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An Airport Gate Assignment Model by Considering Multiple Constraints Deriving from Business Rules

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Abstract. Airport gate is the core resource for airport operation and organization, and thus an optimal airport gate assignment (AGA) schedule plays a critical role to ensure the high-efficiency airport operation. In this paper, considering the actual business rules of airport, the AGA problem is explored and a model based on the actual business rules of airport is established. The model aims to maximize the passenger docking rate and comprehensively considers several constraints deriving from business rules, such as the limitation of adjacent aircraft models, conflict of slide in and out and gate conflict restrictions. The actual business rules of airport are abstracted into the objective functions and constraints of the model. In view of the large-scale complicated combinational optimization problem deriving from the model, an improved immune genetic algorithm is designed to solve the model. Based on the traditional immune genetic algorithm, the proposed algorithm further integrates the variety of population, adaptive crossover probability and memory library to improve the solving efficiency. Moreover, a numerical experiment is designed by using the real-world data from Kunming Changshui International Airport. The experimental results indicate that the proposed model and algorithm have feasibility and effectiveness. The optimal assignment schedule has ability to increase the berth utilization ratio for both passengers and flights.

1. Introduction

As an indispensable resource from airport, gates play an important role in aircraft storage and related services, such as passenger boarding, good loading and aircraft refuelling. In recent years, as the flight number increases rapidly, the limitation of airport gates has become a thorny issue, especially for the contact stands. Considering the difficulties of infrastructure construction in airport, i.e. limitation of space and funds, assigning the flights to suitable gates according to their arrival and departure times is a feasible method to address the issue. Nevertheless, in actual situations, the conventional methods of airport gate assignment (AGA) are mainly based on the subjective experience, which are unable to ensure the optimization and deal with the tasks from the airports in China effectively. Therefore, special attention should be given to the AGA problem to improve the operational efficiency of the airport.

Focused on the AGA problem, several studies have established related models from different perspectives. For example, Xu et al. proposed an AGA model to minimize the total gate blockage time and developed a solution technique by transforming the problem into a finite number of tractable binary programmings[1]. Deng et al. developed an optimization model of AGA aiming at the balanced idle time and shortest walking distance [2]. An ant colony algorithm was designed to solve the constructed model. Liu et al. presented an AGA model considering operational safety constraints[3]. The main objective is to minimize the dispersion of gate idle time periods. Lee et al. proposed a AGA model by using quadratic mixed integer programming to assign gates with balanced passenger flow on each



gate[4]. Cheng et al. proposed an AGA model to minimize the flight delays and improve the resource utilization efficiency[5]. Then, a hybrid tabu search approach was designed to solve the problem. It is worth noting that, in the real-world situation, the assignment of airport gates would be influenced by multiple business rules from airport operation, such as the limitation of adjacent aircraft models and conflict of slide in and out. However, most of exiting studies only considered some basic constraints in AGA models and neglected the constraints deriving from business rules, and thus their results could not satisfy the demands of airport operation to a certain extent. In this paper, we develop an AGA model by considering business rules of airport, and both the constraints deriving from business rules and conventional ones are integrated in the model aiming at maximization of the berth utilization ratio. Furthermore, an improved immune genetic algorithm is designed to solve the model.

2. AGA Modeling

2.1. Basic Assumption

To facilitate model construction, several assumptions are made as follows.

Assumption 1: We assume that the length of the time window is equal to one day. Such an assumption is used to divide the AGA by using time according to actual situations.

Assumption 2: It is assumed that, without special instructions, the flights are composed of a combination of arrival and departure ones.

Assumption 3: We assume that the gates have sufficient capacity to meet the assignment requirements.

Assumption 4: It is Assumed that the relevant data required for AGA are known, such as flight information, gate information and relevant parameters of regarding AGA.

2.2. Data Definition

Before modeling, the variables and symbols used in the model need to be defined, as detailed follows.

- Input variables. The input variables are used to formulate the AGA problem. Related information is listed in Table 1

Table 1. The input variables of the model.

Input variables	Definition
n_f	Number of pending flights
F	Collection of pending flights
F_d	Collection of single flight
x_{ik}	If the flight i leaves at the gate k , it equals to 1, otherwise 0
n_g	Number of gates
G	Collection of gates
N_i^p	Number of passengers on the flight I , $i \in F$
f_k^{bridge}	If the gate has a bridge, it equals to 1, otherwise 0, $k \in G$
g_k	The default boarding gate of the gate k , $k \in G$
N_{kl}	If the gates k and l are connected, it equals to 1, otherwise 0, $k, l \in G$

- Intermediate variables. To simplify calculations, intermediate variables are obtained by preprocessing input variables in the model, as shown in Table 2.

Table 2. Intermediate variables in the model.

