tb_f^g + tc_f^g + td_f^g) = \sum_{g \in H(f)} t_f^g \forall f \in F. \tag{12}$$

Equation 4 represents the flight constraint, indicating that a flight is either executed or cancelled. Equation 5 delineates the finite nature of aircraft resources, constraining each aircraft to operate only one path. Equation 6 imposes an aircraft flow balance constraint, ensuring that a certain number of aircraft can be stationed at the specified airports at the end of the recovery period, ensuring the subsequent flights can proceed as planned. Equation 7 ensures that the flight delay time does not exceed the maximum delay time limit. Equations 8 - 9 represent time constraints. Equation 8 relates to the departure and arrival times of each flight, ensuring that the turnaround time for aircraft is greater than the minimum transfer time. In cases where passengers opt to rebook on another flight due to disruptions, Equation 9 ensures the minimum passenger connection time when changing flights. Equation 10 signifies the balance in passenger transfer arrangements: if a flight is not cancelled, its passengers can stay on the original flight, whereas if the flight is cancelled, all passengers must choose between rebooking or obtaining a refund. Equation 11 represents the aircraft capacity constraint for passengers rebooking onto other flights. Equation 12 provides a detailed categorization of passenger rebooking options, specifying that passengers can rebook on the same airline's flight on the same day, rebook on the same airline's flight on a different day, rebook on the different airline's flight on the same day, or rebook on the different airline's flight on a different day.

4 Solution methodology

Due to the proven NP-hard nature of solving (3), particularly when dealing with a large number of flights, the complexity of the solution primarily arises from the intricacies of the flight network. Consequently, the key to solving (3) lies in the reprogramming of aircraft paths. The problem of reprogramming aircraft paths is fundamentally an integer programming problem, which can be solved using methods such as the simplex method or gradient descent. However, due to issues such as prolonged computation time associated with these methods, researchers have explored alternative approaches, including genetic algorithms (Liu et al. 2010) and particle swarm optimization algorithms (Liu et al. 2008). Nonetheless, these algorithms still encounter challenges such as broad search spaces and slow convergence. In recent years, researchers have proposed the LNS algorithm (Bisaillon et al. 2011; Sinclair et al. 2014). By incorporating a strategy of local search, the LNS algorithm typically offers a more comprehensive exploration of the problem space, particularly well-suited for high-dimensional and complex optimization problems. Additionally, it proves more effective in avoiding local optima. In this paper, we initially reconstruct aircraft paths based on the LNS algorithm. The construction of different aircraft paths results in distinct aircraft recovery costs C_1, while various passenger recovery methods give rise to divergent passenger transfer costs C_2, subsequently impacting the overall cost C of disrupted flight recovery. This, in turn, influences aircraft scheduling at a holistic level. Therefore, this paper initially employs the LNS algorithm to reconstruct aircraft paths. Subsequently, an analysis of different passenger transfer methods and their corresponding proportional combinations is conducted. After obtaining the total cost C of disrupted flight recovery, iterative processes are employed to gradually discover aircraft recovery paths that minimize the overall cost C.

In addressing the disrupted flight recovery problem, we have made enhancements to the traditional LNS algorithm, as depicted in Fig. 2.

4.1 Large scale neighborhood search algorithm

After the construction of an initial feasible solution using the LNS algorithm, the solution is iteratively improved by continuously matching, disrupting, and repairing various parts of the solution within the neighborhood. This improvement process involves three stages: solution disruption, repair, and enhancement, which are repeated until the stopping criteria are met. For any feasible aircraft recovery solution (x_{rp}, y_f), where the corresponding aircraft recovery cost is denoted as $c(x_{rp}, y_f)$, an neighborhood solution set $N(x_{rp}, y_f)$ is defined. The basic idea of the LNS is outlined as follows:

Step 1: Find the neighborhood $N(x_{rp}, y_f)$ corresponding to the feasible solution (x_{rp}, y_f). By iteratively disrupting and repairing the feasible solution (x_{rp}, y_f), find (x'_{rp}, y'_f) such that$(x_{rp}, y_f) = arg\ min_{(x''_{rp}, y''_f) \in N(x_{rp}, y_f)} c(x''_{rp}, y''_f)$

Step 2: If $c(x'_{rp}, y'_f) < c(x_{rp}, y_f)$, update $(x_{rp}, y_f) = (x'_{rp}, y'_f)$ and return to Step 1. Otherwise, proceed to Step 3;

Step 3: Output (x_{rp}, y_f) as the satisfactory solution.

These steps are repeated until the stopping criteria are satisfied.

According to the above algorithmic approach, there are still two key issues that require further consideration. First, it is crucial to determine how to construct the initial feasible solution for the algorithm. Second, it is necessary to establish an effective strategy for finding the final satisfactory solution by continually cycling through the neighborhood range to destroy and repair the feasible solution. In the following sections, we will provide a detailed explanation of these two points.

4.2 Algorithm for construction of initial feasible solutions

Before introducing the method for constructing the initial feasible solution, it is necessary to first define the concept of a flight circle. Suppose that an aircraft p executes n flights on a given day. If the departure airport for the ith flight and the arrival airport for the jth flight are the same ($i < j < n$), then we can consider all flights between the ith and jth flights of aircraft p (including the ith and jth flights) to form a flight circle. In other words, the aircraft flies in a circular pattern at this point.

The general structure of the construction method used by the LNS algorithm for recovering disrupted flights and generating the initial feasible solution is outlined in Algorithm 1. This method relies on several defined sets and parameters, which are described as follows:

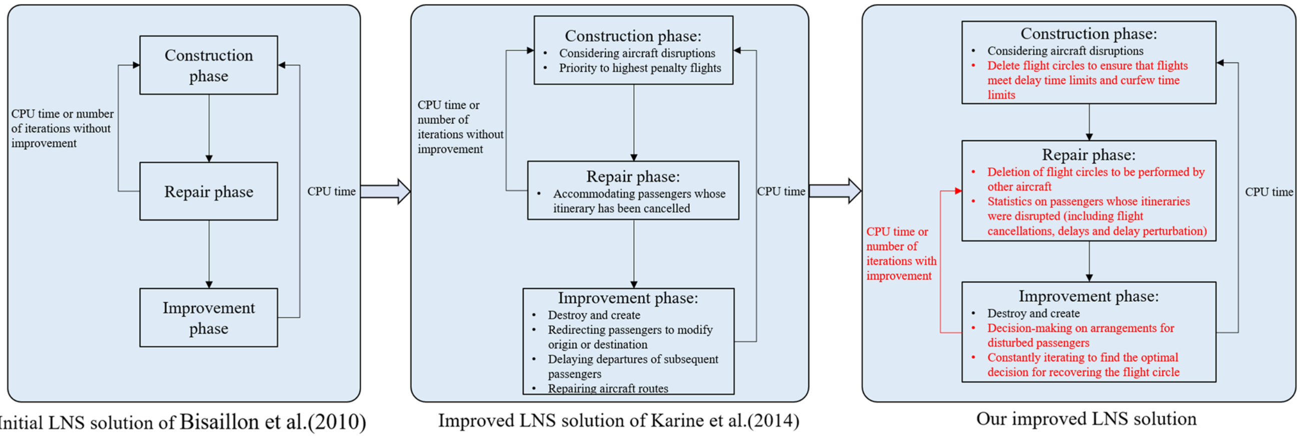


Fig. 2 Comparison between the initial LNS algorithm and improvemented strategies

Index :

dp	Delayed aircraft index, $dp \in Delay\_P$
cp	Disrupted aircraft index, $cp \in Cancel\_P$

Set :

$Delay\_P$	Set of delayed aircraft;
$Cancel\_P$	Set of disrupted aircraft;
F_p	Set of flights executed by aircraft p, $p \in P$

Parameters :

$f_j(p)$	The jth flight operated by aircraft p, $p \in P$, $f_j(p) \in F_p$

The aircraft disruption can be primarily categorized into two scenarios: aircraft cancels and aircraft delays. In the construction of the initial solution, we account for both situations. For cancelled aircraft, we eliminate flight circles comprised of the first flight executed by the affected aircraft. In cases where non-cyclical flights exist, subsequent recovery is initiated, involving the assignment of alternative aircraft to maintain airport traffic balance. Concerning delayed aircraft, we initially determine the earliest available time for the affected aircraft as the actual departure time for its first flight, subsequently adjusting the departure times for the remaining flights accordingly. If any flight exceeds the maximum delay time, a flight circle executed by the affected aircraft is cancelled to ensure the smooth operation of subsequent flights. This not only reduces the overall delay time but may also mitigate delays for subsequent flights. Finally, consideration is given to whether the actual arrival time of the last flight for the delayed aircraft violates the airport curfew. Should the curfew be exceeded, cancellation of a flight circle executed by the affected aircraft becomes necessary to minimize delays for subsequent flights and ensure on-time arrival for the last flight within the curfew period. The recovery of cancelled flight circles in this process is addressed through the methodology outlined in Section 4.2.

4.3 Destruction, repair, and improved solution

4.3.1 Definition of neighborhood

The concept of a path pair is introduced before introducing the neighborhood: a path pair can be generated by combining two paths executed by each aircraft or combining a path executed by an aircraft with a cancellation path calculated by the initial feasible solution. The neighborhood is generated by matching between path pairs, which can be carried out in three ways: insert, swap, and cancel. Insert and swap operations involve modifying two paths by inserting part of the flights from one path into the other, or swapping parts of the flights in one path with parts of the flights in the other path. These operations are performed while ensuring that the constraints presented in the previous chapter are satisfied. The cancellation operation is specific to a particular aircraft path and refers to the cancellation of a flight circle from the original path to improve the overall solution.

4.3.2 Destruction and repair solution

In the improved LNS approach we use, solution destruction and repair mainly rely on insert and swap operations between neighboring paths. Let $route_1$ be the path executed by aircraft p_1 (i.e., $route\_1 = \{f_1(p_1), f_2(p_2), ..., f_{n(p_1)}(p_1)\}$), and let $route_2$ be the path executed by aircraft p_2 (i.e., $route_2 = \{f_1(p_2), f_2(p_2), ..., f_{n(p_2)}(p_2)\}$). The following insert and swap cases can be used to match path pairs consisting of $route_1$ and $route_2$.

