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Abnormal Flight Passenger Recovery Algorithm Based on Itinerary Acceptance

Jiamin Sun, Haiming Li

School of Computer Science and Technology, Shanghai University of Electric Power, Shanghai, China
Email: zjxulhm@163.com

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Abstract

Under the background of the rapid development of the air transport industry, the abnormal phenomenon of flights has become increasingly serious due to various factors such as the gradual reduction of resources, adverse climatic conditions, problems in air traffic control and mechanical failures. In order to reduce losses, it has become a major problem for airlines to use optimization algorithm to study the recovery of abnormal flights. By upgrading the passenger recovery engine, the purpose of this paper is to provide the optimal recovery scheme for passengers, so as to reduce the risk of transferring overseas flights, and thus reduce the economic loss of airlines. In this paper, the optimization model and algorithm based on network flow, combined with actual business requirements, comprehensively consider multiple optimization objectives to quickly generate passenger recovery solutions, and at the same time achieve the optimal income of airlines and the acceptance rate of passenger recovery, so as to balance the two. The practicability and effectiveness of the proposed model and algorithm are proved by some concrete examples.

Keywords

Itinerary Similarity, Abnormal Flights, Passenger Recovery, Heuristic Algorithm, Linear Programming

1. Introduction

In recent years, the Chinese air transportation industry has grown steadily. The pandemic, especially in 2020-2021, significantly impacted air transportation, leading to a notable drop in turnover. However, since early 2022, global airlines have been working towards recovery, resulting in improved performance compared to the previous two years. In 2022, global commercial aviation is expected to have around US$ 727 billion in total revenue, a 43.68% increase year-on-year, with expenditures reaching approximately US$ 737 billion, a 33.76% increase. Regarding infrastructure and equipment, China's civil aviation transportation has experienced substantial growth, with 254 domestic transport airports and 4165 transport aircraft by the end of 2022. This includes 15 4F airports, 39 4E airports, 37 4D airports, 158 4C airports, 4 3C airports, and 1 airport below 3C. Passenger aircraft make up 94.6%, and cargo aircraft account for 5.4% of the total transport aircraft [1].

In recent years, the Chinese government's focus on enhancing air transportation capabilities has led to supportive policies for the aviation industry. Policies from the State Council, Civil Aviation Administration of China, and Ministry of Transport encourage the development of airport hubs, the growth of air transportation companies, and strategic cooperation with leading logistics firms. These efforts, coupled with expanding the air transportation fleet and promoting all-cargo aircraft transportation, are expected to drive continued growth in the Chinese air transport industry.

However, the air transportation system is inherently complex, and airlines face daily challenges, such as flight delays. Researchers attribute irregular flights to various factors, including uncontrollable ones like air control, weather changes, and military activities, as well as controllable factors like passenger issues, airport security concerns, and airline-related problems. These deviations from flight plans create inconvenience for passengers, leading to conflicts and imposing economic compensation losses on airlines, covering air delay, ground delay, aircraft adjustment costs, and normal profit losses.

Abnormal flights or flight delays will not only bring a variety of explicit economic losses, but also bring a variety of psychological negative emotions to passengers, resulting in hidden economic losses. For airlines, the explicit economic loss includes the extra operating cost caused by flight delay, and even the normal profit loss caused by flight cancellation, which is called the passenger trip cancellation cost. For passengers, the explicit economic losses include the loss of passenger delay cost, the loss of passenger transfer cost and the loss of passenger trip cancellation cost, while the implicit economic losses include the loss of passenger reliability cost. The quality and efficiency of airline services directly impact ticket sales, the primary revenue source. Promptly resuming disrupted schedules minimizes losses. If the airline can offer timely alternatives, priority is given to transferring passengers to its flights, reducing financial impact. Lacking available subsequent flights may lead to transfers, incurring financial risks. Decisions on endorsement sequence should consider economic losses. Swiftly restoring passenger traffic and minimizing financial losses are urgent challenges for airlines.

