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Research Article

An Airport Stand Assignment Problem considering the Passenger Boarding Distance

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The continued growth in the civil aviation industry leads to more traffic in the airport, resulting in a decline in operational efficiency and the travel experience of passengers. Studying how to improve operational efficiency and keep passenger satisfaction simultaneously is very significant. This study proposes to use total passenger boarding distance instead of total passenger walking distance to quantify passenger satisfaction and then model the airport stand assignment problem considering these two different objectives together with the gated percentage, respectively, and the NSGA-II algorithm is improved for a better solution speed. This study also performs a case study by applying a dataset of an airport in China. The results of the case study prove that using the total passenger boarding distance can help the airport better balance operational efficiency and passenger satisfaction, which can help provide theoretical support for airport management.

1. Introduction

The civil aviation industry has maintained consistent growth over the past decade, resulting in more air traffic demand [1]. The growth challenges the whole industry, especially airports, which are essential parts of the air transportation system. Airports need to face the challenge of more flights and passengers as a result of more traffic demand. It is an undeniable fact that airports are becoming more and more crowded, leading to a steady decline in both operational efficiency and the travel experience of passengers. As a result, efforts have been undertaken by both industry and academia to address these challenges.

The most important stakeholders in the daily operation of an airport include the airport operator itself, the airlines, and the passengers [2]. An important task for the airport operators is to assign each flight operated by different airlines to different stands and gates, and passengers go to these gates to board the flights on stands [3]. During these procedures, the airport operators provide the service, while the airlines and passengers are the ones being served. This is called as airport gate assignment problem, AGAP for short. During this procedure, passengers, airlines, and airport operators, all have their own interests and requirements [4]. Passengers want more comfortable travel, such as shorter waiting times or boarding distances. Airlines always want their flights to be assigned to specific gates. For example, if an airline uses a specific terminal, the airline always prefers its flights to be assigned to gates in that terminal. The airport operators have to ensure safety and operation efficiency, as well as meet certain requirements of the local civil aviation administration. A general logistic procedure for a stand servicing flights is shown in Figure 1.

Academia has made great effort in the study of AGAP. Among those research studies, passenger satisfaction is one of the most focused research objectives. Passenger satisfaction is a metaphysical concept, so it is generally quantified or characterized by using other characteristics. The most common characteristics include the distance or walking time for the passengers to board their flights [5]. Generally speaking, a shorter walking distance indicates better passenger satisfaction. But a shorter walking distance does not always make passengers satisfy. The reason is, in an airport, there are always two styles of stands, which are remote

FIGURE 1: Logistic procedure for stand-servicing flights.

stands and the stands with boarding gates, which will be called "gated stands" in the rest of this paper. Using gated stands can increase passenger satisfaction [6]. If passengers board a flight at a gated stand, passengers can directly board the aircraft through the gate, which means the boarding distance can be considered as the walking distance. However, if the passengers board a flight at a remote gate, the passenger shall take a shuttle bus, making the total boarding distance to be walking distance together with the driving distance of the shuttle bus. The driving distance of the shuttle bus can be rather long, especially in some hub airports, which can result in significantly reduced passenger satisfaction. Besides, satellite concourses are becoming very common in more and more hub airports. To access a satellite concourse, passengers need to travel with an APM (automated people mover) system [7], which will also increase the boarding distance of passengers and reduce passenger satisfaction. The boarding procedure is shown in Figure 2.

Thus, we consider it would be interesting from both academic and industrial points of view to research would total boarding distance is a better objective. Motivated by the discussion above, we propose using the total passenger boarding distance instead of the passenger walking distance to quantify passenger satisfaction and compare the strategies under these two objectives. We also take the operational preferences of the airport into account and aim to assign more flights to gated stands. The main work of this paper includes the following: (1) constructing a multiobjective stand assignment optimization model based on the passenger boarding distance, (2) improving the NSGA-II algorithm to solve this model, (3) validating this model by applying an airport operational dataset, and (4) comparing and discussing the optimal strategies under the minimal total boarding distance and total walking distance. The paper is organized as follows: Section 2 presents some related literature review, Section 3 discusses the methodology of this research, Section 4 gives out the case study, and Section 5 concludes this research and gives out the further discussion.