To ensure feasibility, $route_1$ and $route_2$ must satisfy a set of constraints: either both routes are normally executed

Algorithm 1 Algorithm for generation of initial feasible solutions.

Require: $Delay\_P$: the set of delayed aircraft; $Cancel\_P$: the set of cancelled aircraft;
Ensure: flight paths that need to be cancelled
if $Cancel\_P! = \emptyset$ **then**
  randomly sort all aircraft in set Cancel_P;
  for all aircraft $p_i \in Cancel\_P$ **do**
    $Cancel\_P = Cancel\_P/\{p_i\}$;
    for all $f_j(p_i) \in F_{p_i}$ **do**
      if The departure airport of $f_1(p_i)$ and the arrival airport of $f_{n_i}(p_i)$ are the same **then**
        set $cancel\_f = \left\{f_1(p_i), f_2(p_i), ..., f_{n_i}(p_i)\right\}$;
        $Cancel\_R = Cancel\_R \bigcup Cancel\_f$;
      else
        Removing a flight circle $fc = \{f_1(p_i), f_2(p_i), ..., f_x(p_i)\}$ from F_{p_i};
        $Cancel\_R = Cancel\_R \bigcup fc$;
      end if
      for $p_m \in P$ and m!=i **do**
        Find the F_{p_m} that satisfies the same arrival airport of $f_{n_m}(p_m)$ and the arrival airport of $f_{n_m}(p_m)$;
        set $F_{p_m} = F_{p_m} \bigcup \left\{f_x(p_i), f_x + 1(p_i), ..., f_{n_i}(p_i)\right\}$;
      end for
    end for
  end for
end if
if $Delay\_P! = \emptyset$ **then**
  randomly sort all aircraft in set Delay_P;
  for all aircraft $p_i \in Delay_P$ **do**
    set $Delay\_P = Delay\_P/\{p_i\}$;
    for all $f_j(p_i) \in F_{p_i}$ **do**
      if j != 1 **then**
        set the actual departure time of $f_j(p_i)$ equals the maximum between the scheduled departure time of $f_j(p_i)$ and the actual arrival time of $f_{j-1}(p_i)$ plus the maximum value between the minimum turnaround time and the minimun connection time of $f_{j-1}(p_i)$;
      end if
      if $f_j(p_i)$exceeded the maximum delay time of this case **then**
        Removing a flight circle $fc = \{f_u(p_i), f_{u+1}(p_i), ..., f_v(p_i)\}\ (1 < u < v < j)$ from F_{p_i};
        if there is no such flight ring exists **then**
          Removing a flight circle $fc = \{f_u(p_i), f_{u+1}(p_i), ..., f_v(p_i)\}\ (1 < u < j < v)$ from F_{p_i};
        end if
        $Cancel\_R = Cancel\_R \cup fc$
      end if
      if the actual arrival time of the last flight executed by aircraft p_i exceeded the curfew of the airport **then**
        Removing a flight circle $fc = \{f_u(p_i), f_{u+1}(p_i), ..., f_v(p_i)\}\ (u < v < n)$ from F_{p_i};
        $Cancel\_R = Cancel\_R \cup fc$
      end if
    end for
  end for
end if

aircraft paths, or $route_1$ is a cancellation path, or $route_2$ is a cancellation path. It is not possible for both $route_1$ and $route_2$ to be cancellation paths simultaneously since if both are cancelled, then any results obtained from matching them will also require cancellation, undermining the recovery efforts. Therefore, we assume that $route_1$ is either a normal aircraft path or a cancellation path, while $route_2$ is a normal aircraft path.

Before executing the insertion algorithm, it is necessary to identify a flight string $route'_1 = \{f_a(p_1), f_{a+1}(p_1), \ldots, f_b(p_1)\} \subseteq route_1$. Then, $route'_1$ can be inserted into $route_2$ using one of three methods: head insert, middle insert, and tail insert.

(1) Head insert
If the departure airport of $f_a(p_1)$ is the same as the arrival airport of $f_b(p_1)$ and has the same value as the departure airport of $f_1(p_2)$, then $route'_1$ should be removed from $route_1$ and inserted into the head of $route_2$. This can be achieved by:
$route_1 = \left\{f_1(p_1), f_2(p_1), ..., f_{a-1}(p_1), f_{b+1}(p_1), ..., f_{n(p_1)}(p_1)\right\}$;
$route_2 = \left\{f_a(p_1), f_{a+1}(p_1), ..., f_b(p_1), f_1(p_2), f_2(p_2), ..., f_{n(p_2)}(p_2)\right\}$.

(2) Middle insert
If there exists a value $1 < x < n(p_2)$ such that the departure airport of $f_a(p_1)$ matches the arrival airport of $f_b(p_1)$ and is the same as the departure airport of $f_x(p_2)$, then $route'_1$ should be removed from $route_1$ and inserted into $route_2$ using the middle-insert method. This can be achieved by:
$route_1 = \left\{f_1(p_1), f_2(p_1), ..., , f_{a-1}(p_1), f_{b+1}(p_1), ..., f_{n(p_1)}(p_1)\right\}$;
$route_2 = \{f_1(p_2), f_2(p_2), ..., f_{x-1}(p_2), f_a(p_1), f_{a+1}(p_1), ..., f_b(p_1), f_x(p_2), f_{n(p_2)}(p_2))\}$.

(3) Tail insert
If the departure airport of $f_a(p_1)$ matches the arrival airport of $f_b(p_1)$ and is the same as the arrival airport of $f_{n(p_2)}(p_2)$, then $route'_1$ should be removed from $route_1$ and inserted at the end of $route_2$ using the tail-insert method. This can be achieved by:
$route_1 = \left\{f_1(p_1), f_2(p_1), ..., f_{a-1}(p_1), f_{b+1}(p_1), ..., f_{n(p_1)}(p_1)\right\}$;
$route_2 = \left\{f_1(p_2), f_2(p_2), ..., f_{n(p_2)}(p_2), f_a(p_1), f_{a+1}(p_1), ..., f_b(p_1)\right\}$.
To illustrate the insertion of neighbor matching graphically, consider the following example of two aircraft paths shown in Table 2. Aircraft 1 executes five flights,

Table 2 Sample aircraft path1

Aircraft	Flight sequences	Departure airport	Arrival airport
1	1425	TSN	NBS
	1431	NBS	TSN
	1270	TSN	SHA
	1027	SHA	SYX
	986	SYX	SHA
2	1003	TSN	NDG
	1017	NDG	TSN
	226	TSN	SHA
	249	SHA	TSN

each involving four airports, while aircraft 2 executes four flights, each involving three airports. The corresponding plots for these two aircraft paths are shown in Fig3i, and the neighborhoods generated by these two aircraft paths are shown in Fig. 3(c) through Fig. 3(h).

There are two ways to swap $route_1$ and $route_2$: middle swap and tail swap.

(1) Middle swap

To perform the intermediate swap algorithm, we must find two flight string routes: $route_1' = \{f_a(p_1), f_{a+1}(p_1), ..., f_b(p_1)\} \subseteq route_1(a > 1, b < n(p_1))$ and $route_2' = \{f_c(p_2), f_{c+1}(p_2), ..., f_d(p_2)\} \subseteq route_2(a > 1, b < n(p_2))$, to ensure that swapping between $route_1$ and $route_2$ is possible. If the departure airport of $f_a(p_1)$ matches the departure airport of $f_c(p_2)$, and the arrival airport of $f_b(p_1)$ matches the arrival airport of $f_d(p_2)$, then $route_1'$ should be removed from $route_1$ and inserted into $route_2$. Next, remove $route_2'$ from $route_2$ and insert it into $route_1$ using the same method. This can be achieved by:

$route_1 = \{f_1(p_1), f_2(p_1), ..., f_{a-1}(p_1), f_c(p_2), f_{c+1}(p_2), ..., f_d(p_2), f_{b+1}(p_1), ..., f_{n(p_1)}(p_1)\}$;