In recent years, with the increasing number of abnormal flights, my country's domestic airlines have begun to pay attention to the recovery management of abnormal flights. The quality of passenger recovery program has a great impact on the operating cost and image reputation of airlines. However, at present, domestic airlines mainly carry out actual business operations by learning from foreign civil aviation work experience. Chinese scholars have begun to conduct in-depth research on the psychology and handling methods of passengers during irregular flights [2], public relations management [2], corresponding service strategies [3] and improving service quality.

In the 1970s and 1980s, foreign scholars began to study the problem of abnormal flight recovery, and developed a usable abnormal flight recovery system in some airlines. However, these scholars mainly focus on the recovery of aircraft and crew, which causes the research on the recovery of passenger travel is not deep enough.

Clarke *et al.* [4] proposed a passenger flow model PFM (Passenger Flow Model), aiming to optimize passenger revenue. They define a passenger's priority based on the passenger's origin and destination (OD) and recover the passenger based on that priority. However, they do not define the priority of the same OD passengers. Barnhart *et al.* [5] defined the passenger flow recovery problem as a multi-commodity network flow problem, aiming to minimize the delay time of disturbed passengers. However, as the number of disturbed passengers increases, the solution time also increases exponentially. Bratu *et al.* [6] used a heuristic algorithm and added some recovery constraints, such as frequent passenger priority and disturbed first recovery. However, the effect of these constraints on determining the priority of passengers is not obvious, and the economic value of passengers is not considered comprehensively. Jafari *et al.* [7] redefined the recovery period, focusing on the synchronous recovery of aircraft route and passenger flow for abnormal flights. They introduced the route recovery concept to reduce the size of the problem, but because the linear programming problem is still very large, it is not efficient to solve. Bisaillon *et al.* [8] solved the problems of aircraft route recovery, aircraft type assignment and passenger flow recovery through three stages of establishment, repair and improvement. Their goal is to restore as many passenger numbers as possible. After constructing feasible aircraft routes, they used a shortest path algorithm to establish an initial route. Then, they tried to enumerate delay times, but this method was less efficient and could not guarantee an optimal solution. Petersen *et al.* [9] defined the aviation recovery problem into four modules, which were divided into flight schedule recovery, crew recovery, passenger flow recovery and aircraft recovery, etc. By using column generation and Benders branch-and-bound algorithm, the overall optimal solution was obtained through iterative calculation of problem decomposition and optimization.

Domestic scholars' research on flight recovery issues is still in its infancy. Currently, airlines' passenger recovery actions and solutions for flight delays mainly rely on manual adjustments, which are no longer able to meet the needs of today's airlines operating a large number of passengers.

Zhao Xiuli *et al.* [10] proposed a comprehensive recovery model and used the Benders decomposition algorithm to solve it. The model mainly includes the main problem of flight recovery and the sub-problem of aircraft, crew and passenger recovery. Lu Honglan *et al.* [11] developed a passenger flow recovery model, which transformed the problem into a transportation matching problem and aimed to minimize the delay cost. They use simplex method to solve the problem, although the storage method and search strategy are optimized, but the solution efficiency is not high. Wang Ying *et al.* [12] analyzed the economic benefits of flight delay compensation and proposed an integrated recovery model of aircraft route and passenger itinerary. They consider passenger flow recovery and recovery costs based on OD pairs, but do not consider passenger value, which may affect the determination of passenger priority recovery sequence. Li Xiong *et al.* [13] studied the economic losses of airlines and passengers caused by flight delays, and analyzed in detail the composition of passenger compensation and hidden losses caused by abnormal flights.

Based on the breakdown of flight delay costs, this paper develops a passenger flow recovery model centered on passenger value. The objective is to minimize airlines' delay losses while considering factors such as aircraft capacity limitations and available flight seats. The paper proposes a suitable solution method for this model. Utilizing an itinerary similarity model, the study identifies available flight itineraries from alternatives, calculates the quality scores of these alternatives, and assesses passengers' acceptance probabilities. Sorting by acceptance degree, the study recommends high-value disrupted passengers to resume their itineraries. Experimental validation confirms the feasibility and effectiveness of both the model and the proposed solution algorithm.