2. Literature Review

Some literatures which related to this study are reviewed in this section, focusing on airport stand assignment and associated modeling techniques and algorithms.

The problem of airport stand assignment has long been a traditional area of research in daily airport management [8]. As indicated in the introductory section, the stand assignment problem influences a variety of stakeholders, with differing perspectives often leading to a broad set of objectives. Related studies need to find a balance between these divergent goals. Moreover, for the stand assignment problem, it is essential for the construction of math models following some universal constraints [9]. For safety, the top-

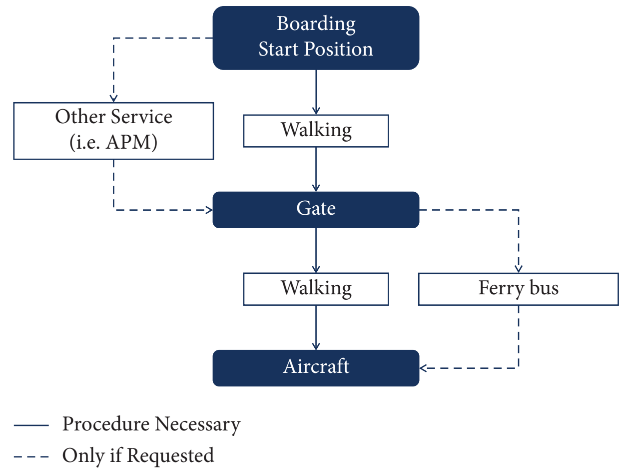

FIGURE 2: The procedures for passenger boarding.

most priority in civil aviation procedures, any potential risks or conflicts in aviation operations are unacceptable. In the context of stand assignment problems, this safety prerequisite is manifested in the following two non-negotiable constraints: uniqueness and exclusivity. The constraint of uniqueness dictates that a single stand can be assigned to just one flight (or aircraft) at most at any moment. The exclusivity constraint, on the other hand, ensures that the aircraft has a sole use of the stand in terms of time and space, that is, one stand can service only one flight (or aircraft) at a time. These two constraints form the basis for all stand assignment research. In addition, the stand assignment problem should generally adhere to a few more constraints, depending on the specific operational rules of different airports. Common extra constraints include the stand-aircraft size constraint [10], the stand-flight characteristic constraint [11], the stand-airline constraint [12], and the time interval constraint [13].

To elaborate, stands can be categorized into various classes depending on the maximum size of the aircraft they can accommodate. Similarly, considering the types of flights they can service, stands can be classified into domestic, international, or mixed categories. Some airports even have exclusive stands dedicated to one or a few specific airlines. Hence, for airports with pertinent regulations and needs, stand assignments must observe the following rules: the size of the aircraft assigned to a stand cannot surpass the stand's capacity—smaller stands cannot accommodate larger aircraft, but smaller aircraft can be serviced by larger stands, demonstrating the stand-aircraft size constraint. Domestic flights cannot be assigned to international stands, nor can international stands be assigned to domestic flights, while mixed stands are not subject to these restrictions—this illustrates the stand-flight attribute constraint. For airports featuring exclusive stands, aircraft from different airlines cannot be assigned those stands, representing the stand-airline constraint. In addition, citing safety considerations, most airports prescribe a buffer time, typically between 10 and 50 minutes [14], for two consecutive aircraft using the same stand. This sensible buffer time is crucial for enhancing operational safety, averting stand conflicts due to unforeseen delays, and strengthening the resilience of the stand assignment strategy [15]. Particular problems should be analyzed and model constraints should be established in a manner that aligns with the specific circumstances of the target airport. Furthermore, in stand assignment research, the model is often judiciously simplified by establishing certain assumptions to enhance the efficiency of the simulation solution. Common assumptions encompass the presumption that each stand operates independently of the others [16], that the aircraft that needs to be assigned stands all operate both an arrival and a departure flight [17], and that all stands are available for assignment at the beginning of assignment [18].