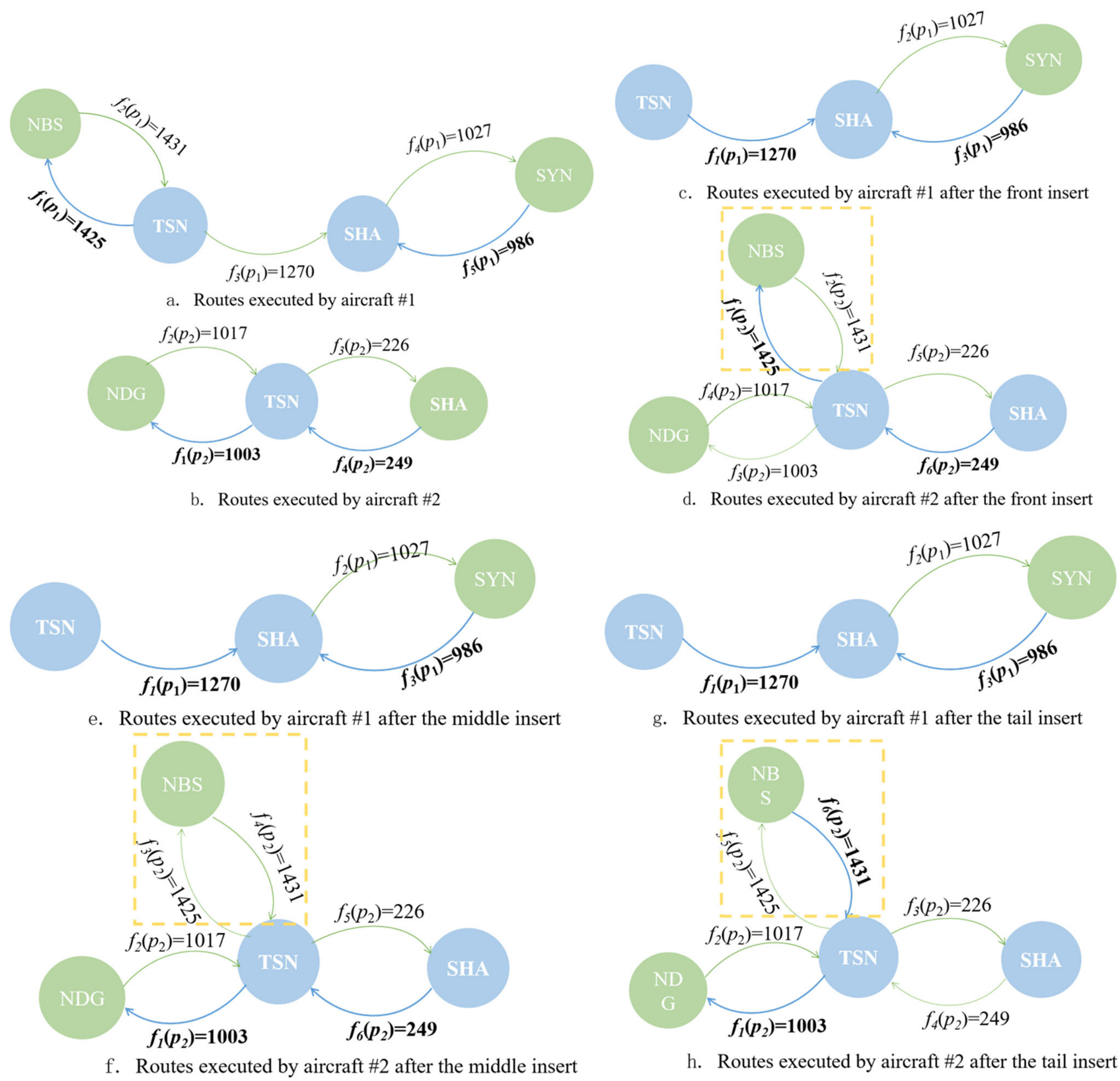


Fig. 3 Insert algorithm

$route_2 = \{f_1(p_2), f_2(p_2), ..., f_{c-1}(p_2), f_a(p_1), f_{a+1}(p_1), ..., f_b(p_1), f_{d+1}(p_2), ..., f_{n(p_2)}(p_2)\}$.

(2) Tail swap
To perform the tail-swap algorithm, we must find two flight string routes: $route_1' = f_a(p_1), f_{a+1}(p_1), ..., f_{n(p_1)}(p_1) \subseteq route_1$ and $route2' = f_c(p_2), f_{c+1}(p_2), ..., f_{n(p_2)}(p_2) \subseteq route_2(a > 1, b < n(p_2))$, to ensure that swapping is possible between $route_1$ and $route_2$.
If the departure airport of $f_a(p_1)$ matches the departure airport of $f_c(p_2)$, and the arrival airport of $f_{n1}(p_1)$ matches the arrival airport of $f_{n2}(p_2)$, then remove $route_1'$ from $route_1$ and insert it at the end of $route_2$. Next, remove $route_2'$ from $route_2$ and insert it at the end of $route_1$ using the same method. This can be achieved by:
$route_1 = \{f_1(p_1), f_2(p_1), ..., f_{a-1}(p_1), f_c(p_2), f_{c+1}(p_2), ..., f_{n(p_2)}(p_2)\}$;
$route_2 = \{f_1(p_2), f_2(p_2), ..., f_{c-1}(p_2), f_a(p_1), f_{a+1}(p_1), ..., f_{n(p_1)}(p_1)\}$.
Consider the following example of two aircraft paths shown in Table 3. Aircraft 3 executes five flights, each involving four airports, while aircraft 4 executes four flights, each involving three airports. The corresponding plots for these two aircraft paths are shown in Figs. 4a and 4b, and the neighborhoods generated by these two aircraft paths are shown in Fig. 4c-f.

4.3.3 Solution improvement

During the solution destruction and repair phase, improvements to the solution are made concurrently. Once the initial feasible solution is obtained, the algorithm continuously matches this solution with different neighborhoods, generating fresh paths and new path costs through repeated iterations. This process of continuously improving the solution is carried out simultaneously with the solution destruction and repair stage.

The general idea of solution improvement is roughly depicted in Fig. 5. The process of solution improvement essentially involves continuous iteration. In the algorithm, let N denote the iteration count. During the calculation of disrupted flight recovery costs, continuous iteration implies the generation of new results. If, after the $(N + 1)$-th iteration, the cost increase is no longer significant and gradually approaches a constant value, then the iteration will cease at the N-th iteration, and the generated path and cost values from the N-th iteration will be adopted.

Table 3 Sample aircraft path2

Aircraft	Flight sequences	Departure airport	Arrival airport
3	1487	XMN	CAN
	1246	CAN	HAK
	1066	HAK	TAO
	347	TAO	CGQ
	358	CGQ	DLC
	1529	DLC	SYX
4	1456	PVG	CAN
	1699	CAN	FOC
	328	FOC	TAO
	377	TAO	STX

5 Computation experiment

5.1 Experiment data

The effectiveness of the aforementioned algorithm and an analysis of passenger transfer costs and their corresponding proportions will be elaborated in this chapter. We conducted experiments using real flight data provided by a Chinese airline. The airline operates 141 aircraft of 5 different types, conducting over 600 flights daily and transporting approximately 80,000 passengers. Among the known flight schedules, 5 airports have curfew time restrictions, prohibiting takeoffs and landings during specific periods, and 4 airports are affected by typhoons, resulting in a temporary suspension of takeoffs, landings, and parking. In this experiment, 21% of the total flights are impacted by weather conditions, involving up to 20 grounded aircraft. During the 1-day recovery period, various recovery operations such as insertion, swapping, and potential cancellations will be executed for these affected flights.

In accordance with practical considerations, the maximum allowable delay time for flights is set at 24 hours, meaning any delays exceeding this duration will result in flight cancellations. Additionally, during the recovery process, it is essential to ensure turnaround times for aircrafts and ensure connection times for passengers. The minimum turnaround time for each airport is set at 90 minutes based on practical considerations. The delay cost for aircraft is set at 100 yuan per hour, and for passengers, it is 60 yuan per hour per seat. The refund cost for the airline is equal to the base fare for the same day. Passenger transfer methods include rebooking on the same airline's flight on the same day, rebooking on the same airline's flight on a different day, rebooking on the different airline's flight on the same day, and rebooking on the different airline's flight on a different day. It is noteworthy that rebooking with a different airline refers to

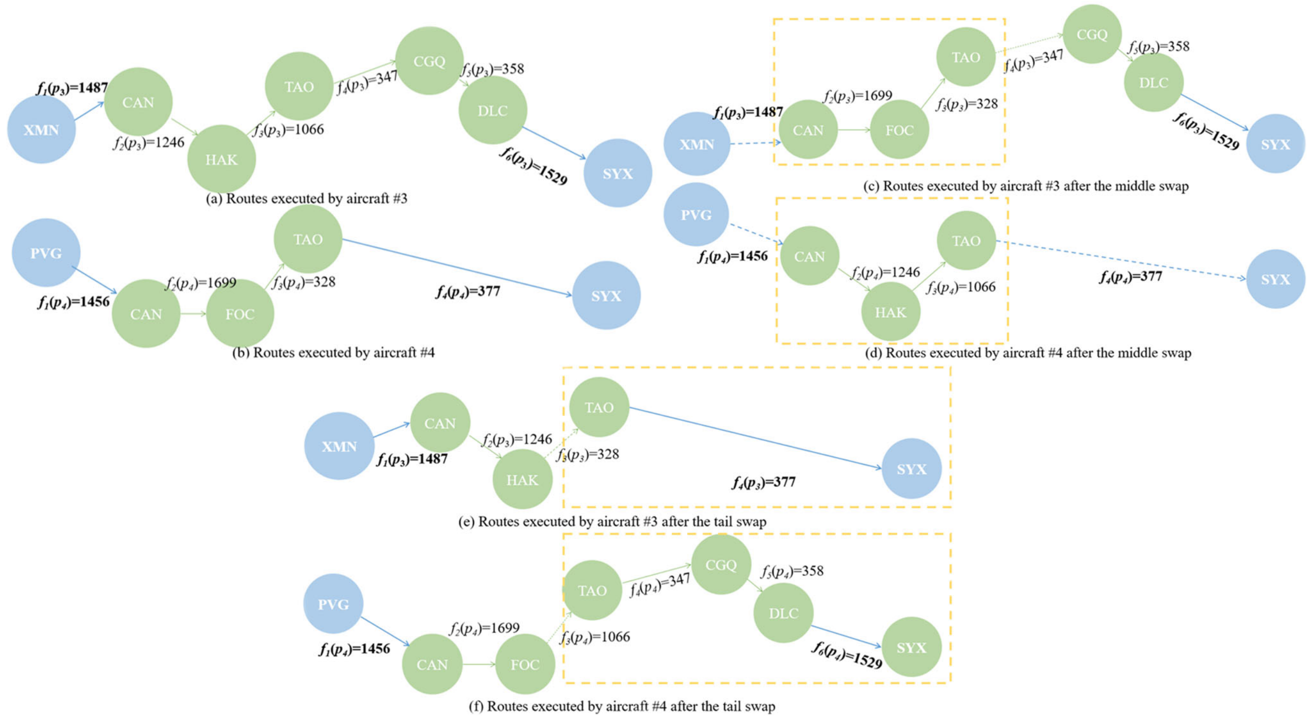


Fig. 4 Swap algorithm

rebooking with airlines that have a cooperation agreement with the airline in question (Navarro-Meneses 2022). The corresponding transfer costs for different passenger transfer methods are detailed in Table 4. Flight recovery costs encompass cancellation costs, delay costs, costs incurred from the airline's perspective, and costs for compensating passenger losses. The specific costs and ratios for the recovery of disrupted flights are detailed in Table 5.

In addition, there is a possibility of aircraft swapping between flights, which may involve a change in aircraft type. The different capacities of the 5 aircraft types involved in this experiment and the substitution relationships between these types are outlined in Table 6. 'B' represents the capacity of the business class, 'E' represents the capacity of the economy class, and 'capacity' denotes the total capacity of both classes for a given aircraft type. In the table, No.1-No.5 represent five distinct aircraft models. A value of '1' indicates that the aircraft originally scheduled for the flight can be substituted by an aircraft of the current model, while '0' indicates that substitution is not feasible due to capacity constraints or other factors such as terrain, weather conditions, etc.