Input variables	Definition
Q_{ik}	If the flight i matches gate k , it equals to 1, otherwise 0, $i \in F, k \in G$
M_{ij}	If the flight i conflicts with the flight j , it equals to 1, otherwise 0
P_{ij}	If the flight i and flight j assigned to adjacent gates have conflict with respect to aircraft type and occupancy time, it equals to 1, otherwise 0.
B_{ij}	If the flight i and flight j have conflict for occupancy time, it equals to 1, otherwise 0.

- Decision variables. The decision variable of AGA problem is denoted as x_{ik} , which equals to 1 if flight i is assigned to gate k , otherwise it equals to 0.

2.3. Objective Function

In conventional AGA methods, maximizing the flight docking rate is often regarded as the metric to evaluate the AGA plan. However, such methods do not consider the difference in flight priority caused by the difference in the number of passengers from different flights. Therefore, this paper uses the maximum passenger docking rate as the optimization function, as shown in Eq. (1).

$$\max \frac{\sum_{k=1}^{n_g} \sum_{i=1}^{n_f} x_{ik} f_k^{\text{bridge}} N_i^p}{\sum_{i=1}^{n_f} N_i^p} \quad (1)$$

2.4. Constraints

Based on the actual business rules from airport operation, the constraints in the model are listed as follows.

- An aircraft can only dock at one gate, as shown in Eq. (2).

$$\sum_{k=1}^{n_g} x_{ik} = 1 \quad \forall i \in F, \forall k \in G \quad (2)$$

- There must be a safe idle time between two adjacent aircrafts assigned to the same gate, as given in Eq. (3).

$$\sum_{j \in R_i} x_{ik} + x_{jk} \leq 1 \quad \forall i, j \in F, \forall k \in G \quad (3)$$

- The types of aircraft and gates need to be matched, and the arrival time need to be greater than the sum of idle times of gate and adjacent aircrafts, as shown in Eq. (4).

$$x_{ik} = 0 \quad \forall Q_{ik} = 0, \forall i \in F, \forall k \in G \quad (4)$$

- A certain time interval should be taken between the events of slide in and out for the aircrafts docked at two adjacent gates, as shown in Eq. (5).

$$x_{ik} + x_{jl} \leq 1 \quad \forall N_{kl} = 1, \forall M_{ij} = 1, \forall i, j \in F, \forall k, l \in G \quad (5)$$

- As the aircrafts dock at gates, the constraints regarding adjacent gates should be satisfied, as shown in Eq. (6).

$$x_{ik} + x_{jl} \leq 1 \quad \forall N_{kl} = 1, \forall P_{ij} = 1, \forall i, j \in F, \forall k, l \in G \quad (6)$$

- Overnight flights docked at remote stands could be dragged to contact stands, but could not be dragged to other remote stands, as show in Eq. (7) and Eq. (8).

$$x_{ik} = 0 \quad \forall k \in \left\{ k \mid x'_{ik} = 0, f_k^{bridge} = 0 \right\}, \forall i \in F_d \quad (7)$$

$$x_{ik} = 1 \quad \forall k \in \left\{ k \mid x'_{ik} = 1, f_k^{bridge} = 1 \right\}, \forall i \in F_d \quad (8)$$

- There exists a buffer time between two boarding events from same gates, as shown in Eq. (9).

$$x_{ik} B_{ij} + x_{jl} B_{ij} \leq 1 \quad \forall g_k = g_l, \forall i, j \in F, \forall k, l \in G \quad (9)$$

3. Solution Method

The gate assignment model proposed in this paper is a large-scale complex combinatorial optimization problem, and traditional polynomial time algorithms are difficult to solve such problems. However, the intelligent optimization algorithm can effectively deal with the complicated optimization problems [6]. Considering the characteristics of the model, this paper attempts to solve the model with the help of immune genetic algorithm. In contrast to other algorithms, the immune genetic algorithm has ability to fast search the satisfying solutions. Moreover, in order to ensure the solving efficiency, we further improve the traditional immune genetic algorithm by integrating the variety of population, adaptive crossover probability and memory library into the solution procedure. Owing to space constraints, this section only describes the improved portions of the algorithm, as presented below, and the detailed procedure regarding the traditional immune genetic algorithm can be read in Reference [7].

- Variety of population. In the improved immune genetic algorithm, the traditional immune genetic algorithm is used in the early stage of genetic evolution, while the adaptive crossover probability is used in the later stage of genetic evolution. Furthermore, according to the adaptive crossover probability, we select the parent antibody with needs of crossover operation.
- Adaptive crossover probability. This study introduces variety of population strategies to reduce the possibility of early convergence and improve the speed of population convergence. In this way, the antibody population is divided into three subpopulations, and then a migration operator is designed to exchange several antibodies in each subgroup.
- Memory library. In the process of population evolution, due to selection, crossover, mutation and other genetic operations, the better antibody structure in the current population may be destroyed, which will affect the efficiency and convergence of the algorithm. In order to solve this problem, a memory library is designed in this paper to keep the individuals with higher affinity to the next generation, so as to speed up the convergence of the algorithm.

