Study on an airport gate assignment method based on improved ACO algorithm

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Abstract

Purpose – This study aims to propose a new airport gate assignment method to effectively improve the comprehensive operation capacity and efficiency of hub airport. Gate assignment is one of the most important tasks for airport ground operations, which assigns appropriate airport gates with high efficiency reasonable arrangement.

Design/methodology/approach – In this paper, on the basis of analyzing the characteristics of airport gates and flights, an efficient multi-objective optimization model of airport gate assignment based on the objectives of the most balanced idle time, the shortest walking distances of passengers and the least number of flights at apron is constructed. Then an improved ant colony optimization (ICQACO) algorithm based on

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the ant colony collaborative strategy and pheromone update strategy is designed to solve the constructed model to fast realize the gate assignment and obtain a rational and effective gate assignment result for all flights in the different period.

Findings – In the designed ICQACO algorithm, the ant colony collaborative strategy is used to avoid the rapid convergence to the local optimal solution, and the pheromone update strategy is used to quickly increase the pheromone amount, eliminate the interference of the poor path and greatly accelerate the convergence speed.

Practical implications – The actual flight data from Guangzhou Baiyun airport of China is selected to verify the feasibility and effectiveness of the constructed multi-objective optimization model and the designed ICQACO algorithm. The experimental results show that the designed ICQACO algorithm can increase the pheromone amount, accelerate the convergence speed and avoid to fall into the local optimal solution. The constructed multi-objective optimization model can effectively improve the comprehensive operation capacity and efficiency. This study is a very meaningful work for airport gate assignment.

Originality/value – An efficient multi-objective optimization model for hub airport gate assignment problem is proposed in this paper. An improved ant colony optimization algorithm based on ant colony collaborative strategy and the pheromone update strategy is deeply studied to speed up the convergence and avoid to fall into the local optimal solution.

Keywords Robust optimization, Performance analysis, Airport gate assignment, Improved ant colony optimization algorithm, Multi-objective optimization model

Paper type Research paper

1. Introduction

Gate is an important resource in the airport. It is one of the most critical factors to realize the rapid and safe calling, ensure the effective cohesion and improve the comprehensive operation efficiency of the whole airport (Ding *et al.*, 2004). The airport gate assignment is to assign the appropriate gates to the arrival and departure flights according to the layout of gates, the type of aircrafts, the arrival and departure time of flights and so on. The goal of gate assignment is to ensure that the flights are normal and without delay. And the airport gate assignment result not only is related to the safe and smooth operation of the airport scene but also has great influence on ensuring the normal implementation of flight plan, reducing transportation costs and providing good service for passengers (Vranas *et al.*, 1994). Therefore, the gate assignment has great theoretical significance and practical value to ensure the safe and smooth operation of airport.

Due to the limitations of more financial resources and time through establishing new gates, the reasonable and efficient gate assignment methods can effectively improve the utilization efficiency of airport gates. Therefore, the airport gate assignment problem has been more deeply and extensively studied, and a lot of airport gate assignment models and methods are proposed in recent decades (Robert and Michael, 1997; Merve and Nilay, 2012; Deng *et al.*, 2017a; Dell'Orco *et al.*, 2017). These proposed gate assignment models and methods can be summarized as the expert system method, the mathematical programming method and artificial intelligence method (van Schaijk and Visser, 2017; Yu *et al.*, 2017; Daş, 2017). Because one hub airport has the complex layout and more flights, the gate assignment is an non-deterministic polynomial (NP) hard problem. The expert system method is to establish the knowledge base system through the configuration principle and considering non-quantitative criteria. This method ignores the key factors, which result in the unsatisfactory configuration results. The mathematical programming method is to select the optimization objective function and use the 0-1 integer programming to explore the configuration feasibility. The artificial intelligence algorithm is to assign the complex optimization problems, and it often falls into the local optimal solution. However, when the number of flights is thousands, it is difficult to meet the requirement of real-time process. Because many impact factors will affect gate assignment result, the various factors need be considered to construct an optimization objective function according to the actual operation demand of airport. And a fast and effective algorithm need be designed to solve the optimization objective function of airport gate assignment. Therefore, it has greatly theoretical significance and actual application value to study the airport gate assignment.

Ant colony optimization (ACO) algorithm is a typical swarm intelligence optimization algorithm (Colorni *et al.*, 1999). Pheromone in the ACO algorithm plays an important role in the mutual collaboration between ants. The ants can leave pheromones on the passed path and choose walking path according to the pheromone concentration. It uses the pheromone to better control the diversity of population, avoid to fall into premature stagnation and take on strong spatial exploration capabilities. However, because the traditional ACO algorithm uses the fixed increasing and reducing the pheromone to update the pheromone concentration, which is easy to appear the slow convergence speed, it falls into the local optimal value and uses the long operation time and so on. Therefore, the traditional ACO algorithm needs to be improved to improve the optimization performance of the ACO algorithm.