Stand assignments play a crucial role in determining operational efficacy and ensuring passenger satisfaction [19]. A well-devised stand assignment strategy can curtail delays, enabling airlines to adhere more closely to their timetables [20] and elevating the overall efficiency during an airport's ground turnaround [21]. Despite multiple stakeholders being involved in stand assignment, the study of passenger satisfaction-based slot allocation is the oldest and most popular branch of research related to stand assignment, dating back to the 1970s [22]. Earlier studies typically aimed to minimize passengers' total walking distance within the terminal to gauge their satisfaction [9]. Subsequent research continued to spotlight this aspect, with current studies examining objectives such as the total distance passengers moving within the terminal [23], the total walking distance for transit passengers [24], or the average distance each passenger moves [25]. For airline-oriented research in the context of stand assignments, common studies focus on minimizing taxi distances [26] and durations [27] and diminishing delays emanating from stand assignments [28]. When considering airport-oriented stand assignment, the emphasis tends to be on assigning more flights to gated stands, maximizing the duration gated stands are occupied [29], or increasing the volume of passengers boarding via these gated stands [6].

The study of multiobjective optimization of stand assignment problems is also becoming popular in recent years. The research in this domain primarily addresses the diverse considerations related to passengers, airlines, and airport operators [30, 31]. Academics formulate mathematical models for multiobjective optimization of these problems and employ advanced optimization algorithms to decipher these models, resulting in a range of Pareto optimal outcomes. By doing so, scholars can balance the interests of all stakeholders and promote a benign game to achieve a multi-win situation. The algorithms utilized for multiobjective optimization fall into the following two primary categories: exact algorithms and heuristic algorithms [32]. While exact algorithms guarantee the procurement of Pareto optimal results, heuristic algorithms, although not ensuring exact optimal outcomes, are adept at handling vast problems and discrete models. Typical heuristic algorithms to tackle multiobjective optimization issues include evolutionary algorithms such as the nondominated sorting genetic algorithm-II (NSGA-II) and clustering algorithms such as the multiobjective particle swarm optimization (MOPSO). Notably, heuristic algorithms tend to be slower, demand more computational resources, and exhibit lesser convergence compared to exact algorithms. However, in response to the limitations of both exact and heuristic methods, hybrid algorithms have been introduced recently as a means to address multiobjective optimization challenges more efficiently [33].

The abovementioned literature review underscores that the stand assignment challenge frequently encompasses multiple stakeholders, with passenger satisfaction often being a paramount concern. Given this, contemporary research on stand assignment predominantly leans towards a multi-objective optimization methodology. In addition, the viability of heuristic algorithms to tackle extensive stand assignment issues is acknowledged. Given this backdrop of existing research, this paper's primary contribution lies in introducing an innovative evaluation technique, which uses the total distance passengers need to board to measure their satisfaction with stand assignment. Leveraging these evaluation criteria, we construct a multiobjective stand assignment optimization model that considers the percentage of gates used. Utilizing the improved NSGA-II algorithm, this novel evaluation approach is then tested and contrasted using real-world airport operational data. The detailed methodology of this investigation is elaborated further in Section 3.

3. Methodology

This section introduces the stand assignment model and the corresponding solution algorithm. The model is for optimizing an airport stand assignment problem with two optimization objectives as follows: minimizing the passenger boarding distance or walking distance and maximizing the proportion of flights assigned to gated stands.

3.1. Definition of the Mathematical Elements. In this subsection, we will first define all the mathematical elements necessary for the modeling in Table 1.

