Hindawi
Mathematical Problems in Engineering
Volume 2021, Article ID 6693127, 8 pages
https://doi.org/10.1155/2021/6693127

Research Article

Robust Airport Gate Assignment Based on the Analysis of Flight Arrival Time

Caimao Tan [1] **and Junliang He** [2]

[1] *China Institute of FTZ Supply Chain, Shanghai Maritime University, Shanghai, China*
[2] *Engineering Research Center of Container Supply Chain Technology, Ministry of Education, Shanghai Maritime University, Shanghai, China*

Correspondence should be addressed to Junliang He; soldierlianglian@163.com

Received 30 December 2020; Revised 22 January 2021; Accepted 5 February 2021; Published 18 February 2021

Academic Editor: Lu Zhen

At present, hub airport is facing a lot of emergency situations, e.g., the management of irregular flight, which affects the sustainable development of the airport. Most of the methods for evaluating the robustness of airport gate assignment have been proposed by giving an independent evaluation function based on their experience, and thus, subjective factors are involved in varying degrees. Therefore, this paper puts forward an objective evaluation method based on the analysis of airport flight arrival, which gives a digital transformation strategy for the airport resource scheduling. A novel evaluation method based on data analysis of flight arrival time, and a mathematical model are formulated accordingly. In order to solve the proposed NP-hard problem, a new hybrid genetic algorithm combined with a heuristic algorithm is designed. In numerical experiments, the actual flight data of an international hub airport are used to analyze and verify the effectiveness of the proposed method. The results showed the advantages in scheme stability, operating cost savings, and risk reduction of the proposed method.

1. Introduction

Air transportation and maritime transportation are the main parts of international freight transport [1, 2]. During the past thirty years, the air transport traffic has roughly doubled [3]. Airport gate assignment (AGA) is about finding an assignment of flight to terminal or ramp positions called gate, and it is a key activity in airport operations [4]. Airport gate assignment is generated in advance based on the flight initial schedule, including the number of flights, departure/arrival time, and flight's ground service time [5]. However, irregular flight arrival challenges the AGA of the airport and leads to difficulties in the implementation of the initial plan.

Uncertainties are common in the scheduling of production and operation [6–8]. Flight delays or arrival in advance is common at many airports. About 30 percent of flights were irregularly arrived, and it was the fourth straight year that delays increased on intra-European flight, according to the statistics of the AEA (Association of European Airline). The flight irregular arrival poses tremendous challenges to airport management in airline recovery (flight recovery, aircraft recovery, crew recovery, and airport gate plan recovery) and passenger arrangement. More importantly, if this situation has not been handled properly could trigger a wider-scale flight irregular arrival. Therefore, a robust assignment plan seems to be very judicious and necessary.

Up to now, there are numerous works on gate assignment problem, and various models and solution methods were proposed. A comprehensive overview of exploring methods and models is given by Orden [9]. Therefore, a brief review of robust airport assignment is presented in this paper which is highly related to robust airport gate assignment (RAGA). Bolat [10] proposed a mathematical model to assign the flight with the minimum range of unoccupied time periods of gates. Following the robust gate assignment, Bolat [11] has given a procedure to provide solutions with a minimum dispersion of idle periods for

static aircraft-gate assignment problems. Subsequently, Bolat [11] formulated a mathematical model with a quadratic function for minimizing the variance of idle time at the gates to make the initial assignments insensitive to variations in flight schedules.

Lim and Wang [12] attempted to accurately build an evaluation criterion for the ability of an aircraft-to-gate assignment to handle uncertainty on aircraft schedule. A RAGA method was presented by a stochastic programming model, and then it was transformed into a binary programming model by introducing the unsupervised estimation functions without knowing any information about the real-time arrival and departure time of aircraft in advance. Dorndof et al. [4] transformed the AGA problem into a clique partitioning problem (CPP), and several major advantages to this transformation are explained, including the availability of effective algorithms for the CPP, increased simplicity in approach by placing data on the objectives and restrictions within a complete graph, and the easy integration of a robustness objective.