4. Case Study

4.1. Experimental Scenario

Based on the actual data of Kunming Changshui International Airport, this section designs experiments to verify the model. The flight data of an airline company from Changshui International Airport on Dec. 24, 2019 are selected to carry out the gate assignment experiment. 81 flights would be assigned to 19 available gates, including 10 contact stands and 7 remote stands. All flights in the experiment are domestic flights, involving three types of aircraft. See Table 3-5 for some flight and gate information.

Table 3. Departure (overnight) flight data.

Flight number	Serial	Aircraft model	Actual time of arrival	Estimated time of departure	Number of passengers	Original Gate
1		A319	14:48	7:30	117	19
2		A320	16:54	7:00	186	5
...	

10	A319	0:37	12:55	136	17
11	A319	0:50	10:30	130	13

Table 4. Overnight flight data

Flight number	Serial	Aircraft model	Actual time of arrival	Estimated time of departure	Number of passengers
12		A320	7:59	9:00	171
13		A319	8:02	8:25	141
...	
86		A320	22:34	0:05	265
87		A320	22:37	23:50	181

Table 5. Gate data

Gate number	Serial	Property of corridor bridge	international/ domestic	Aircraft allowed to parking	Models	Default boarding gate
1		Near gate	domestic	737/319/320		No.7
2		Near gate	domestic	737/319/320		No.8
...	
9		Near gate	domestic	737/319/320		No.4
10		Near gate	domestic	737/319/320		No.5

4.2. Result Analysis

In the experiment, the minimum safety time interval between consecutive flights at the same airport is set as 10 minutes, and the that between adjacent aircraft slipping in and out is set as 5 minutes, according to the actual investigation. For the improved immune genetic algorithm, the population size is set as 100 and the evolutionary generation is set as 200 generations.

After running the experiment, the part of results are shown in Table 6. In terms of improving the utilization rate of contact stands, the number of flights allocated to contact stands is 78, and the number of flights allocated to remote stands is 9. The flight docking rate is equals to 89.65%, and the number of passengers who use corridor bridge equals to 15,407. The rate of passengers staying on the bridge reached 93.92%. According to statistics, in the case of manual allocation of parking spaces at the airport that day, 68 of 87 flights are allocated to contact stands and 19 flights are allocated to remote stands. The rate of bridge landing is 78.16%, and the number of passengers leaning on the bridge is 15046. The passenger docking rate is 76.15%, which is 11.49% higher than the actual manually allocated flight docking rate at the airport, and the passenger docking rate increased by 17.77%. It can be seen that both the passenger docking rate and the flight docking rate are improved. Note that, the comparison of present work with the reported research is not implemented because other methods proposed in existing methods are not applied in the actual situation.

Table 6. Calculation result of model allocation

Flight number	Docked flight	Collision probability	Passenger number
1	6, 31, 39, 53, 61, 70, 81	0.8875	1712
2	11, 26, 45, 83	0.5919	867
...
18	54		89
19	30, 46, 75	0.3132	290
Total		5.2972	16403

The convergence curve of the improved immune genetic algorithm solution process is shown in Figure 1. It can be seen from the figure that the algorithm has a good efficiency for solving the model.

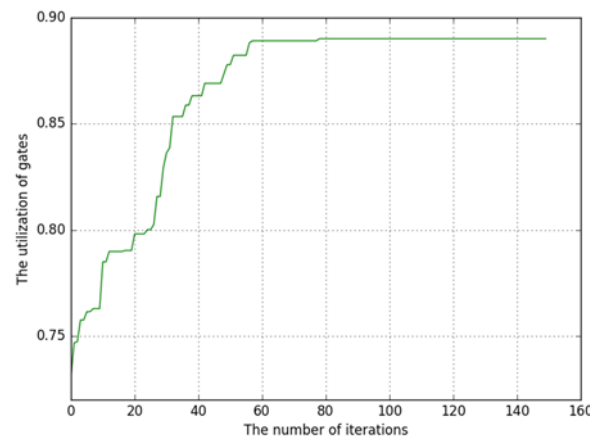


Figure 1. Iterative curve of improved immune genetic algorithm.

5. Conclusions

In this paper, based on the basic constraints of AGA, complex business rules constraints such as aircraft towing, restrictions on adjacent aircraft models, and conflicts between flight slip in and out are further considered to develop an AGA model. The model aims to maximize the passenger docking rate. The improved immune genetic algorithm is designed to solve the model. The algorithm effectively avoids the phenomenon of population degradation while maintaining population diversity, and significantly improves the running speed of the algorithm. In addition, based on the actual data from Kunming Changshui International Airport, we design an experiment to verify the model. The experimental results indicate that the model and algorithm proposed in this paper are feasible and effective.

In the actual operation of airport, the flight delay propagation often has an impact on the AGA. In this study, the AGA model aims to improve the passenger docking rate, and thus lose to buffer the space for delay propagation. In order to improve the anti-interference of the results, future research will add robust constraints in the AGA model to further improve the anti-delay characteristics.

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