Regarding the sets, we denote the set of all outbound flights as $P_O = \left\{p_{o_1}, \ldots, p_{o_p}\right\}$ and the set of all available airport stands as $Q = \left\{q_1, \ldots, q_q\right\}$. Regarding the parameters, for flight $\in P_O$, a_i^f and d_i^f are defined start and end time at a stand, as given in the data. n_i stands for the number of passengers who take flight $i \in P_O$, which is calculated by c_i, the passenger load factor for flight $i \in P_O$ and s_i, the number of seats for flight $i \in P_O$. D_{ie} is the boarding distance for each passenger when flight $i \in P_O$ is using the stand $e \in Q$ while d_{ie} is the walking distance for each passenger when flight $i \in P_O$ is using the stand $e \in Q$. Also, t_s signifies the necessary gap in time between two consecutive flights at the same stand for safety reasons. Regarding the variables, g_i^e serves as an indicator of stand assignment, which equals 1 if the flight $i \in P_O$ is assigned to the stand $e \in Q$; otherwise, 0. The variable c_a^i categorizes the aircraft type for $i \in P_O$. flight A value of 2 indicates a double −aisle aircraft, 1 signifies a singleflight − aisle aircraft, and 0 marks a regional aircraft. The stand size is denoted by c_b^e. It assumes a value of 2 if the stand $e \in Q$ can accommodate a double-aisle aircraft and 1 otherwise. The

Table 1: Mathematical elements for modeling.

Symbol	Definition
(a) Sets	
P_O	All departure flights, $P_O = \{p_{o_1}, \ldots, p_{o_p}\}$
Q	Set of all available stands, $Q = \{q_1, \ldots, q_q\}$
(b) Parameters	
a_i^f, d_i^f	The start and ending time for flight $i \in P_O$ using a stand
n_i	Number of passenger for flight $i \in P_O$
c_i	Passenger load factor for flight $i \in P_O$
s_i	Number of seats for flight $i \in P_O$
D_{ie}	Boarding distance for each passenger when flight $i \in P_O$ using the stand $e \in Q$
d_{ie}	Walking distance for each passenger when flight $i \in P_O$ using the stand $e \in Q$
t_s	Safety time interval for all stands
(c) Variables	
g_i^e	Decision variable of stand assignment for flight $i \in \mathrm{P}_O$ using the stand $e \in Q$
c_a^i	Variable of the aircraft type for flight $i \in P_O$
c_b^e	Variable of the stand size $e \in Q$
h_e	Variable for the boarding bridge of the stand $e \in Q$
y_{ij}^e	Variable for if two flights $i, j \in P_O$ using a same stand $e \in Q$

presence of a boarding bridge at the stand $e \in Q$ is indicated by h_e, with 1 meaning yes and 0 meaning no. Lastly, the variable y_{ij}^e is set to 1 if the flight $j \in P_O$ follows flight $i \in P_O$ at the stand $e \in Q$; otherwise, it remains 0.

3.2. Modeling the Stand Assignment Problem. When tackling the stand assignment problem, a systematic approach is essential. This entails designating each flight to a specific stand, reflecting its unique features while adhering to particular optimization goals. Within the scope of this study, the foundational premises and limitations concerning stand assignment are as follows:

(1) An individual aircraft is restricted to a single stand; simultaneously, a stand cannot cater to multiple aircrafts.

(2) The compatibility between the dimensions of the aircraft and the stand is crucial. Thus, only larger stands can accommodate bigger aircraft but smaller aircraft have the flexibility to occupy any stand.

(3) For safety protocols, when two consecutive flights are designated to the same stand, a sufficient time interval must be ensured between them.

Furthermore, it is assumed that all the stands in the dataset are available for assignment throughout the entire period under consideration. Initially, no aircraft is present at any of the stands in the dataset. A series of Pareto optimal solutions can be achieved by adhering to these constraints and focusing on the objective functions.