Next, we will conduct experiments using the aforementioned data and analyze the cost of disrupted flight recovery in conjunction with different passenger transfer methods.

5.2 Computational results and analysis

5.2.1 Recovery strategies under different fleet sizes

To validate the effectiveness of the model-solving algorithm at different scales, we conducted experiments using five different aircraft models with fleet sizes ranging from 5 to 141 aircraft. The experiment configurations included fleets consisting of 5 aircraft with 2 different types, 25 aircraft with 3 different types, 50 aircraft with 5 different types, 100 aircraft with 5 different types, and 141 aircraft with 5 different types, respectively.

The algorithm employs different matching strategies based on the matching scale during neighborhood matching. The convergence of the minimum cost depends on the number of iterations and the total number of aircraft involved. Figure 6 illustrate the relationship between the number of iterations and the recovery cost of the algorithm when there are fewer than 50 aircraft and more than 50 aircraft, respectively. When the total number of aircraft is less than 50, the number of iterations is relatively small, and the recovery cost is higher due to the reduced number of matchable aircraft, resulting in fewer feasible recovery solutions.

Regardless of the neighborhood scale, the algorithm uses two matching strategies, insert, and swap. However, for

Fig. 5 Improvement strategy of the solution

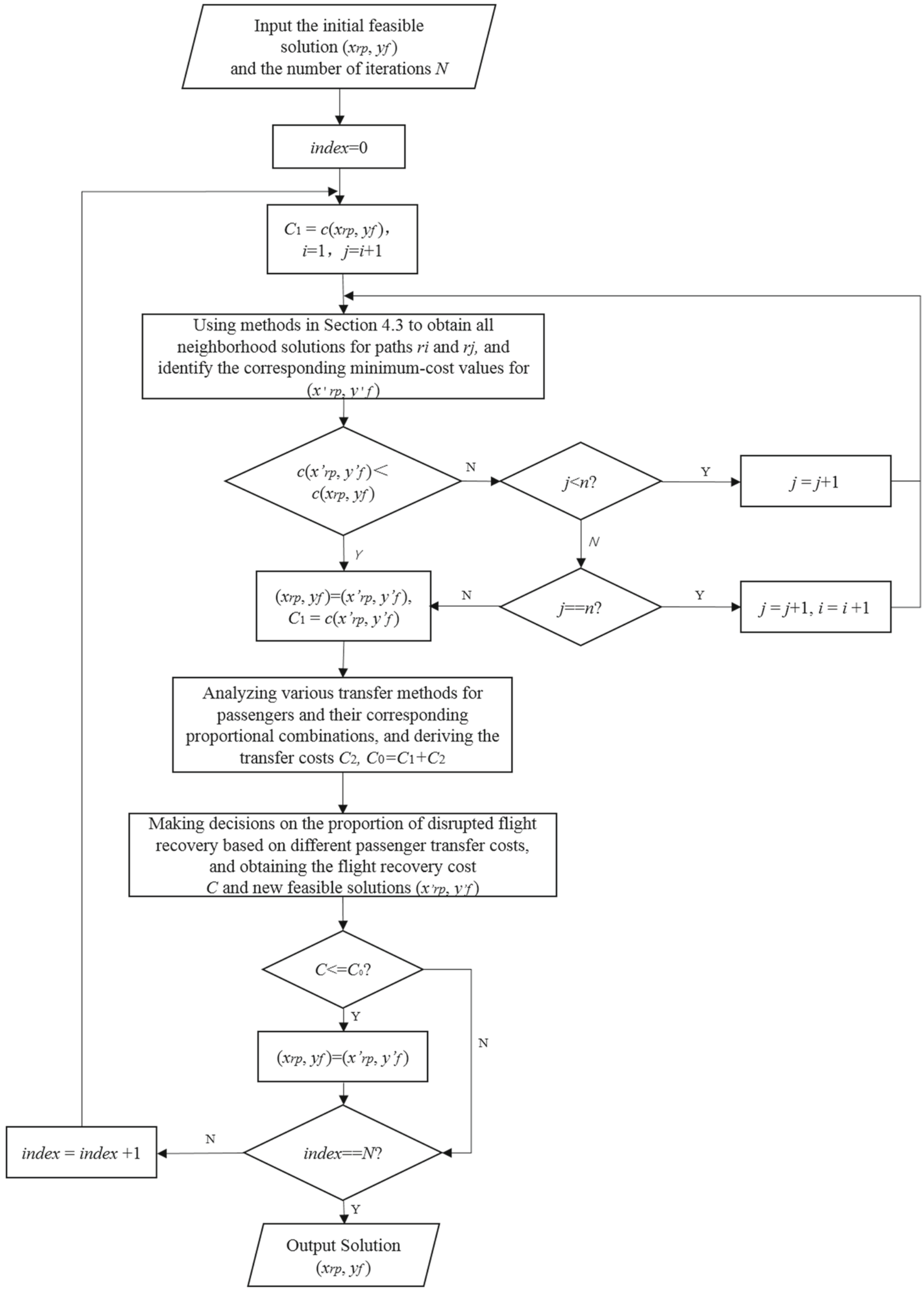


Table 4 Transfer costs for different methods of passenger transfer

Passenger transfer methods	Passenger transfer costs
Refunding	Flight base fare
Rebooking on the same airline's flight on the same day	Cost of passengers' meals
Rebooking on the same airline's flight on a different day	Cost of passengers' meals + Cost of passengers' overnight stay
Rebooking on another airline's flight on the same day	Cost of passengers' meals + 80% of flight base fare
Rebooking on another airline's flight on a different day	Cost of passengers' meals + Cost of passengers' overnight stay + 80% of flight base fare

Table 5 Recovery costs of flights in different scenarios and the percentage of passengers refunding and rebooking

Situations	Costs for airlines			Costs for passengers	
	Aircraft	Endorsing rate	Endorsing cost	Refunding rate	Refunding cost
Cancellation	1000	<50%	60/h	> 50%	Flight base fare
Delays of more than 300 minutes	100/h	>50%	60/h	5%	Flight base fare
Delays of more than 420 minutes	100/h	>70%	60/h	15%	Flight base fare

neighborhoods with a scale less than 50, insert and swap are alternated continuously to reduce the recovery cost for feasible solutions, as shown in Fig. 6(a). In contrast, for neighborhoods with a scale greater than 50, the algorithm first employs the insert strategy, followed by the swap strategy if some flights cannot be recovered. In this way, flights with smaller cancellation costs can be selected for swap, leading to further optimization of the solution.

It should be noted that for neighborhood scales larger than 50, a set of results with insignificant changes may occur in iterations 3-6. However, this does not result in cost convergence. This situation may occur because the recovery cost and the flight cancellation cost do not differ significantly when the algorithm uses the insert strategy to recover flights. Additionally, using the swap strategy may cause the recovery cost to fluctuate within a small range, as shown in the interval [7, 10]of iterations in Fig. 6(b). However, this can optimize the feasible solution to a smaller cost in subsequent iterations, and the solution starts to converge at iteration 20.

Figure 7 depicts the comparison between the recovery costs using our strategy and the direct cancellation of flights, under the scenario of disruption with 10 aircraft experiencing delays of more than 3 hours and 11 aircraft being cancelled, within a fleet of 141 aircraft consisting of 5 different models. In this context, 'Direct cancellation' represents the cost incurred by cancelling all flights operated by the cancelled aircraft before the recovery actions, while 'Our Strategies' represents the cost after the recovery of cancelled aircraft using the approach outlined in this paper. The results indicate that our best cost achieved approximately an 80% savings compared to the cost incurred by directly cancelling flights, and all costs were kept within 1,000,000 Chinese Yuan. Among the 11 cancelled aircraft, 9 were successfully recovered, involving the recovery of 32 cancelled flights, significant reduction in delay time for 13 delayed flights, and the normalization of operations for 3 subsequent flights affected by delays. The cost savings achieved by our approach in various fleet sizes and refund rates compared to the direct cancellation of flights are presented in Table 7.

Figure 8 illustrates the recovery costs calculated based on different passenger refund rates for various fleet sizes. The vertical axis represents the fleet size, with simulations involving 5 aircraft representing a small airline, 25 and 50 aircraft representing medium-sized airlines, and over 100 aircraft representing large airlines. The horizontal axis represents the recovery costs. It is evident that as the fleet size increases, the required recovery costs decrease. This is attributed to the larger number of aircraft providing more opportunities for inserting cancelled aircraft and enabling more possibilities for the swapping of delayed flights, thereby reducing aircraft delay times. Additionally, lower passenger refund rates correspond to lower costs. Therefore, in the event of disrupted flight occurrences, minimizing passenger refund rates can significantly reduce recovery costs for airlines.