2. Calculation Method of Flight Itinerary Similarity

Flight itinerary similarity involves comparing two or more different flights to assess their degree of similarity or dissimilarity across various aspects [14] [15] [16]. Airlines or airline booking platforms often require the matching of different flights with travelers' preferences to offer optimal choices. In such instances, flight similarity is employed to identify which flights align most closely with the customer's requirements.

To calculate the similarity of flight itineraries, various metrics and methods can be used, such as:

- Time factors: similarity of departure time and arrival time, transfer time, flight time.
- Routes and airports: departure and landing airports, transfer airports, route similarities.
- Airline: The same or different airlines, cabin type, service quality.
- Price: Similarity of fares.

The precise calculation of flight similarity can be tailored to specific requirements and accomplished through mathematical models, algorithms, and data analysis tools. These analyses are instrumental in aiding travelers in making informed choices, optimizing flight planning, enhancing travel efficiency, and refining aviation operations and airport management.

The itinerary similarity calculation model is a pivotal component of the passenger recovery algorithm for abnormal flights. By assessing the similarity between distinct itineraries, suitable alternative itineraries for passengers can be swiftly identified, mitigating the impact on passenger travel and elevating the service quality of airlines. This section provides a detailed introduction to the design of the travel similarity calculation model.

2.1. Alternative Itinerary Matching Method

After the abnormal flight itinerary occurs, we need to find the alternative itinerary that is similar to the abnormal flight from all the flight plans. The alternative itinerary needs to be the same departure arrival and departure time.

Abnormal flight itinerary and alternative itinerary matching rules:

Step 1: Identify the initial departure and final arrival airport codes for each segment of the entire itinerary. Utilize these codes to filter sets of alternative itineraries with the same departure and arrival airports from the airline's flight plan.

Step 2: Iterate through all abnormal itineraries and determine the set of alternative itineraries for each abnormal case.

Matching criteria for alternative itineraries: Initially, locate the departure and arrival airports of the abnormal itinerary. Subsequently, identify all passing country codes and the minimum connection time (MCT) between airports as per the airport pair list. Finally, filter out all alternative itineraries meeting the specified conditions using the airport code, country code, and shortest transit time.

Step 3: Conclude the cycle for abnormal trips and match all available alternative trips for the given abnormal itinerary.

The pseudo code is as follows:

```
For item in all abnormal itineraries{
    firstCode = the first departure airport code of item;
    lastCode = the last arrival airport code of item;
    countryCodes = all passing country codes of item;
    transferTime = the shortest transfer time of item;
    For alterItinerary in all alternative itineraries{
        firstCode_ = the first departure airport code of item;
        lastCode_ = the last arrival airport code of item;
        countryCodes_ = all passing country codes of item;
        transferTime_ = the shortest transfer time of item;
        If(firstCode = firstCode_
          and lastCode = lastCode_
          and countryCodes = countryCodes_
          and transferTime <= transferTime_){
              alterItinerary is meet the conditions;
```

(16) }
(17) }
(18) }

2.2. QSI Flight Itinerary

QSI (Quality Score of Itinerary) Flight itinerary quality score is a metric used to evaluate and compare the quality of different flight itineraries. This score can be based on a number of factors, including flight punctuality, service quality, in-cabin experience, flight comfort, etc.

After identifying the relevant factors, assigning weights to each factor allows for the calculation of individual scores. These scores are then amalgamated to generate a comprehensive flight itinerary quality score. This metric aids passengers or travelers in making informed decisions, enabling them to select flights that align with their preferences. Airlines can leverage this score to enhance their services and meet passenger expectations more effectively.

Here we calculate the quality score of the QSI alternative itinerary mainly based on three factors: the number of transfers in the itinerary, the total time in minutes of the itinerary, and the number of hours in which the departure time of the itinerary falls. Follow these three factors in three steps.

QSI alternative itinerary quality score scoring rules:

Step 1: Set the initial quality score of the alternative itinerary to zero.