Based on the earlier research motivation and the outlined problem description, the objective functions can be written as follows:

$$\min D_t = \sum_{i \in P_O} \sum_{e \in Q} n_i \cdot D_{\mathrm{ie}}, \tag{1a}$$

or

$$\min d_t = \sum_{i \in P_O} \sum_{e \in Q} n_i \cdot d_{\mathrm{ie}}, \tag{1b}$$

$$\max G_R = \frac{\sum_{i \in P_O} \sum_{e \in Q} g_i^e \cdot h_e}{\sum_{i \in P_O} \sum_{e \in Q} g_i^e}, \tag{2}$$

Equation (1a) represents the minimum total boarding distance, while equation (1b) represents the minimum total walking distance. Equation (2) represents maximizing the gated percentage. The objective functions should follow the constraints as follows:

$$n_i = [c_i \cdot s_i + 0.5], \quad i \in P_O, \tag{3}$$

$$g_i^e \cdot g_j^e \geq y_{ij}^e, \quad i, j \in P_O, e \in Q, \tag{4}$$

$$\sum_{e \in Q} g_i^e = 1, \quad i \in P_O, e \in Q, \tag{5}$$

$$g_i^e \cdot g_j^e \cdot \left(d_j^f - a_i^f\right) \cdot \left(d_i^f - a_j^f\right) \leq 0, \quad i, j \in P_O, e \in Q, \tag{6}$$

$$c_b^e - c_a^i \geq 0, \quad i \in P_O, e \in Q, \tag{7}$$

$$\left|\left(a_j^f - d_i^f\right)\right| \cdot g_i^e \cdot g_j^e \geq y_{ij}^e \cdot t_s, \quad i, j \in P_O, e \in Q. \tag{8}$$

Equation (3) indicates the method to calculate the number of passengers with the passenger load factor and the seat number on flights. Equation (4) limits the relation among y_{ij}^e, g_i^e, and g_j^e for logical reasons. Equations (5) and (6) mean an individual aircraft is restricted to a single stand and a stand cannot cater to multiple aircrafts. Equation (7) means only larger stands can accommodate bigger aircraft but smaller aircraft have the flexibility to occupy any stand. Equation (8) limits that when two consecutive flights are designated to the same stand, a sufficient time interval must be ensured between them.

3.3. Algorithms. In our research, we employ the NSGA-II algorithm, a well-established heuristic technique designed for tackling multiobjective optimization challenges [34]. For a multiobjective optimization problem, a set of solutions usually exists which is not comparable in merit among them. The set of solutions is called Pareto optimal, in which none of the objective functions can be improved without degrading some of the other objective values [35]. If a solution is inferior to the Pareto solution set in each objective function, it is called a solution dominated by the Pareto solution set. The NSGA-II algorithm finds the Pareto solution set by a fast nondominated ranking and then selects the better individuals in the iteration according to the ranking to participate in the crossover variation to find the Pareto optimal solution to the solution problem.

The algorithm applied in this research is an improved NSGA-II algorithm based on a previous research [36]. To explain this algorithm in more detail, the individual chromosomes are coded in natural numbers, and the assignment scheme represented by each individual is a feasible solution to the problem. The length of each chromosome equals the number of flights to be assigned, and the gene at each gene locus is the aircraft position assigned to that flight. For example, if the total number of flights to be assigned is 10 and the available stands are numbered 1, 2, 3, and 4, the chromosome length of each individual is 10, and the chromosome coded as shown in Figure 3 would indicate that flight 1 is assigned to stand 3, flight 2 is assigned to stand 1, flight 3 is assigned to stand 2, and so on. However, the NSGA-II algorithm intrinsically exhibits randomness in its initialization and cross-variance procedures. Concurrently, the stand assignment problem is a quintessential NP-hard issue. As a result, performing random initialization or cross-variance can produce numerous nonviable solutions, hampering the efficiency in identifying optimal solutions.

Consequently, we have refined the initialization and cross-variance techniques, detailing the modifications in the pseudocode provided subsequently in Algorithm 1.