Yan et al. [5] addressed the AGA problem with both deterministic and stochastic flight departure/arrival time. A 0-1 integer programming model was formulated to minimize the total inconsistency value. In the study of Diepen et al. [13], each gate plan consists of a subset of flights that can be assigned to a single gate of the corresponding type, and gates with identical characteristics are aggregated in gate types. Besides, Diepen et al. [13] have given a cost function based on the idle time between consecutive flights to evaluate the robustness of the AGA plan 10. Narciso and Piera [14] studied AGA procedures from an airport management perspective. A simulation-based experimental approach that evaluates the minimum amount of stands at the terminal necessary to cope with arrival/departure pattern traffic under a time delay limit was presented. Dorndorf et al. [4] divided the objectives of AGA into deterministic goals (e.g., maximization of the total assignment preference score and a minimal number of unassigned flights during overload periods) and stochastic goals (minimizing the expected number of any kind of constraint violations). Meanwhile, a procedure for recovery planning that has proved its practical relevance at numerous airports was presented. Schaijk et al. [15] presented a novel method to improve the robustness of solutions to the AGA problem, which aims to reduce the need for gate replanning due to unpredicted flight schedule disturbances. The deterministic gate constraints were replaced by stochastic gate constraints which incorporate the inherent stochastic flight delays in such a way so as to ensure the expected gate conflict probability of two flights assigned to the same gate at the same time does not exceed a user-specified value. Xu et al. [16] proposed a RAGA model to minimize the $(1-\alpha)$-quantile of the total real-time overlap between consecutive flights at the same gate (the total gate blockage time), so that the realized total gate blockage time is worse than its quantile with a probability α. Besides, a solution-dependent uncertainty budget is introduced to develop a robust counterpart for the RAGA problem.

All these studies on RAGA are specific and effective. However, the vast majority of the robust evaluation function is subjective-based and characteristic while there is a very important fact that the flight irregular arrival patterns of different airports are diverse. Besides, for evaluating the robustness of the AGA plan, many evaluation functions based on subjective experience are involved. Therefore, a more specific research on the method to evaluate the robustness of AGA in an objective way is necessary.

This paper proposed an assignment robustness evaluation approach, which is based on the analysis of airport flight irregular arrival patterns, and hence, the author's subjective factors are ignored to an extent. A mixed-integer programming model is built accordingly. A hybrid genetic algorithm is designed, since the AGA problem is a typical NP-hard problem. In numerical experiments, the real data of an international hub airport are used to analyze on the RAGA model and its robustness is provided.

2. Background

2.1. Robustness. Robustness is a term used in the system control field, which refers to the ability of the system to withstand the internal and external environment interference and maintain the system stability. In general, robustness can be understood as stability, insensitivity, or fault tolerance. Robustness has been a hot issue in recent years, and it has been applied to many fields. For airport gate assignment, the robustness is the anti-interference ability of the gate assignment plan. In other words, it means the capacity to reduce flight plan alteration and restore to the normal state caused by the flight delay or arrival in advance.

In many other fields, the measurable indicators of robustness are specified. For example, in the engineering structure area, the structural properties, local damage, and structural reliability can be served as a quantitative indicator of robustness. However, for airport gate assignment, there still has no uniform standard.

Generally, the interval (buffer time) variance between consecutive flights assigned in the same gate can be a proper indicator. The smaller the variance is, the stronger the robustness is. It seems a reasonable indicator. However, it may not always be correct in certain cases. Bloat [17] denied this perspective and pointed out that this method could lead to the opposite result in specific instances. As shown in Figure 1, the variances of assignment plan A and plan B are equal to 1.67 and 0.92, respectively, while the former is more optimal in airport practice although the former variance is bigger.

2.2. Robustness Evaluation. This paper attempts to consider robustness as the tolerance ability for irregular flight arrivals. Specifically, the robustness of gate assignment represents the flight irregular arrival (delay or in advance) tolerating the interval of consecutive flights. As Figure 2 shows, for a given flight i, the robustness would be directly related to the interval (x_i) between flight $(i-1)$. It means that this interval can tolerate x_i delay of flight i or x_i arrival in advance of flight $i-1$.