Step 2: Compute the quality score based on the number of transfers. A maximum of two transfers is agreed upon. Utilize the parameter configuration table to set the corresponding quality score according to the number of transfers.

$$X_1 = \text{Table } 1_i \; i \text{ is the number of transfers} \tag{1}$$

Step 3: Calculate the total trip time score. The calculation rule involves dividing the maximum trip minutes by the total duration minutes of the trip, utilizing the hyperparameter.

$$X_2 = \text{MaxMinutes} \Big/ \left(\left| \text{TotalMinutes} \right| + 1 \right) \tag{2}$$

Among them: Max Minutes represents the maximum number of minutes specified by the hyperparameter, and Total Minutes stands for the total duration in minutes for the entire journey—essentially, the difference in minutes between the departure time of the first leg and the arrival time of the last leg.

Step 4: Compute the quality score for the departure time window of the trip (X_3). The 24-hour day is segmented into two-hour intervals, and the configuration data for the intervals is acquired based on the departure time hours.

$$X_3 = \text{Table } 2_i \; i \text{ is the departure time hours} \tag{3}$$

For instance, if the departure time is 10:05 in the morning, and the departure falls within the range [10 - 12), then the score (X_3) is set to 15. Finally, establish the formula for calculating the quality score of the flight itinerary:

Definition 1: After comprehensively considering the number of transfers, the total trip time, and departure time window, we give the QSI calculation formula:

$$\text{QSI} = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \tag{4}$$

X_1 is the number of transfers in the trip, β_1 is its corresponding weight;

X_2 is the total travel time, β_2 is its corresponding weight;

X_3 is the trip departure time window, β_3 is its corresponding weight.

The pseudo code is as follows:

(1) Init all scores set to 0

(2) for item in alternative itinerary list{

(3) transfersCount = the number of transfers of item;

(4) X_1 = Table1 (transfersCount);

(5) total Minutes = the time of the last arrive segment - the time of the first depart segment;

(6) $X_2 = \text{MaxMinutes}/(|\text{TotalMinutes}|+1)$;

(7) time_window = the trip departure time window;

(8) X_3 = Table2(time_window);

(9) the QSI of item = $\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$

(10) }

2.3. The Itinerary Similarity

The itinerary similarity reflects the degree of fit between the alternative itinerary and the abnormal itinerary. The itinerary similarity calculation rules are:

Calculated based on the absolute value of the absolute value of the minute difference in arrival time (Y_1), the absolute value of the difference in the number of itinerary segments (number of transfers) (Y_2),the minute difference in departure time between the abnormal itinerary and the alternative itinerary (Y_3).

Definition 2: According to the above description, we give the calculation formula of itinerary similarity:

$$\text{SIM} = \alpha_1 \left(\frac{\gamma_1}{e^{\delta_1/Y_1}} + \frac{\gamma_2}{e^{\delta_2/Y_2}} + \frac{\gamma_3}{e^{\delta_3/Y_3}} \right) \tag{5}$$

α_1 is the itinerary similarity weight;

Y_1 is the trip arrival time difference, γ_1 is the trip arrival time difference weight, and δ_1 is the trip arrival time difference parameter;

Y_2 is the difference in the number of stops in the trip, γ_2 is the difference in the number of stops in the trip, and δ_2 is the difference parameter in the number of stops in the trip;

Y_3 is the trip departure time difference, γ_3 is the trip departure time difference, and δ_3 is the trip departure time difference parameter.

2.4. Itinerary Acceptance

Trip acceptability refers to the probability that a passenger is willing to accept a specific alternative trip. This probability can be affected by a variety of factors, including price, travel time, service quality, destination, etc. In order to calculate the trip acceptance probability, we need to use the previous two steps to calculate the trip similarity score and trip quality score.

Definition 3: After comprehensively considering the QSI and the SIM, we give the calculation formula of itinerary acceptance:

$$\mathrm{Rec} = \alpha_1 * \mathrm{SIM} + \alpha_2 * \max\left(1, \frac{\mathrm{QSI}_1}{\mathrm{QSI}_2}\right) \tag{6}$$

α_1 is the itinerary similarity weight, α_2 is the itinerary quality weight;

SIM is the trip similarity, QSI_1 is the quality score of the new alternative trip, QSI_2 is the quality score of the original trip.