To go into more detail, for the initialization, a series of available stands for the first flight is generated. Then, a stand is randomly selected from the set of available stands as the initial stand for the first flight. After this flight is assigned, the occupancy schedule for this stand is updated. Repeat the abovementioned operation to initialize the next flight in the order of the flights until all flights are assigned a stand. The crossover procedures first set the number of chromosome crossovers as w and randomly generate the crossover point q, so the crossover position is from q to $q + w - 1$. Genes from the paternal chromosome outside the crossover position are passed directly to the offspring. Then, update the occupancy schedule for all stands. Starting from the gene q of the maternal chromosome, we sequentially determine whether the inheritance of the maternal chromosome to the offspring will produce a conflict. If so, a series of available stands for flight q is generated and then a stand for flight q is randomly selected from this set. If not, the gene q of the maternal chromosome is passed directly to the offspring. Then, we update the occupancy schedule for all stands and repeat the abovementioned operation. The next gene of the maternal chromosome is judged sequentially until the crossover termination point is reached. The mutation process first randomly selects a gene r on the chromosome as the point of variation. Then, a series of available stands for flight r is generated and randomly selected a stand from the set as the stand for flight r. Upon deriving the optimized strategy, it will be presented as a feasible result.

4. Case Study

4.1. General Information. An operational dataset for one day in April 2023 of Beijing Capital Airport (ICAO: ZBAA, IATA: PEK), which is one of the hub airports in China, is applied for this case study. The dataset includes all domestic flights operated in terminal 3. Terminal 3 mainly service Air China (ICAO: CCA, IATA: CA) and some other airlines, and the layout of terminal 3 is presented in Figure 4. The domestic flights are operated in the area of T3C and T3D. The T3C area has 37 gated stands and the T3D area has 10 gated stands. If passengers need to board a flight at the T3D area, they need to take the APM. The sample of stands information is presented in Table 2.

3	1	2	4	1	3	4	2	3	2

Figure 3: Sample of the chromosome.

The dataset for the case study included 252 flights using 93 stands. The information including flight no., type of aircraft, and the number of seats on the aircraft are known in the dataset. The start and ending times for an aircraft using a stand, also called a_i^f and d_i^f, are also known. The sample of the dataset is presented in Table 3.

The next step is to determine the value of the mathematical elements. The elements including P_O, Q, a_i^f, d_i^f, s_i, c_a^i, c_b^e, and h_e can be directly known from the stands information and the dataset. For other elements, n_i is calculated by s_i and c_i from equation (3), and the value of c_i can be found in the operation report of airlines and CAAC (Civil Aviation Administration of China). In this case study, the c_i for Air China is 73.7\%, and for other airlines, c_i is 77.6%. The D_{ie} and d_{ie} can be valued via the passenger boarding procedure as shown in Figure 2, the distance for walking, APM travel distance and ferry bus travel distance are known from the airport and OSM (open street map), a geographic information system. Considering the practical operation, the safety interval time t_s is 10 minutes in this case study.

4.2. Findings and Discussion. The algorithm is implemented using MATLAB 2020a. Initially, objective functions aiming to minimize the total boarding distance are addressed, setting the population size at 100 and capping the genetic iterations at 300. Notably, convergence is attained after roughly 100 generational iterations. Due to the scale of the dataset being not large enough, there are only 3 sets of solutions on the Pareto front surface. We selected the one with the minimum boarding distance, and the result is shown in Figure 5. The yellow lines represent the gated percentage, while the blue lines represent the boarding distance. The solid lines represent the optimized results and the dotted lines represent the result calculated with the dataset. The total boarding distance after optimization is 39,693,900 meters and the gated percentage is 70.24%. In comparison, the boarding distance calculated from the dataset is 44,956,020 meters and the gated percentage is 75.79%.