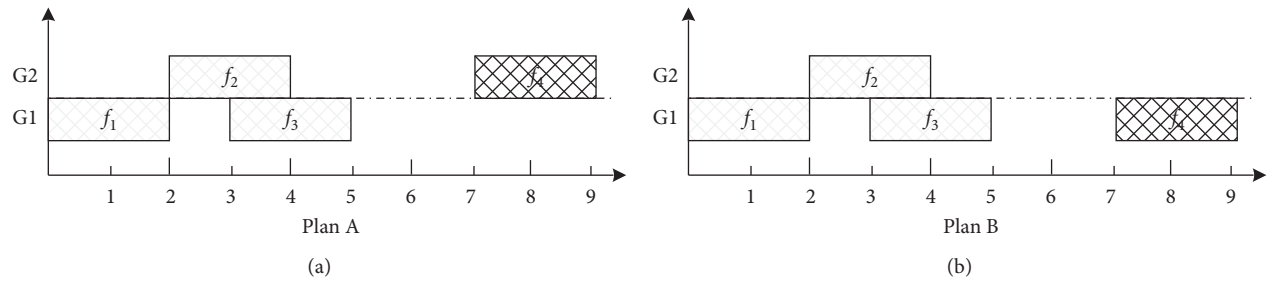

Figure 1: Illustration of two different AGA plans.

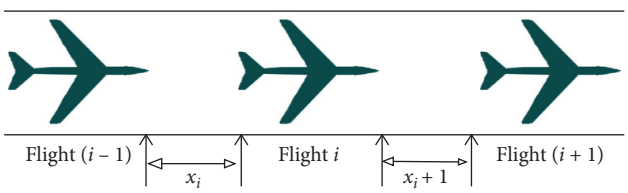

Figure 2: Flight interval diagram.

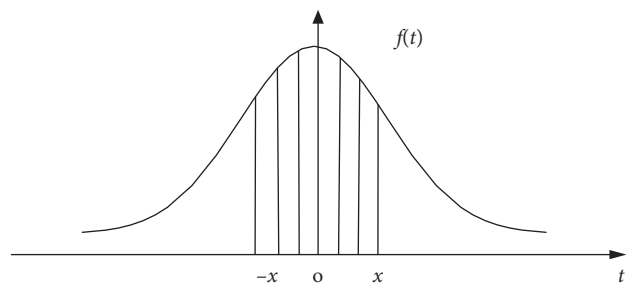

Figure 3: Probability distribution of flight irregular arrival.

Let us assume that $f(t)$ is the probability density function of airport flight irregular arrival (as shown in Figure 3), and the interval time is $x\,(x \geq 0)$, the flight in which the irregular arrival time $t \in [-x, x]$ can park normally. Define $\phi(x) \in (0,1)$ as the robustness value; we can reach the following robustness evaluation expression based on the theory of statistical:

$$\begin{aligned}\phi(x) &= P\{-x \leq t \leq x\} = F(x) - F(-x) \\ &= \int_{-x}^{x} f(t)\mathrm{d}t, \quad t \in (-\infty, \infty).\end{aligned} \tag{1}$$

Accordingly, when we get the distribution of flight irregular arrival at an airport, then we will be able to figure out the detailed robustness evaluation function.

3. Model Building

3.1. Notation Description. Define $F = \{f_1, f_2, \ldots, f_M\}$ as the airport flight set and $G = \{g_1, g_2, \ldots, g_N\}$ as the airport gate set. The gate opening time window is $[s, t]$ and $0 \leq s < t \leq 24$. The flight estimated arrival time and estimated departure time are a_i and d_i, respectively, and for all of the flights, $s \leq a_i < d_i \leq t$ should be satisfied. A concept of dummy flight is applied in this model to calculate the interval of first flight in each gate. Define the gate dummy flight set $F' = \{f_{m+1}, f_{m+2}, \ldots, f_{M+N}\}$; it is remarkable that one gate corresponds to one dummy. Let δ represent the minimum flight connection time andρ represent the safety time interval of two consecutive flights in the same gate, and for a given flight $f_i \in F'$, $a_i = -(\delta + \rho)$ and $d_i = s - \rho$. Let f_{im} represent the number of passengers from flight i to gate m [18], $r_{m,n}$ represent the distance between gate m and gate n, and ζ be an infinite positive.

x_{im} is equal to 1 when flight i is assigned to gate m, otherwise equal to 0. y_{im} is equal to the time interval of flight i with the former consecutive flight in the gate m. FF_{im} is equal to 1 when flight i is the first flight parking in gate m, otherwise equal to 0. LF_{im} is equal to 1 when flight i is the last flight parking in gate m, otherwise equal to 0. ψ_{ijm} is equal to 1 when flight i and flight j are assigned to gate m, and flight i and flight j are parked in succession or sequentially, otherwise equal to 0.