3. Abnormal Flight Passenger Recovery Model

3.1. Greedy Algorithm Recovery Model

The greedy algorithm is a problem-solving approach that relies on heuristics [17]. It is a widely used method for finding optimal solutions to problems by establishing optimization criteria for decision-making [18] [19] [20]. The algorithm iteratively selects choices in a top-down manner, breaking down the solution process into steps where only the optimal choice based on the current situation is made each time. In each step's selection process, the problem is simplified into a smaller sub-problem, leading to the eventual attainment of a satisfactory solution. Due to the selection strategy employed by the greedy algorithm, it operates in a downward direction without backtracking, saving considerable search time for the optimal solution. However, drawbacks exist, as the global solution obtained may not always be globally optimal, and the algorithm tends to find local optimal solutions.

Greedy algorithms have many classic applications, such as Huffman coding, Prim and Kruskal's minimum spanning tree algorithm, and Dijkstra's single-source shortest path algorithm, all of which use this kind of thinking. When it comes to protecting passengers on abnormal flights, we first sort them by passenger quality, then prioritize high-value customers, and prioritize protecting high-value customers on alternative itineraries with high similarity [21]. Algorithm steps.

Step 1: Sort all passengers on the abnormal flight in descending order according to passenger value [22] score.

Step 2: Process all passengers who need to be protected in a loop, and then take out all available alternative itineraries corresponding to the currently protected passenger's itinerary. All alternatives have been sorted in advance according to the itinerary acceptance degree from large to small. We then process the alternative itineraries in a loop, algorithm The process is as follows.

1) The set of alternative itineraries is sorted from large to small according to the previously calculated itinerary acceptance.

2) Take out the alternative itinerary with the highest acceptance rate.

3) Read the original cabin information of the current protected passenger and the number of remaining seats in the same cabin as the current alternative itinerary. If the current number of remaining seats is greater than 1, the current al-

ternative itinerary is selected and enters the next step. Otherwise, exit the current alternative itinerary and return. Go to step 1).

4) The number of remaining cabins in the current alternative itinerary is reduced by one. The currently protected passenger finds the alternative itinerary, ends the process, and processes the next passenger according to the same process.

The pseudo code is as follows:

```
(1) Sort all passengers order by passenger value score desc;
(2) For passenger in all passengers{
(3)         itineraryList = get all available alternative itineraries of passenger;
(4)         Sort the itineraryList order by the itinerary acceptance degree from large to small;
(5)         For itinerary in itineraryList {
(6)                remainingSeats = the number of remaining seats of itinerary ;
(7)                If (remainingSeats >1){
(8)                        the current alternative itinerary is selected;
(9)                }
(10)        }
(11) }
```

3.2. Mathematical Programming Recovery Model

Linear programming (LP) [23] [24] [25] [26] is a mathematical modeling technique used to optimize a linear objective function subject to a set of linear constraints. It is widely applied in fields such as operations research, management science, and economics to assist decision-makers in optimizing resource allocation. In this paper, a decision problem is formulated as an optimization problem with the goal of either maximizing or minimizing a linear objective function.

3.2.1. Symbol Definition

F is the set of all alternative itineraries under any abnormal itinerary; H is the set of all segments in the alternative itinerary.

X_i is alternate trip. i is the serial number of alternate trip. The value of the variable is 1 or 0. When X_i equal to 1, it indicates that this alternative trip is selected, otherwise the current alternative trip is abandoned.

C_i is The coefficient of the alternative itinerary, the calculation formula is: acceptance probability * passenger value, where the passenger value is the ranking Value value in the pnr data.

L_h is The number of passengers who need to be protected for segment h in the alternative itinerary P_h is Number of remaining seats in segment h.