Similarly, the objective functions with minimized total walking distance are also processed. The population size is also 100 and the maximum number of genetics is also 300. The algorithm achieved a convergence after about 200 generations of iterations and there are 2 sets of solutions on the Pareto front surface. Here, the result with the minimum

Input: a_i^f, d_i^f, c_a^i, c_b^e, Dis_i, dis_i, Stand, flight, Fn_1, Generations U, N_U
Get $\mathrm{totalnum}_1$ by Fn_1 + flight
Initialize the population ($N_U \cdot \mathrm{totalnum}_1$)
for $i \leftarrow 1$ to N_U **do**
  Selection cells in mating pool
  Crossover and mutate of cells
  Offspring cells into new population
  if stand assignment not satisfy constraints **then**
    Regenerate and replace set of flights' stands
  end if
  Calculate objective functions result
  Nondominate sort the cells
  Calculate the crowd distance
  Sort population in descending order
end for
Output: Best solution for stand assignment

Algorithm 1: The NSGA-II algorithm for stand assignment pseudocode.

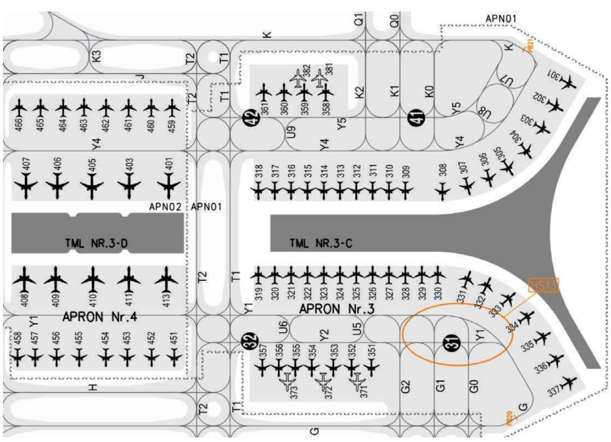

Figure 4: Layout of PEK terminal 3.

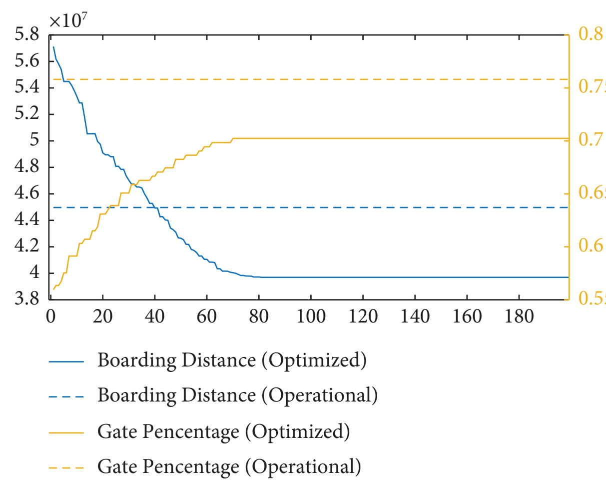

Figure 5: Process of finding optimized boarding distance and gated percentage.

Table 2: Data sample for the case study sample of stands information.

Stands	Size	Gated
301	Large	Yes
311	Medium	Yes
551	Medium	No
932	Large	No
...	...	...

Table 3: Data sample for the case study sample of the dataset.

Flight nos.	Aircraft	a_i^f	d_i^f	Seats
CA1519	A350-900	07 : 30	09 : 30	312
GJ8888	A321-200N	09 : 20	10 : 25	210
SC2126	B737-800	12 : 05	13 : 25	176
CA1583	B787-9	12 : 35	16 : 00	293
...	...	...	...	...

walking distance is shown in Figure 6. Same with Figure 5, the yellow lines represent the gated percentage, while the blue lines represent the boarding distance, and the solid lines represent the optimized results while the dotted lines represent the result calculated with the dataset. The total walking distance after optimization is 14,563,760 meters and the walking distance calculated from the dataset is 16,349,850 meters. The gated percentage is 68.26%.