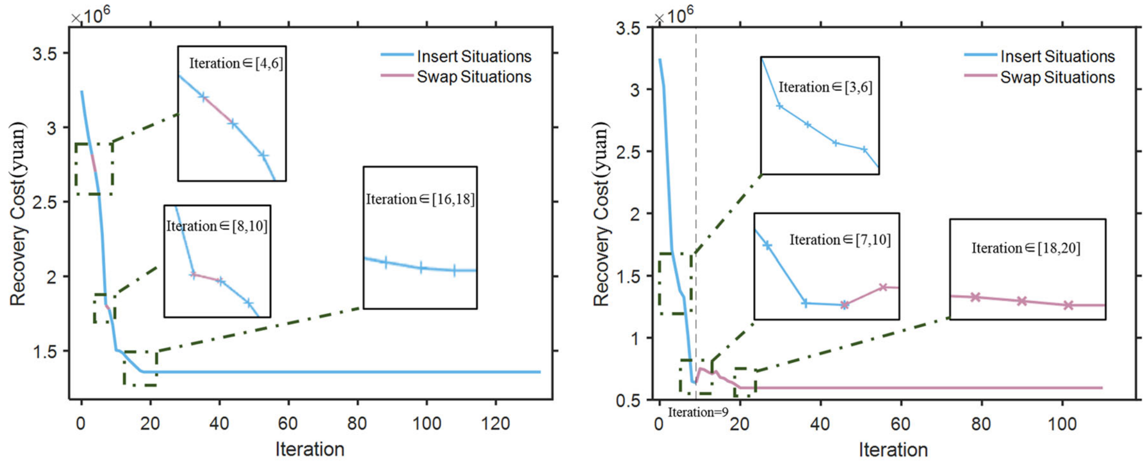
Table 6 Substitution relationship between different aircraft types and capacities

	No.1	No.2	No.3	No.4	No.5
B	16	9	8	9	36
E	184	174	152	131	224
Capacity	200	185	160	140	260
No.1	1	1	1	1	0
No.2	0	1	1	1	0
No.3	0	0	1	1	0
No.4	0	1	1	1	0
No.5	1	1	0	0	1

5.2.2 Analysis of passenger transfer cost

We have conducted an analysis of recovery costs for fleets of different sizes. Next, we will delve into a detailed analysis of passenger transfer costs from three perspectives: (1) the impact of different transfer methods on total recovery costs, (2) a comparison between aircraft recovery costs and passenger transfer costs, and (3) the influence of passenger transfer methods on flight recovery decisions.

In addition to passenger refund rates, a more detailed analysis of passenger rebooking is required to provide airlines with more direct business guidance. Following the airline's customary practices for passenger transfer, passenger rebooking can be categorized into four scenarios: rebooking on the same airline's flight on the same day, rebooking on the same airline's flight on a different day, rebooking on the different airline's flight on the same day, and rebooking on the different airline's flight on a different day.



(a) Number of aircraft less than 50

(b) Number of aircraft more than 50

Fig. 6 Iteration times with different scales

Each rebooking scenario corresponds to different passenger transfer costs. Therefore, it is necessary to enumerate the proportions of passengers for each rebooking scenario and analyze the corresponding recovery costs for both flights and passengers. This analysis aims to identify the most balanced solution.

We assign different weights to various rebooking proportions, and their weighted sum constitutes the rebooking coefficient (ρ). Given that the passenger transfer cost for rebooking on the same day with the same airline is relatively low, higher weights are assigned to this scenario. The rebooking coefficients corresponding to some rebooking proportions are outlined in Table 8, where BT represents the proportion of passengers choosing to rebook on the same airline's flight on the same day, BO represents the proportion of passengers choosing to rebook on the same airline's flight on a different day, QT represents the proportion of passengers choosing to rebook on the different airline's flight on the same day, and QO represents the proportion of passengers choosing to rebook on the different airline's flight on a different day. Different weighted proportions for each rebooking scenario result in different rebooking coefficient (ρ) values. In other words, each rebooking proportion corresponds uniquely to a rebooking coefficient (ρ) value, and Appendix A provides the correspondence between rebooking coefficients (ρ) and the proportions of passenger rebooking.

(1) The impact of different transfer methods on total recovery costs

Under the scale of 141 aircraft, the flight recovery costs corresponding to different passenger transfer proportions are illustrated in Fig. 9(a). At this scale, 10 aircraft experience delays of over 3 hours, and 11 aircraft are unable to take off due to disrupted flight factors. After recovery, 9 out of the 11 parked aircraft are successfully recovered, involving the recovery of 32 cancelled flights, significant reduction in the delay time for 13 delayed flights, and the normalization of 3 subsequently affected flights. For clarity, the top view projection diagram of Fig. 9(a) is presented in Fig. 9(b). It can be observed that by controlling the passenger rebooking coefficient between 50 and 100, and keeping the ticket refund rate below 70%, the airline's recovery cost can be maintained within 600,000 RMB.

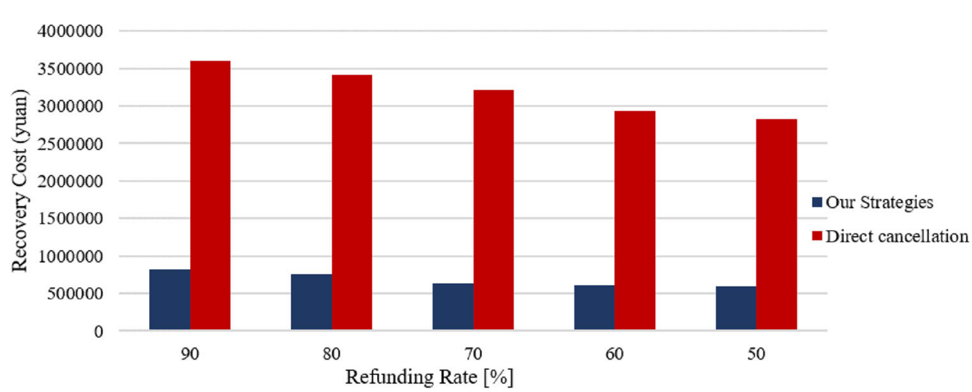


Fig. 7 Comparison with direct flight cancellation

Table 7 Percentage of savings from our approach compared to direct cancellation of flights for different fleet sizes

Refund rate	Fleet size	Iteration times	Percentage of flights that recovered(%)	Percentage of cost savings(%)
90	5	4	21.28	21.4991
	25	6	42.28	54.82
	50	13	53.56	55.1849
	100	18	84.82	58.2048
	141	22	85.88	77.3302
80	5	2	11.43	4.2029
	25	4	42.32	5.5971
	50	9	58.73	56.3567
	100	16	65.48	59.3297
	141	21	94.32	77.9739
70	5	3	33.85	3.3693
	25	4	59.78	53.5632
	50	11	71.62	53.5632
	100	20	74.88	56.8932
	141	22	81.96	80.1023
60	5	3	12.44	−0.659
	25	7	56.68	51.5295
	50	15	58.89	51.5295
	100	19	82.88	54.9162
	141	25	90.23	79.5323
50	5	6	17.56	17.0848
	25	6	45.32	51.9566
	50	11	57.99	51.9566
	100	13	90.74	55.2163
	141	21	93.57	78.8624

(2) *A comparison between aircraft recovery costs and passenger transfer costs*
When disrupted flight situations occur, with passengers choosing different refund rates, we compare aircraft recovery costs (C_1) with passenger transfer costs (C_2). Dividing the refund rate into intervals of 10%, Figs. 10(a) to 10(i) depict the cost distribution for refund rates ranging from 10% to 90%. In Figs. 10(a), 10(b), and 10(c), where the refund rate is below 40%, the intervals for rebooking coefficients [43.1, 60.4], [46.9, 65.2], and [62.8, 72.7], respectively, show an intersection between aircraft recovery costs (C_1) and passenger transfer costs (C_2). In cases where the rebooking coefficient is below this interval, passenger transfer costs (C_2) are higher, representing a larger proportion of the total costs, emphasizing the impact of passenger transfer costs. Conversely, when the rebooking coefficient is above this interval, aircraft recovery costs (C_1) domi-

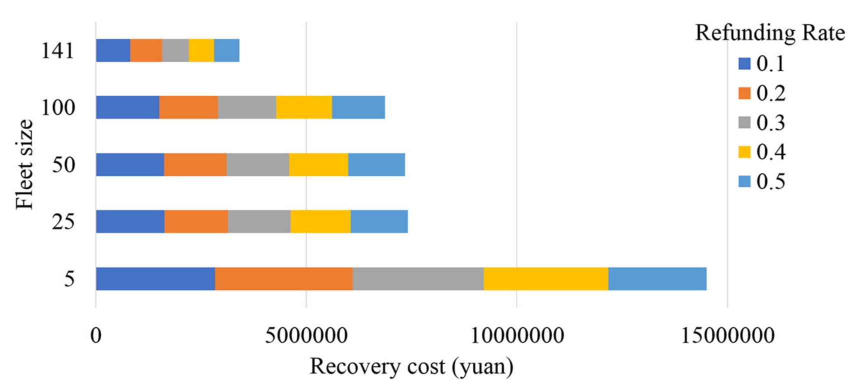


Fig. 8 Cost distribution under varying fleet sizes

Table 8 Rebooking coefficients corresponding to different combinations of rebooking methods and proportions (partial)

BT	*BO*	*QT*	*QO*	ρ
0	0	0	100%	1
0	0	40%	60%	5.8
0	20%	30%	50%	15.8
10%	20%	30%	40%	25.7
40%	30%	20%	10%	59.8
60%	20%	10%	10%	72.8
100%	0	0	0	100

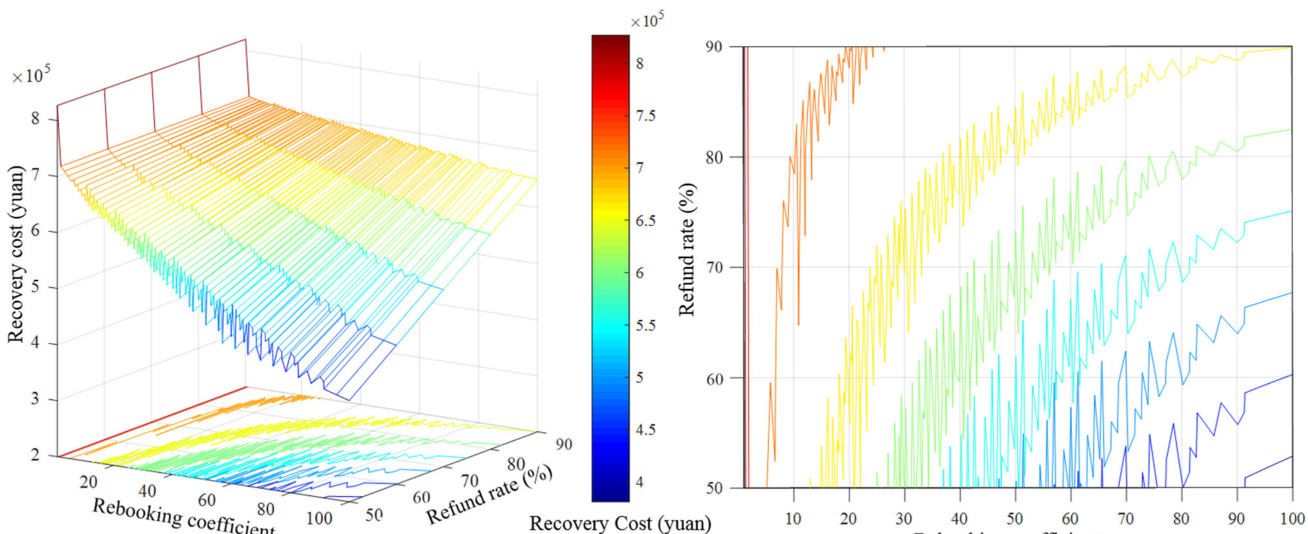
nate, representing a larger proportion of the total costs, emphasizing the influence of aircraft recovery costs. In scenarios with a refund rate exceeding 40%, as shown in Figs. 10(d) to 10(i), regardless of changes in rebooking scenarios, passenger transfer costs (C_2) consistently surpass aircraft recovery costs (C_1). Moreover, with increasing refund rates, the gap between passenger transfer costs and aircraft recovery costs widens. In such cases, passenger transfer costs constitute a larger proportion of the total costs. Therefore, when aiming for a recovery strategy with minimal costs, careful consideration of the impact of passenger transfer methods is crucial.