3.2. Mathematical Model. A mathematical model is formulated as follows:

$$\text{minimize } z_1 = \sum_{i \in F} \sum_{m \in G} \sum_{n \in G} x_{im} f_{in} r_{mn}, \tag{2}$$

$$\text{maximize } z_2 = \sum_{i \in F} \sum_{m \in G} \phi(y_{im}), \tag{3}$$

$$\sum_{m \in G} x_{im} = 1, \quad \forall i \in F \cup F', \tag{4}$$

$$\sum_{i \in F \cup F'} FF_{im} \leq 1, \quad \forall m \in G, \tag{5}$$

$$\sum_{i \in F \cup F'} LF_{im} \leq 1, \quad \forall m \in G, \tag{6}$$

$$FF_{im} \leq x_{im}, \quad \forall i \in F \cup F', m \in G, \tag{7}$$

$$LF_{im} \leq x_{im}, \quad \forall i \in F \cup F', m \in G, \tag{8}$$

$$x_{im} - LF_{im} = \sum_{j \in F \cup F_I} \psi_{ijm}, \quad \forall i \in F \cup F', m \in G, \tag{9}$$

$$x_{jm} - FF_{jm} = \sum_{i \in F \cup F_I} \psi_{ijm}, \quad \forall i \in F \cup F', m \in G, \tag{10}$$

$$a_j + \zeta\left(1 - \psi_{ijm}\right) \geq d_i + \rho, \quad \forall j \in F \cup F', j \in F, m \in G, \tag{11}$$

$$a_i + \delta \leq d_i, \quad \forall i \in F, \tag{12}$$

$$y_{jm} = \sum_{i \in F \cup F_I} \psi_{ijm}\left(a_j - d_i\right), \quad \forall j \in F \cup F', m \in G, \tag{13}$$

$$FF_{i(i-M)} = 1, \quad \forall i \in F', \tag{14}$$

$$x_{im}, FF_{im}, LF_{im} \in \{0, 1\}, \quad \forall i \in F \cup F', m \in G, \tag{15}$$

$$\psi_{ijm} \in \{0, 1\}, \quad \forall i, j \in F \cup F', m \in G. \tag{16}$$

The assignment objective function reflects the administrator's decision-making preference, and it affects the effectiveness of the assignment plan. The objective functions of this model are to minimize the passenger walking distance and to maximize the assignment plan robustness simultaneously and correspond to formulas (2) and (3), respectively. Formula (4) is the flight gate uniqueness constraint which defines one flight must be assigned to a proper gate. Formulas (5)–(10) are the logical constraints to ψ_{ijm}, these constraints ensure ψ_{ijm} is equal to 1 only when flight i and flight j are assigned to gate m, and flight i and flight j are parked in succession or sequentially, otherwise equal to 0. Formula (11) ensures the consecutive flight intervals in the same gate. Formula (12) ensures the flight satisfies the minimum connection time. Formula (13) is the computational expression of flight intervals. Formula (13) is the assignment constraint of dummy flight, and the dummy flight of each gate must be the first parking flight of the gate. Formulas (15) and (16) show the domain of variables.

4. Hybrid Genetic Algorithm

The AGA problem is a typical quadratic assignment problem, which has been considered as an NP-hard problem [19]. Generally speaking, an NP-hard problem cannot be solved effectively by general optimization methods with large scale [20, 21]. Genetic algorithm has been widely used in many engineering fields to solve the NP-hard problem, and its effectiveness has been commendably verified. In this paper, based on the classical genetic algorithm, a heuristic algorithm is combined with the actual operation of AGA. The hybrid genetic algorithm procedure is shown in Algorithm 1.