3.2.2. Mathematical Model

The mathematical model of the passenger recovery model is as follows:

$$\min(z) = \sum_i C_i X_i \tag{7}$$

s.t.

$$\sum_{f \in F} X_f \leq 1, \ \forall f \in F \tag{8}$$

$$\sum_{h \in H} L_h X_i \leq P_h, \forall h \in H, \forall i \in I \tag{9}$$

$$L_h, P_h \geq 0 \text{ , And Non-negative Integers} \tag{10}$$

The objective function formula (7) indicates that the total loss cost of all disrupted passengers' relocation and resumption of itineraries is minimized, including the delay cost of the disrupted passengers, the cancellation cost of the disrupted passengers, the endorsement penalty cost of the disrupted passengers, and the disruption costs of the disrupted passengers. The cost of loss of credibility.

Constraint (8) Abnormal itinerary coverage constraint: For any abnormal itinerary, an alternative itinerary must be found, and F is the set of all alternative itineraries under any abnormal itinerary.

Constraint (9) Constraint on the number of remaining seats in a flight segment: for any flight segment, one flight segment may belong to multiple alternative trips, and multiple alternative trips may share the same flight segment. The total number of passengers to be protected by multiple alternative trips sharing the same flight segment should be less than the remaining seats in the current alternate travel segment.

Constraint (10) is a variable value constraint, requiring the number of passengers to be protected and the remaining seat number of the flight segment to be non-negative integers.

3.3. Algorithm Summary

Finally, we summarize the overall algorithm flow.

Step 1: Initial data configuration, including system weight parameters, DDS historical row data, MCT airport transit time configuration data, PNR passenger itinerary information data, real-time available flight data, real-time booking data.

Step 2: Score the quality of all available alternatives in multiple dimensions.

Step 3: Calculate the similarity between the alternative trip and the original trip.

Step 4: Calculate the acceptability of the passenger for the alternative itinerary.

Step 5: Calculation of recovery scheme. This paper provides two recovery schemes, one is a greedy algorithm based on heuristic algorithm, which gives priority to the recovery of high-value passengers, and the other is to establish a mathematical planning model to solve the problem of minimizing the passenger transfer cost.

Step diagram as the showing in Figure 1.

4. Experimental Analysis

The data of 35,632 seats booked by a domestic airline were used in the experiment. The parameters of the model are mainly related to the configuration table of the number of trip transfers, the configuration table of the hours of departure time and the weight parameters required in calculating the acceptance of the trip.