Hence, to formulate a rational recovery strategy, a comprehensive consideration of cost distributions under different refund rates and rebooking scenarios is necessary. In situations with low refund rates, a balance between aircraft recovery costs and passenger transfer costs is essential. Conversely, in scenarios with high refund rates, primary consideration should be given to the impact of passenger transfer methods on disrupted flight recovery. Decisions regarding the recovery of flights should be influenced by the refund and rebooking situations of passengers.

(3) *The influence of passenger transfer methods on flight recovery decisions*

The next step involves studying the relationship between the variation in passenger transfer method proportions and the scale of flight recovery. We define the extensive recovery as the attempt to recover as many disrupted flights as possible, while small-scale flight recovery refers to the partial recovery of disrupted flights.

The cost of recovering disrupted flights is closely related to the number of flights recovered, while passenger transfer costs indirectly influence decisions on the number of flights to recover. Therefore, during the flight recovery process, we arrange flights in ascending order of recovery costs and prioritize the recovery of flights with lower costs. Figure 11 illustrates the cost distribution for different passenger refund and rebooking ratios. Legends marked with "*" represent the total cost after recovering all recoverable flights at passenger refund rates of 10%, 20%, and 30%, while other legends indicate the minimum cost when recovering a subset of flights. Figure 14 clearly presents the percentage of disturbed flights that are recovered when only a subset of flights is recovered, based on our case study results.



(a) The flight recovery cost corresponding to different proportions of passenger transfer methods

(b) Top view projection diagram of (a)

Fig. 9 Flight recovery costs for different methods of passenger transfer

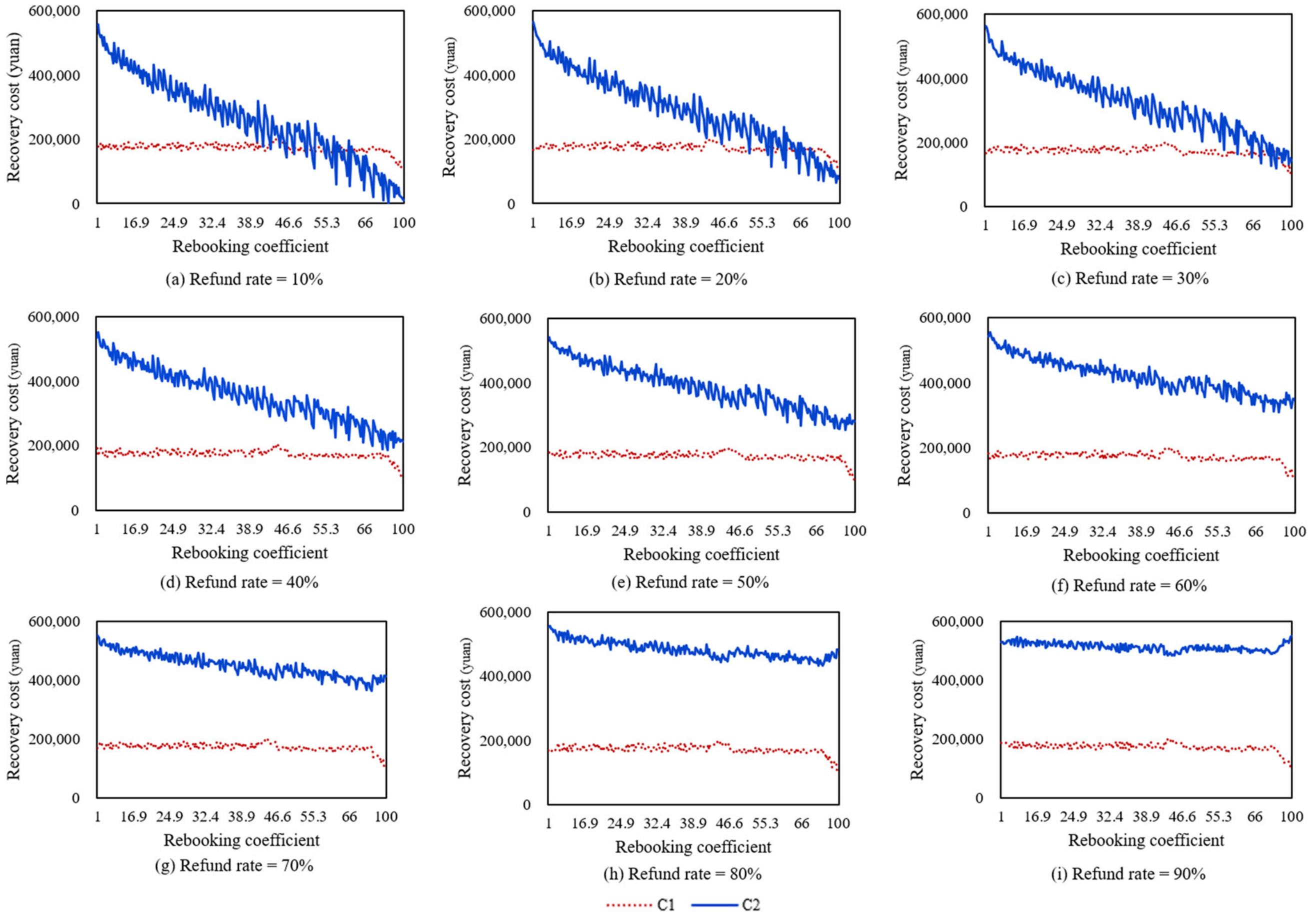


Fig. 10 Aircraft recovery costs C_1 compared to passenger transfer costs C_2

In Fig. 11(a), a comparison is presented between extensive and partial flight recovery scenarios when the refund rate is 10%. When ρ value is less than 20, the cost of recovering all flights exceeds the cost of partial recovery. This is because passengers are more inclined to rebook on flights for other dates or be reassigned to flights with other airlines. In this case, even if all disrupted routes are recovered, the operational cost of flights will be higher than the passenger transfer cost when flights are cancelled. This makes comprehensive recovery economically impractical. Therefore, the strategy in this scenario should be to selectively recover flights with lower costs and cancel flights with higher recovery costs. Within the range indicated by the yellow dashed line, the comprehensive recovery cost for all flights is lower than the cost of partial recovery. This is because most passengers prefer to rebook on flights with the same airline on the same

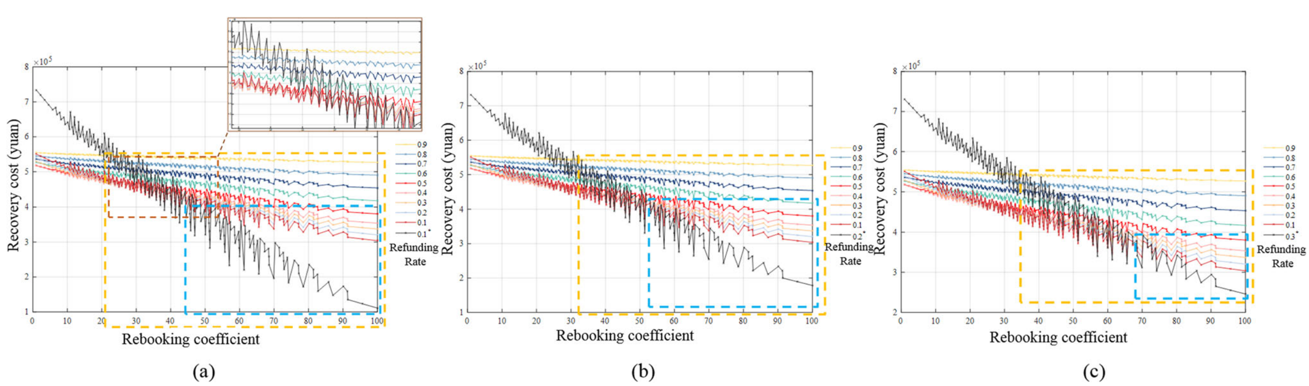


Fig. 11 Comparisons between extensive flight recovery under refund rates of 10%, 20%, and 30%, and partial flight recovery across all refund rate

day, resulting in lower rebooking costs. The sum of passenger transfer costs and aircraft recovery costs remains lower than the cost of flight cancellation. Consequently, it is possible to recover the disrupted flights to the maximum extent, and the vacant seats from the original flights can continue to be sold. This satisfies passenger demands while increasing the airline's profit.

In Figs. 11(b) and 11(c), similar to the scenario described above, as the overall refund rate increases, the critical rebooking coefficient (ρ) values corresponding to choosing to recover all disrupted flights to the maximum extent also increases. the critical rebooking coefficient (ρ) values for Figs. 11(b) and (c) are 53.1 and 68.4, respectively. After reaching these values, it becomes feasible to fully recover the disrupted flights. Similarly, the cost of partially recovering disrupted flights is lower when ρ values is less than 23 (corresponding to Fig. 11(b)) and 26.8 (corresponding to Fig. 11(c)). For overall refund rates of 10%, 20%, and 30%, the corresponding the critical rebooking coefficient (ρ) values intervals are [20, 44.3], [23, 53.1], and [26.8, 68.4], respectively. Within these intervals, the cost of fully recovering flights falls between the costs of partially recovering flights at refund rates of 10% and 90%. Whether to fully recover the disrupted flights in these intervals depends on the specific refund rate, considering the ρ values for each case.