4.1. Chromosome Design. The appropriate chromosome coding method is significant for the efficiency of the genetic algorithm. The general binary code is not suitable for the airport gate assignment problem obviously. In order to avoid the increase in the length of the chromosome dramatically with the number of airport flights, real number coding method is applied, and the chromosome structure is shown in Figure 4. The chromosome locus represents the gate number, and the value corresponds to the assigned flight.

4.2. Population Initialization. In the genetic algorithm, the initial population generation has a profound influence on the performance of the algorithm. Compared with the general assignment problem, the random initial population generation method may generate a lot of infeasible solutions for the AGA problem, and this would reduce the feasible solution set greatly. Therefore, a heuristic algorithm is designed in the population generation. The proposed heuristic algorithm basic steps are as shown in Figure 5.

The size of the initial population in the genetic algorithm usually adopts a constant number. Generally speaking, the larger the population size is, the better the solution is. However, the computing time will also be increased with the population size synchronously, and the normal value is 100~1000 [22]. In this paper, the number of population is set to 100.

4.3. Fitness Evaluation. Since the model established in this paper is a multiobjective model, a method is applied to convert the multiobjective optimization problem into a monoobjective, and the fitness function can be designed as shown in formula (17). As mentioned above that $\phi(y_{i,m}) \leq 1$, so that $k \geq 1$.

$$\text{Fit} = \sum_{i \in F} \sum_{m \in G} \sum_{n \in G} x_{i,m} f_{i,n} r_{m,n}\left(k - \phi\left(y_{i,m}\right)\right). \tag{17}$$

4.4. Genetic Operation. Genetic operations included crossover, mutation, and selection. In order to overcome the infeasible solution problem caused by the crossover and mutation, the crossover and mutation operation is improved.

4.4.1. Crossover. Crossover is the exchange of parent chromosome genes, this paper used the single-point crossover, and the crossover point cuts are randomly selected. To prevent genetic algorithms from local optimum and improve the search performance, the crossover probability of the chromosome Pc is set at a relatively high level of 0.9.

4.4.2. Mutation. Mutation is the genetic factor which randomly changes and creates a new chromosome gene, and this could maintain the population diversity. In order to avoid infeasible individuals, chromosome gene reparation is necessary. In this paper, the procedure for population initialization is used to repair the infeasible solutions.

4.4.3. Selection. The usual population selection method includes fitness proportion, expected value selection, ranking selection method, and elite preservation method, and this paper is exercised by the tournament selection method [23, 24].

```
(1) Begin
(2) t = 0;
(3) Initialize P (t);
(4) Evaluate P (t);
(5) While not finished do
(6) Begin
(7) t = t + 1;
(8) Genetic operate P (t);
(9) Evaluate P (t);
(10) End
(11) End
```

Algorithm 1: Procedure of hybrid GA.

Gate no.	1	3	4	8	1	...	S_i
Flight no.	f_1	f_2	f_3	f_4	f_5	...	f_i

Figure 4: Chromosome representation.