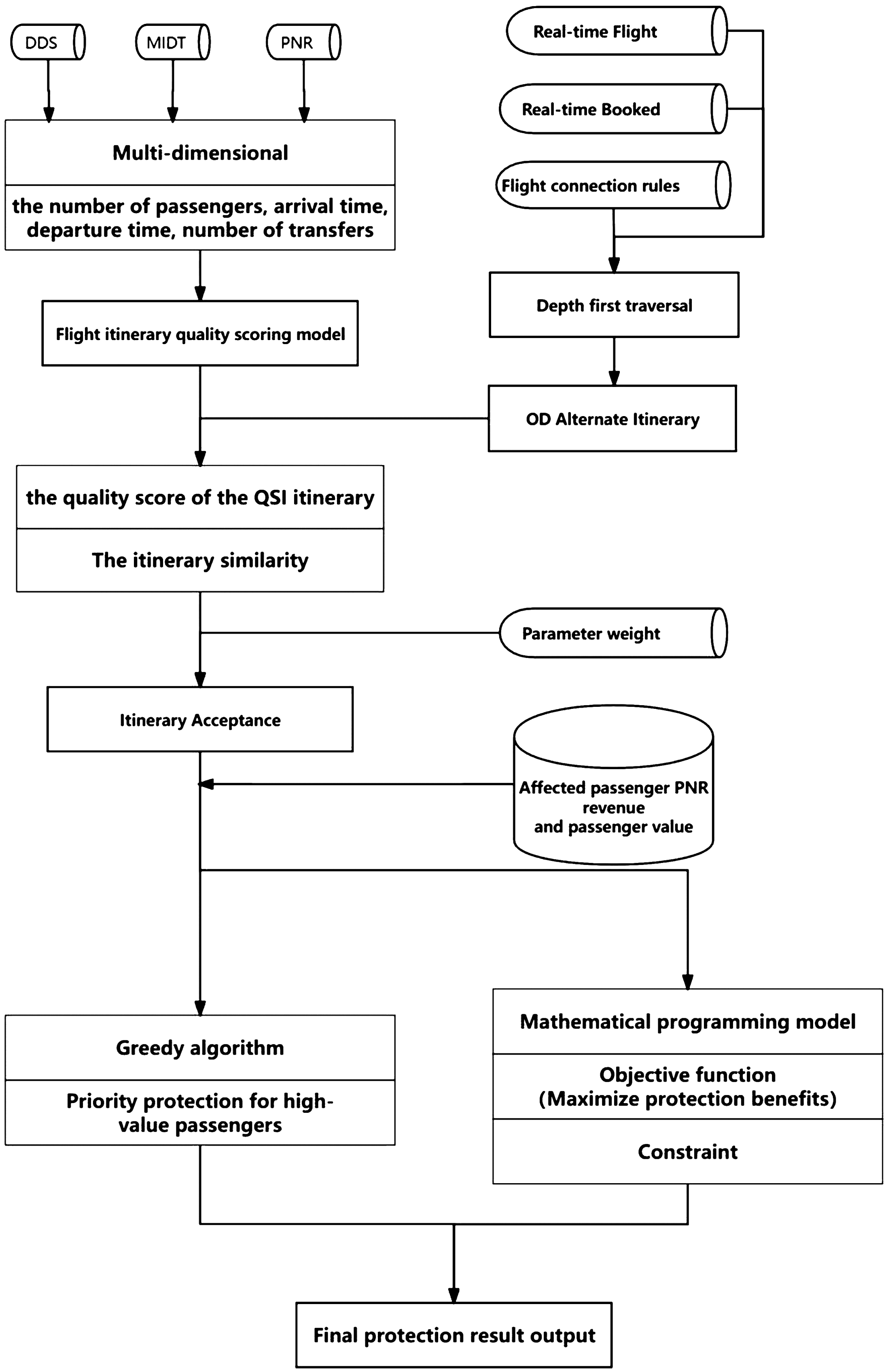

Figure 1. Passenger recovery system flow chart.

4.1. Transfers Configuration

Calculating the QSI itinerary quality score requires determining the entire number of transfers for the alternative itinerary. In principle, the fewer the number of transfers, the higher the quality score, and passengers will tend to choose it. The configuration is shown in Table 1 below.

4.2. Departure Time Hours Configuration

The calculation of QSI itinerary quality score also needs to determine the hour of the departure time of the alternative trip. Passengers are also very sensitive to the departure time, and the general passengers are not inclined to leave too early or too late. The better the departure time, the higher the itinerary quality score. The configuration is shown in Table 2.

The notation [0 - 2) in the table denotes the interval that is closed at the beginning and open at the end, covering the 0^{th} hour up to, but excluding, the 2^{nd} hour.

4.3. Weight Configuration

In the calculation of travel acceptance, both itinerary quality score and itinerary similarity are utilized, and various weight configuration parameters are incorporated into the calculation formula. The configuration details are presented in Table 3 below.

4.4. Passenger Recovery Results Analysis

In the event of a delay, airlines typically implement a passenger recovery policy that directly protects passengers in the order of disruption. The performance indicators for protecting passenger flow according to this scheme are detailed in Table 4.

Table 1. Transfers configuration.

Number of transfers	quality score
0	100
1	30
2	10

Table 2. Departure time hours configuration.

departure time hours	quality score	departure time hours	quality score
[0 - 2)	3	[12 - 14)	10
[2 - 4)	3	[14 - 16)	15
[4 - 6)	5	[16 - 18)	30
[6 - 8)	5	[18 - 20)	15
[8 - 10)	30	[20 - 22)	10
[10 - 12)	15	[22 - 24)	5

Table 3. Weight configuration.

configuration	value
α_1	0.9
α_2	0.1
γ_1	0.7
γ_2	0.2
γ_3	0.1
δ_1	2880
δ_2	0
δ_3	2880

α_1 is the itinerary similarity weight, α_2 is the itinerary quality weight, γ_1 is the trip arrival time difference weight, and δ_1 is the trip arrival time difference parameter, γ_2 is the difference in the number of stops in the trip, and δ_2 is the difference parameter in the number of stops in the trip, γ_3 is the trip departure time difference, and δ_3 is the trip departure time difference parameter.