Figure 12 illustrates the comparison between extensive flight recovery and partial flight recovery when the overall refund rates are 40%, 50%, 60%, and 70%. According to the information in the graph, when the refund rate exceeds 40%, there is no scenario where the cost of recovering all flights is entirely lower than the cost of partial flight recovery. At this point, the decision to recover all flights depends on the refund rate of some flights. In such cases, seat vacancies and high operating costs make the decision more inclined towards partial flight recovery, thereby alleviating the financial burden on the airline. When the corresponding refund rates for different refund rates are below 32.4, 37.6, 51.2, and 91.4, it is imperative to choose partial flight recovery as the corresponding recovery cost is lower. In situations beyond these thresholds, a detailed comparison of the recovery costs, considering specific refund rates and ρ, is necessary to identify the optimal proportion for flight recovery.

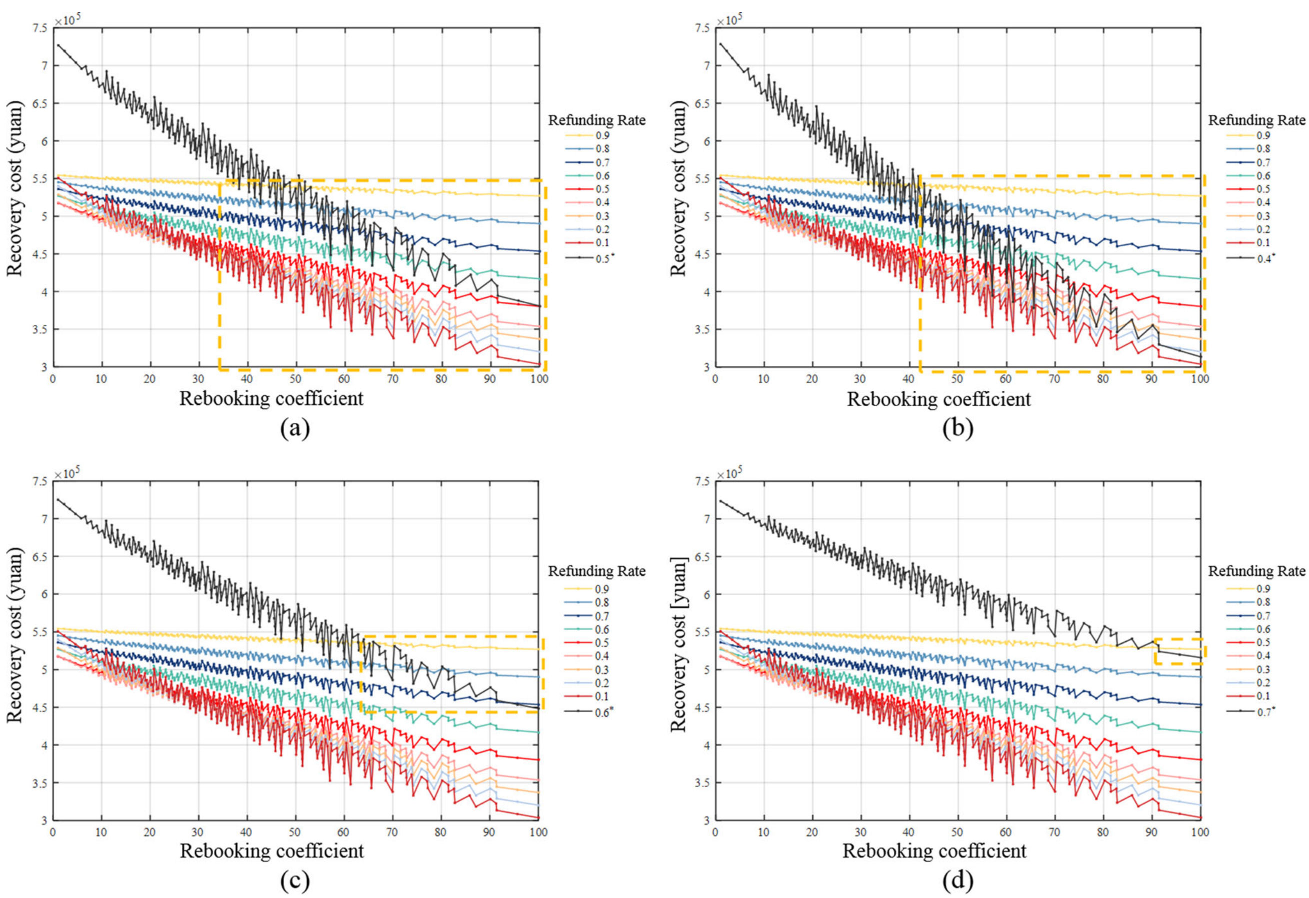


Fig. 12 Comparisons between extensive flight recovery under refund rates of 40% , 50%, 60% and 70%, and partial flight recovery across all refund rate

Figure 13 compares the scenarios of extensive flight recovery and partial flight recovery at 80% and 90% refund rates. At refund rates exceeding 80%, attempting to recover all recoverable flights would incur prohibitively high costs, even surpassing the costs of only recovering a portion of the flights. This indicates that, under high refund rates, the attempt to fully recover all disrupted flights is no longer economically viable. On the contrary, a more prudent decision is to recover only a portion of the disrupted flights, especially those with lower refund rates and lower recovery costs. Therefore, when facing high refund rates, airlines need to be more cautious and meticulous in devising recovery plans.

The analysis above examines the appropriate flight recovery strategies under different passenger transfer methods. It is evident that different flight recovery strategies should be employed based on varying rebooking coefficients and passenger refund rates. The integration of these analysis results will be presented next. Additionally, when adopting a partial flight recovery strategy, the specific percentage of flights to be recovered is illustrated in Fig. 14.

The horizontal axis represents the rebooking coefficient (ρ), and the vertical axis represents the overall passenger refund rate when disrupted flights occur. Figure 14(a) illustrates the recommended flight recovery strategies under different refund and rebooking ratios. Strategy A signifies partially recovering disrupted flights, Strategy C indicates attempting to recover all recoverable flights, and Strategy B implies the decision to fully recover depends on the flight's refund rate. It corresponds to the curves representing the full recovery strategy in Figs. 11 to 13 (coordinates marked with '*') and the intersecting portions with the curves representing the partial recovery strategy. Figure 14(b) depicts the specific percentage of recovered flights corresponding to different flight recovery strategies.

The portion below the green line represents the partial recovery strategy, i.e., Strategy A. In the current refund and rebooking ratio conditions, the partial recovery strategy is deemed the optimal choice. When the overall refund rates are 10%, 20%, and 30%, there exists a certain range of rebooking coefficients (ρ) allowing flights to be maximally recovered, namely Strategy C and the portion above the yellow line in Fig. 14(b). Upon comparison, it is observed that the starting point of the Strategy C interval aligns precisely with the intersection range of aircraft recovery costs and passenger rebooking costs in Figs. 10(a), (b), and (c). This indicates that under the dominance of aircraft recovery costs, disrupted flights can be recovered to the maximum extent possible, validating the accuracy of our experiments.

The portion between the green line and the yellow line in Fig. 14(b) corresponds to Strategy B. Within this interval, the recovery of flights becomes a variable decision space. As indicated by the earlier data analysis graphs, there is a discontinuity in the minimum cost within this interval between 'recovering partial flights' and 'recovering all recoverable flights.' Additionally, within this interval, the proportion of recovered flights when adopting the strategy of recovering partial flights is also related to the flight refund rate.

When considering flight recovery strategies, for the same rebooking coefficient (ρ), we can compare the cost of the strategy to recover all flights with the cost of the strategy to partially recover flights at different refund rates. Through such a comparison, we can choose the lower-cost strategy for recovery. Table 9 provides the rebooking coefficient (ρ) intervals for Strategy B decision-making under different rebooking coefficients (ρ) and refund rates. This table helps us understand, under different passenger transfer proportions, which refund rate corresponds to the comparison of the recovery cost of partially recovered flights. For example, when the refund rate of disrupted flights is 10%, adopting Strategy B for recovery should be compared with the refund proportion of partially recovered flights at a rate of 90%, in the interval [20, 23.7] for rebooking coefficient (ρ). If the cost

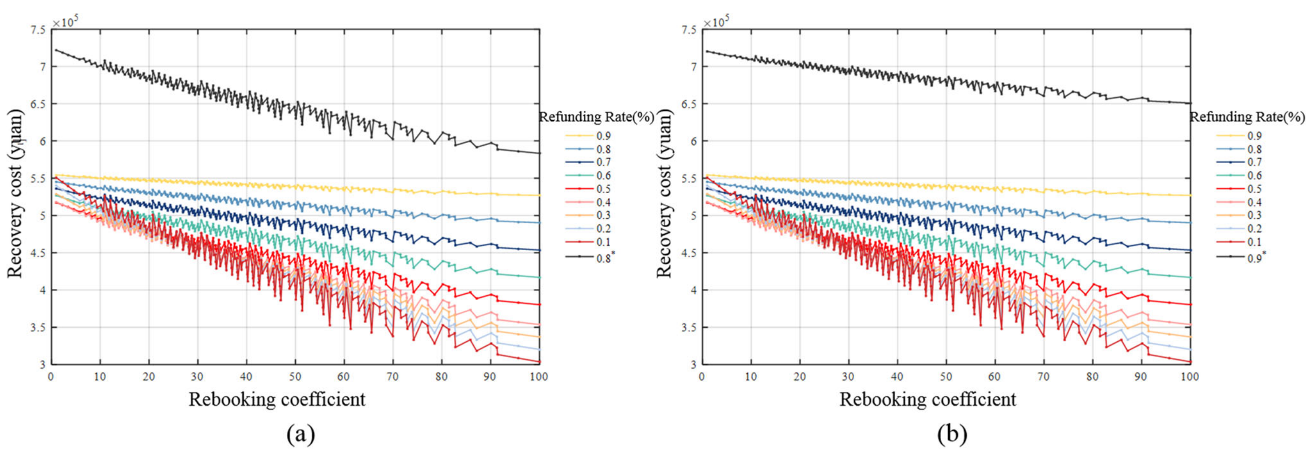


Fig. 13 Comparisons between extensive flight recovery under refund rates of 80% and 90%, and partial flight recovery across all refund rates