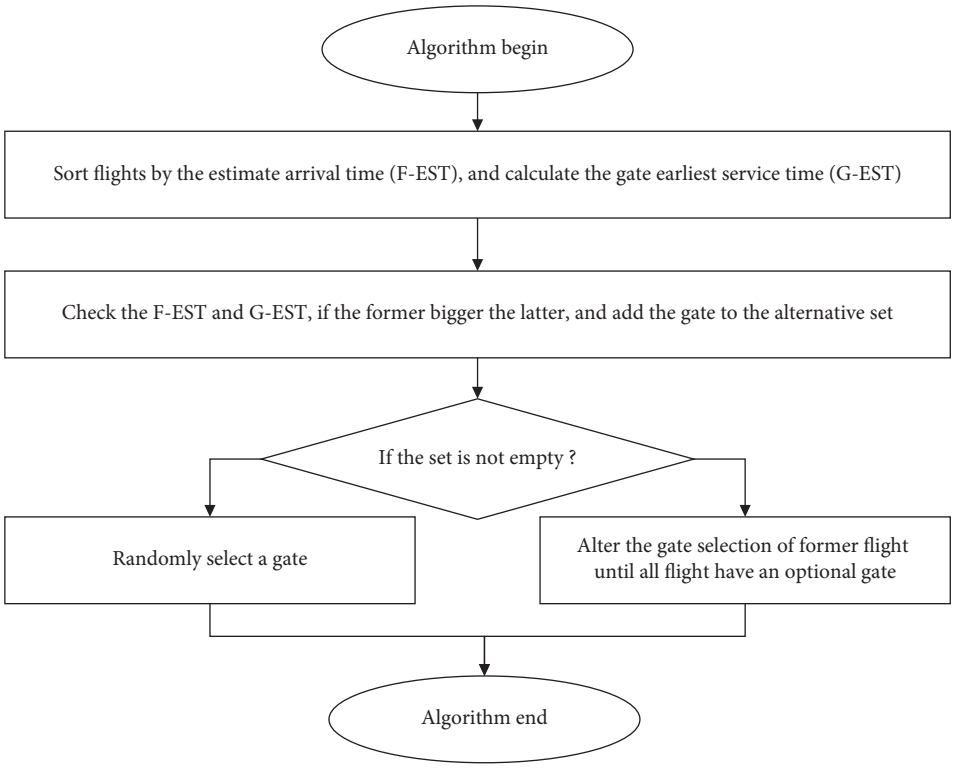

Figure 5: Process for population generation.

5. Numerical Experiment

5.1. Case Study. We analyzed 919 flights (including 531 domestic flights and 388 international flights) irregular arrival time of an international hub airport from November 4, 2015, to November 6. As shown in Figure 6, these data are in line with the normal distribution.

In order to get the accurate distribution parameter values, the SPSS is used to analyze those flights of irregular arrival data. With K-S (Kolmogorov–Smirnov) test, the detailed parameters are shown in Table 1.

Accordingly, the flight probability distribution density function and robustness evaluation function of this airport can be defined as follows:

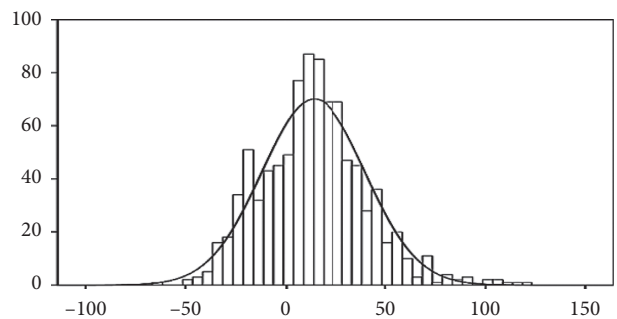

Figure 6: Flight irregular arrival histogram.

Table 1: The K-S test results.

Indicators	Mean	Standard deviation	Significance (2-tailed)
Value	13.84	24.15	0.056

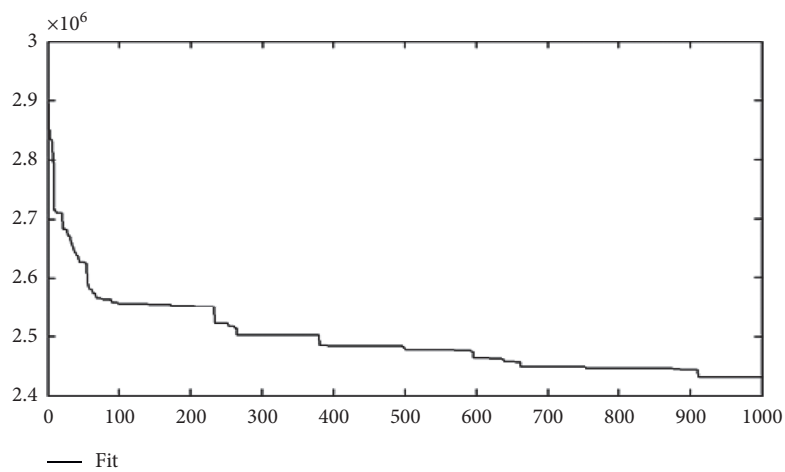

Figure 7: Optimal value convergent graph.