It can be found after the optimization that the total boarding distance decreased by 11.71%, while the gated rate also decreased by 5.55%. When considering the walking distance, the total walking distance decreased by 10.92%, and the gated rate decreased by 7.53%. This indicates a large range of optimization in terms of both boarding distance and walking distance. Compared to walking distance, the boarding distance can be improved with less gated percentage reduction. We also calculate the walking distance under the minimized boarding distance and the boarding distance under the minimized walking distance, respectively, are 16,969,250 meters and 53,214,460 meters. Both distances have some increases compared with those calculated from the dataset, and it is reasonable for other objectives to get

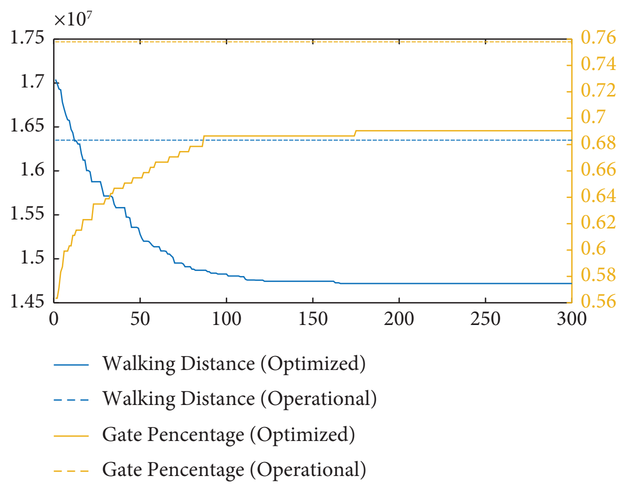

Figure 6: Process of finding optimized walking distance and gated percentage.

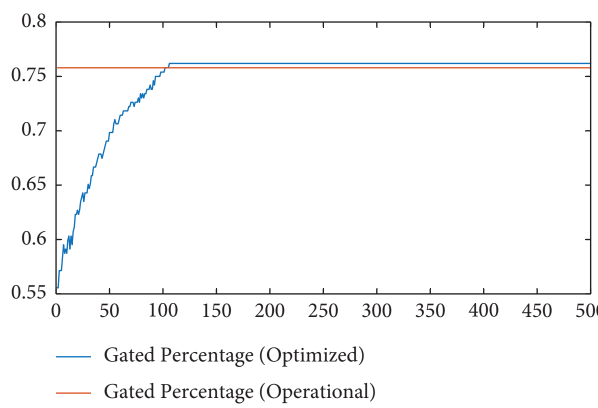

Figure 7: Optimization result on the gated rate.

worse when one objective is optimized. The passenger walking distance only increases by 3.79% when achieving the minimized passenger boarding distance, while the boarding distance increases by 18.37% when achieving the minimized walking distance. This means that the optimizing boarding distance can be achieved without significantly increasing the passenger walking distance and better accommodating the need of the airport for the gated percentage.

To compare, we also process a single-objective optimization only considering the gated percentage, and the result is presented in Figure 7. The maximized gated percentage is 76.19%, while the gated percentage calculated from the dataset is 75.79%. This indicates the stand assignment strategy in practice is very near the strategy with the maximized gated percentage. This means the airport considers more about the gated percentage more than any other objectives. The result also illustrates the decrease in gated percentage during the optimization of the boarding distance and walking distance. Improving other objectives will inevitably lead to a decrease in the gated percentage. From this perspective, it may also be a good idea to consider the boarding distance than the walking distance. As this may help the airport sacrifices less on the gated percentage but still ensure the passenger satisfaction. Studying a triobjective optimization considering boarding distance, walking distance, and gated rate may also be interesting.

5. Conclusion

In this study, we discuss using the boarding distance to evaluate passenger satisfaction instead of using the passenger total walking distance in an airport stand assignment problem. The main work includes modeling and improving the NSGA-II algorithm for a better solution speed. We also conduct a case study using operational data from a Chinese airport. This research can assist airports in enhancing their operational management and shaping strategies from a theoretical perspective.

In the coming works, we are going to consider more realistic scenarios and consider the interests of more stakeholders. It would also be interesting to consider the robustness of the stand assignment strategy. Finally, we believe it would be inspiring to connect this work together with the total operational management of airports and data-driven intelligent airport operation.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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