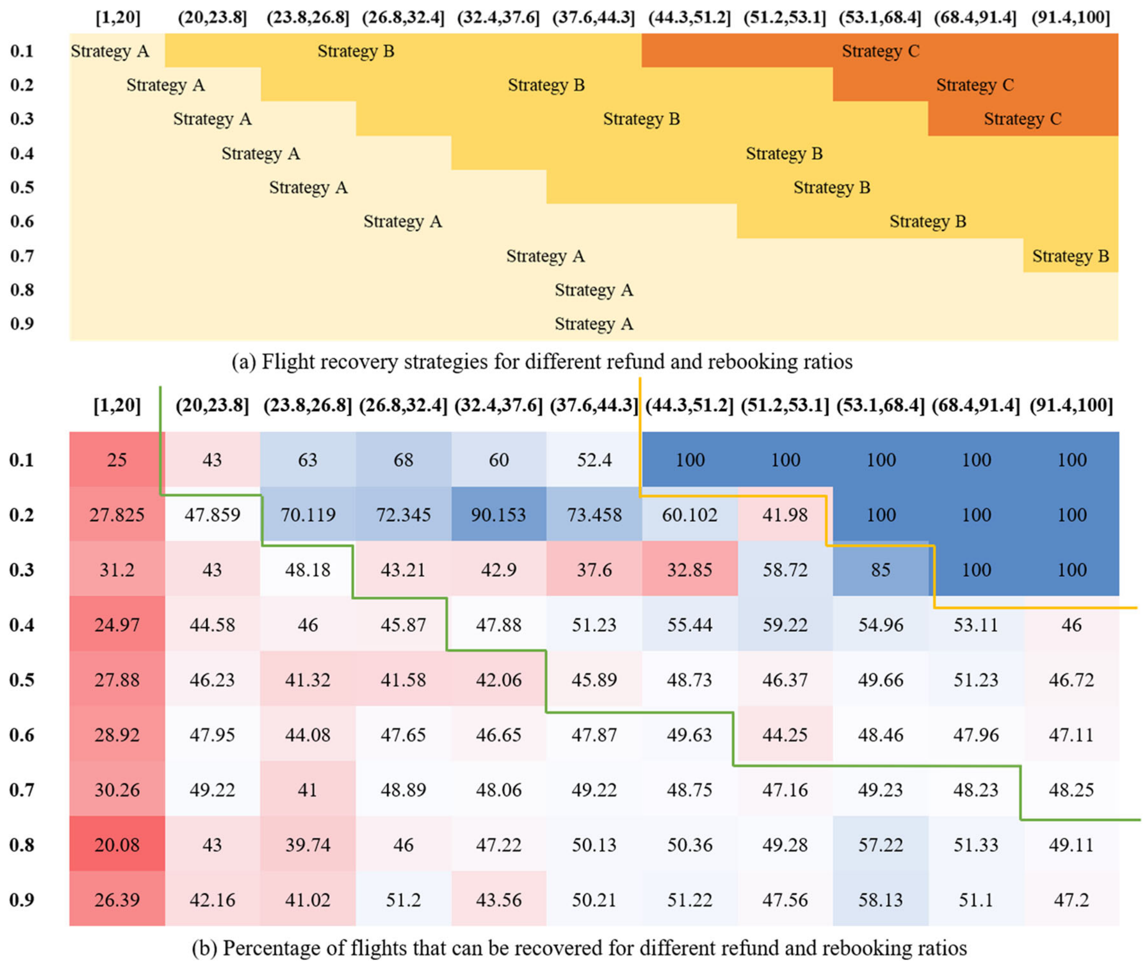


Fig. 14 The flight recovery strategies and corresponding ratios associated with different passenger transportation modes

is lower than the recovery cost of partially recovered flights at a rate of 90%, the strategy should be to maximize the recovery of disrupted flights; otherwise, partial flight recovery should be considered.

The choice of which flights to recover depends on the recovery costs of flights corresponding to different refund rates, as discussed in the previous cost analysis charts. Through such an analysis, when facing different passenger choices of refund and rebooking methods during disrupted flight occurrences, we can more accurately determine the flight recovery strategy that the airline should adopt. This aims to minimize the impact of flight delays and cancellations on passengers and the airline. Simultaneously, while respecting the preferences of passenger transfers, it provides

Table 9 The rebooking coefficient range corresponding to the comparison between extensive recovery and partial recovery when making decisions under Strategy B

The overall flight cancellation rate	The cancellation rate for partially recovered flights								
	90%	80%	70%	60%	50%	40%	30%	20%	10%
10%	[20,23.7]	(23.7,24.6]	(24.6,28.2]	(28.2,32.5]	(32.5,33.7]	–	–	–	(33.7,44.3]
20%	[23.8,24.5]	(24.5,29.3]	(29.3,33.1]	(33.1,37]	(37,40]	(40,40.6]	(40.6,41.3]	(41.3,42.6]	(42.6,53.1]
30%	[26.8,29.3]	(29.3,34.3]	(34.3,38.8]	(38.8,43.1]	(43.1,46.9]	(46.9,51.3]	(51.3,55.7]	(55.7,56.5]	(56.5,68.4]
40%	[32.4,37.9]	(31.9,41.8]	(41.8,46.9]	(46.9,56.5]	(56.5,65.6]	(65.6,77.2]	(77.2,91.4]	(91.4,100]	–
50%	[37.6,45.8]	(45.8,51.8]	(51.8,66]	(66,100]	–	–	–	–	–
60%	[51.2,61.7]	(61.7,90.1]	(90.1,100]	–	–	–	–	–	–
70%	[91.4,100]	–	–	–	–	–	–	–	–

Table 10 Comparative analysis of running times for different algorithms at varied fleet sizes

Fleet size	Number of aircraft types	Running time		
		GA	PSO	LNS
5	2	49.75s	31s	17.52s
25	3	97.56s	92.86s	55.90s
50	5	387.90s	335.76s	319.37s
100	5	658.21s	673.21s	532.79s
141	5	719.98s	899.52s	579.58s

the airline with the most favorable business guidance to optimize operations and enhance passenger satisfaction.

5.3 CPU time

In all experiments, calculations were performed on a PC with an Intel Core i7-6700 CPU and 16GB of RAM. The proposed solutions were implemented using Python programming. The computational times for our approach, genetic algorithm(GA), and particle swarm optimization algorithm(PSO) under different fleet sizes are compared in Table 10.

It can be observed that the LNS algorithm demonstrates faster computational speed compared to the genetic algorithm and particle swarm algorithm under the same fleet size and hardware environment. This indicates that the LNS algorithm exhibits higher efficiency in handling large-scale problems, fully leveraging its advantages in global search and local optimization. This performance improvement may stem from the better adaptability of the LNS algorithm to the problem structure and higher efficiency in local search. This is crucial for practical problems that require obtaining feasible solutions within a limited time.

6 Conclusions

Disrupted flight recovery encompasses the meticulous process of reorganizing and reinstating flights to regular operation following alterations or disruptions in the original flight schedule. The primary objective is to expedite the recovery of disrupted flights promptly and comprehensively, all while minimizing costs. The multifaceted nature of disrupted flight recovery costs includes aircraft recovery, maintenance, crew reassignment, and passenger transfer costs. Notably, passenger transfer costs are often treated as a relatively stable component, although research methods or literature may diverge in their emphasis on various cost aspects. Our study focuses on the limitedly explored impact of different combinations of passenger transfer methods on flight recovery costs. In this context, our paper meticulously analyzes five passenger transfer methods and their respective proportional combinations: ticket refunds, rebooking on the same airline's flight on the same day, rebooking on the same airline's flight on a different day, rebooking on the different airline's flight on the same day, and rebooking on the different airline's flight on a different day. We formulate an disrupted flight recovery model that considers three stable costs and variations in passenger transfer costs, enhancing it through the implementation of LNS algorithm. A global iterative search algorithm is employed to solve the model. The ensuing simulation experiments, conducted on a dataset from a Chinese airline, yield the following conclusions:

(1) A larger fleet size and a lower ticket refund rate correlate with reduced flight recovery costs.
(2) The optimal flight recovery ratios hinges on the passenger refund rate and rebooking method. Effective control of passenger transfer methods and disrupted flight recovery ratios maximizes the comprehensive reduction in recovery costs for both flights and passengers.
(3) When the passenger refund rate surpasses 40%, passenger transfer costs become the predominant factor in the total cost of disrupted flight recovery. Partially recovering disrupted flights becomes the optimal choice at this juncture.

The research findings of this study provide a multidimensional perspective on disrupted flight management, offering both theoretical underpinnings for airlines and practical guidance for strategic development, enhanced passenger satisfaction, and operational cost control. This study holds positive implications for the safety, intelligence, and high-quality development of civil aviation. However, it should be noted that the research results presented in this paper are currently not integrated with existing flight scheduling management systems, and are only applicable to initial enterprise needs. In future research, we will further investigate the impact of flight delay time on passenger transfer methods and costs, as well as explore flight recovery decisions in greater depth to better integrate them with airlines' flight management systems and make them more suitable for real-world scenarios. These future research endeavors will facilitate a more nuanced exploration of decision-making in flight recovery and pave the way for further advancements in the field of civil aviation management.

Appendix A Rebooking coefficients corresponding to different combinations of rebooking methods and proportions

It is available to readers at the following web address: https://1drv.ms/x/s!AnJypRYcZa_Kh3dlKiyCqGHiU7Kl?e=XkzWlQ

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Data Availability Due to commercial restrictions, the data supporting the findings of this study are not publicly available, but can be obtained from the authors upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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