$$f(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\left((t-13.84)^2/2\times 24.15^2\right)}, \quad -\infty < t < \infty, \tag{18}$$

$$\phi(x) = P\{-x \le t \le x\} = F(x) - F(-x) = \int_{-x}^{x} f(t)\mathrm{d}t = \int_{-x}^{x} \frac{1}{\sqrt{2\pi}\times 24.15} e^{-\left((t-13.84)^2/2\times 24.15^2\right)}\mathrm{d}t. \tag{19}$$

5.2. Efficiency of the Proposed Solution Method. To verify the validity of the GA algorithm, this paper used the airport real flight information in the model which includes 100 arrival flights and 28 alternative gates. The gate flight interval time is 5 minutes and the minimum connection time is 40 minutes.

The proposed algorithm is solved by MATLAB R2011a, and all of the computation experiments are conducted on a workstation with Intel Xeon CPU with 64 GHz RAM. The effective results can be obtained in nearly 10 minutes, and the convergence of the optimal value is good. Figure 7 is a convergent graph when $k = 2.0$, and the optimal solutions with different k values are shown in Table 2.

5.3. Effectiveness of the Proposed Method. To verify the effectiveness of the proposed RAGA model in the robustness, the comparison between the RAGA model and the general AGA model [22] is made by the gate assignment deal with a series of flight irregular arrival interferes. To decrease data contingency, 10 groups of flight interfere data which were randomly generated (based on airport flight irregular arrival pattern) are tested, and each group contains 10 irregular flights.

The airport gate real-time assignment (AGRA, [25]) model is used to recover the airport initial gate assignment plan (generated by the general AGA model, Diepen et al.'s [13] RAGA model, and the proposed RAGA model,

Table 2: Optimal solutions with different k values.

Parameter	Z_2	Z_1
$k = 1.0$	2867250 m	96.58
$k = 1.5$	2740390 m	95.54
$k = 2.0$	2529600 m*	92.79*
$k = 2.5$	2556110 m	90.70
$k = 3.0$	2526340 m	99.92

Table 3: Results of the AGA model and the RAGA model.

Statistical indicators	AGA	Diepen et al.'s	RAGA
Passenger walking distance	2438890 m	2682330 m	2529600 m
Mean of flight gate change	16	7	4
Variance of flight gate change	0.99	1.8	0.23

respectively), and the recovery objective is minimum gate plan change. The recovery results are shown in Table 3. As we can observe the distinct advantages in robustness the RAGA model has over the AGA model, there is only a relatively weak position in passenger walking distance.

6. Conclusion Remarks

This paper proposed a robustness evaluation approach for airport gate assignment and an assignment mathematical model. Meanwhile, to solve the NP-hard problem of large scale, a hybrid genetic algorithm is also designed. The numerical experiments showed a positive result of the proposed evaluation method, mathematical model, and hybrid algorithm. Moreover, a digital transformation strategy can be obtained for the airport resource scheduling. Therefore, this study has a certain practical significance to airport gate management.

Since the main purpose of this paper is to address the assignment robustness, as a result, many practical assignment issues have been ignored in the model building, such as aircraft model, airline specific gate, and parking priority.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] J. L. He, Z. W. Jin, C. M. Tan, Y. Wang, and H. Yu, "Yard template generation in a container terminal considering time requirement of vessel operation," *Asia-Pacific Journal of Operational Research*, 2021.

[2] L. Zhen, "Modeling of yard congestion and optimization of yard template in container ports," *Transportation Research Part B: Methodological*, vol. 90, pp. 83–104, 2016.

[3] C. Yu, D. Zhang, and H. Y. K. Lau, "An adaptive large neighborhood search heuristic for solving a robust gate assignment problem," *Expert Systems with Applications*, vol. 84, pp. 143–154, 2017.

[4] U. Dorndof, F. Jaehn, and E. Pesch, "Modelling robust flight-gate scheduling as a clique partition problem," *Transportation Science*, vol. 42, pp. 292–301, 2008.

[5] S. Yan, C.-H. Tang, and Y.-Z. Hou, "Airport gate reassignments considering deterministic and stochastic flight departure/arrival times," *Journal of Advanced Transportation*, vol. 45, no. 4, pp. 304–320, 2011.