Table 4. Performance indicators of random recovery scheme.

Performance	value
Total number of passengers	35,632
Total number of delayed passengers	3580
Total number of canceled passengers	290
Total number of endorsed passengers	3300
Average delay time of disturbed passengers/min	271
Average cost/yuan	6400

Table 5. Performance indicators of passenger flow recovery scheme.

Performance	value
Total number of passengers	35,632
Total number of delayed passengers	3580
Total number of canceled passengers	290
Total number of endorsed passengers	3300
Average delay time of disturbed passengers/min	103
Average cost/yuan	3201

The performance indicators of passenger recovery after passenger flow recovery by using the passenger flow recovery model in this paper are shown in Table 5.

Through the comparison of the two tables and Figure 2 above, it is evident that the average deployment cost of the adjusted passenger recovery plan is

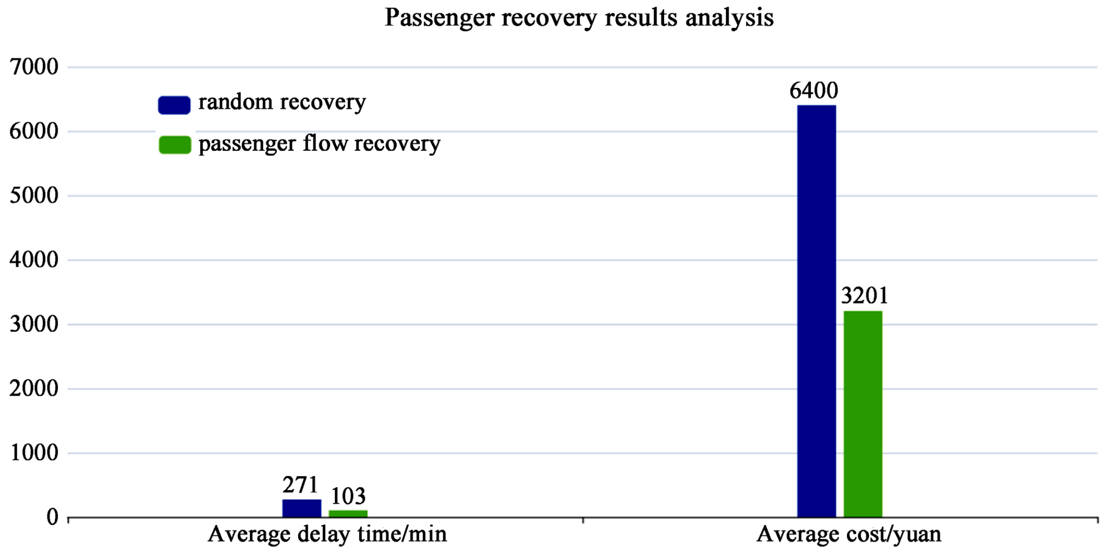

Figure 2. Passenger recovery results analysis chart.

3201 yuan. In contrast, if we consider the average delay cost resulting from the random recovery of disrupted passenger journeys after an irregular flight, which amounts to 6400 yuan, the optimized passenger recovery plan achieves a reduction of 3199 yuan in average deployment cost before and after optimization.

5. Conclusion

This paper addresses the challenge of airlines recovering disrupted passengers during abnormal flights. It considers factors such as passenger economic value, aircraft capacity limitations, itinerary similarity, and itinerary acceptance, while also breaking down the costs associated with flight delay losses. Notably, implicit cost losses are taken into account, leading to the construction of a passenger flow recovery model and a corresponding solution algorithm. This model is designed to accurately address the passenger flow recovery problem. Through calculation examples, the paper demonstrates that the proposed model and algorithm enable airlines to formulate an optimized, feasible, and cost-effective passenger flow recovery plan. This approach minimizes economic losses and enhances the airline's reputation simultaneously.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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