[6] J. He and C. Tan, "Modelling a resilient yard template under storage demand fluctuations in a container terminal," *Engineering Optimization*, vol. 51, no. 9, pp. 1547–1566, 2019.

[7] L. Zhen, "Tactical berth allocation under uncertainty," *European Journal of Operational Research*, vol. 247, no. 3, pp. 928–944, 2015.

[8] J. He, C. Tan, and Y. Zhang, "Yard crane scheduling problem in a container terminal considering risk caused by uncertainty," *Advanced Engineering Informatics*, vol. 39, pp. 14–24, 2019.

[9] V. Orden, "Gate assignment: methods and models," Masters thesis, Utrecht University, Utrecht, Netherlands, 2002.

[10] A. Bolat, "Assigning arriving flights at an airport to the available gates," *Journal of the Operational Research Society*, vol. 50, no. 1, pp. 23–34, 1999.

[11] A. Bolat, "Models and a genetic algorithm for static aircraft-gate assignment problem," *Journal of the Operational Research Society*, vol. 52, no. 10, pp. 1107–1120, 2001.

[12] A. Lim and F. Wang, "Robust airport gate assignment," in *Proceedings of the 17th IEEE International Conference on Tools with Artificial Intelligence (ICTAI 2005)*, Hong Kong, China, 2005.

[13] G. Diepen, J. M. Van Den Akker, J. A. Hoogeveen, and J. W. Smeltink, "Finding a robust assignment of flights to gates at amsterdam airport schiphol," *Journal of Scheduling*, vol. 15, no. 6, pp. 703–715, 2012.

[14] M. E. Narciso and M. A. Piera, "Robust gate assignment procedures from an airport management perspective," *Omega*, vol. 50, pp. 82–95, 2015.

[15] V. Schaijk, R. P. Oscar, and H. G. Visser, "Robust flight-to-gate assignment using flight presence probabilities," *Transportation Planning and Technology*, vol. 40, pp. 928–945, 2017.

[16] L. Xu, C. Zhang, F. Xiao, and F. Wang, "A robust approach to airport gate assignment with a solution-dependent uncertainty budget," *Transportation Research Part B: Methodological*, vol. 105, pp. 458–478, 2017.

[17] A. Bolat, "Procedures for providing robust gate assignments for arriving aircrafts," *European Journal of Operational Research*, vol. 120, no. 1, pp. 63–80, 2000.

[18] R. A. Bihr, "A conceptual solution to the aircraft gate assignment problem using 0, 1 linear programming," *Comput. Ind. Eng.*vol. 19, no. 1–4, pp. 280–284, 1990.

[19] L. Zhen, Z. Liang, D. Zhuge, L. H. Lee, and E. P. Chew, "Daily berth planning in a tidal port with channel flow control," *Transportation Research Part B: Methodological*, vol. 106, pp. 193–217, 2017.

[20] L. Zhen, E. P. Chew, and L. H. Lee, "An integrated model for berth template and yard template planning in transshipment hubs," *Transportation Science*, vol. 45, no. 4, pp. 483–504, 2011.

[21] L. Zhen, Z. Xu, K. Wang, and Y. Ding, "Multi-period yard template planning in container terminals," *Transportation Research Part B: Methodological*, vol. 93, pp. 700–719, 2016.

[22] D. X. Wei and C. Y. Liu, "Airport gate reassignment problem," *Journal of Transportation Systems Engineering and Information*, vol. 7, pp. 57–69, 2009.

[23] C. Tan and J. He, "Integrated proactive and reactive strategies for sustainable berth allocation and quay crane assignment under uncertainty," *Annals of Operations Research*, 2021.

[24] J. He, Y. Wang, C. Tan, and H. Yu, "Modeling berth allocation and quay crane assignment considering QC driver cost and operating efficiency," *Advanced Engineering Informatics*, vol. 47, Article ID 101252, 2021.

[25] X. Chen, X. Lu, and J. F. Zhu, "The model and algorithm of airport gate assignment," *Journal of Traffic and Transportation Engineering*, vol. 6, pp. 88–90, 2006.