In this paper, the domestic airports and their operation managements need to be deeply studied and analyzed. From the view of passengers, airlines and airport operation and control, the objectives of the most balanced idle time, the shortest walking distances of passengers and the least number of flights at apron are selected to comprehensively construct an efficient multi-objective optimization model of airport gate assignment according to actual operation demand. And the formula and range of pheromone update strategy in the traditional ACO algorithm is improved to speed up the convergence speed and avoid to fall into the local optimal solution. The improved ant colony optimization (ICQACO) algorithm is designed to obtain the better optimization performance for solving complex problem. Then the designed ICQACO algorithm is used to solve the constructed multi-objective optimization model to obtain a rational and effective airport gate assignment result for all flights in the different period. An actual flight data from Guangzhou Baiyun airport of China is selected to verify the effectiveness of the constructed model and the designed ICQACO algorithm. The experiment results are analyzed and compared in detail.

The remainder of the paper is organized as follows. The related works are described in Section 2. The airport gate assignment problem is described in Section 3. The optimization model of airport gate assignment is constructed in Section 4. In Section 5, the ACO algorithm and its improvement are deeply studied. The gate assignment method based on the ICQACO algorithm is introduced in detail in Section 6. In Section 7, data simulation and experiment analysis are introduced in detail. Finally, the conclusions are offered and future research direction is discussed in Section 8.

2. Related works

The gate assignment problems have been deeply studied, and better research results are obtained in recent years. A lot of researchers have proposed many airport gate assignment models and solving algorithms. For gate assignment models, Takashi *et al.* (1987) proposed a novel approach for the one-dimensional gate assignment problem. The original minimization problem is transformed into a restricted problem and then a heuristic algorithm is applied to it. Cheng (1997) proposed a knowledge-based airport gate assignment system integrated with mathematical programming techniques to provide a solution that satisfies both static and dynamic situations within a reasonable computing time. Haghani and Chen (1998) proposed a new integer programming formulation of gate assignment problem, which is solved by using an efficient heuristic solution procedure. Luo *et al.* (2002) proposed a single-airport ground-holding problem model based on discrete-event system. Yan and Huo (2001) proposed a multiple objective model to help airport authorities to efficiently and effectively solve gate assignment problems. The model is formulated as a multiple-objective zero-one integer program. Yan and Tang (2007) proposed a simulation framework that not only is able to analyze the effects of stochastic flight delays on static gate assignments but also can evaluate flexible buffer times and real-time gate assignment rules. Drexl and Nikulin (2008) proposed an airport gate assignment problem with multiple objectives based on minimizing the number of ungated flights and the total passenger walking distances or connection times and to maximize the total gate assignment preferences. Diepen *et al.* (2012) proposed a completely new integer linear programming formulation that is based on so-called gate plans and the possibility of directly assigning flights to physical gates using the column generation formulation, where we then take into account other criteria as well. Zhao and Cheng (2014) proposed a mixed integer model to formulate airport gate assignment problem. Kim and Feron (2014) proposed a queuing model based on simulating the airport departure process. Prem Kumar and Bierlaire (2014) proposed a mathematical model based on maximization of passenger connection revenues, minimization of zone usage costs, maximization of gate plan robustness that are observed at a real airport. Liu *et al.* (2016) proposed an optimization model based on minimizing the dispersion of gate idle time periods for the problem considering operational safety constraints. Yu *et al.* (2016) proposed a model with considering schedule robustness, facility and personnel cost during tows and passenger satisfaction level, which is solved by using four different algorithms including diving, local branching and relaxation induced neighborhoods. Behrends and Usher (2016) proposed a framework that integrates the passenger or freight movement within a terminal with the taxiing of the aircraft to support an integrated approach to solving the gate assignment problem.

For solving algorithms, Yan and Tang (2007) proposed a heuristic approach embedded in a framework designed to help the airport authorities make airport gate assignments that are sensitive to stochastic flight delays. Genç *et al.* (2012) proposed a method that combines the benefits of heuristic approaches with some stochastic approach instead of using a purely probabilistic approach to top-down solution of the problem. Fu *et al.* (2016) proposed an efficient multi-keyword fuzzy-ranked search scheme that is able to address the aforementioned problems. Xue *et al.* (2017) proposed a self-adaptive artificial bee colony algorithm based on the global best candidate for solving global optimization problems. Liu *et al.* (2016) proposed a speculative approach for spatial-temporal efficiency with multi-objective optimization. Kong *et al.* (2016) proposed a belief propagation-based optimization method for solving task allocation problem. Gu *et al.* (2015) proposed an effective incremental support vector ordinal regression formulation based on a sum-of-margins strategy. Gu and Sheng (2017) proposed a regularization path algorithm for ν-support vector classification. Gu *et al.* (2017) proposed a structural minimax probability machine for constructing a margin classifier. Pan *et al.* (2015) proposed an efficient motion estimation and disparity estimation algorithm for reducing the computational complexity. Rong *et al.* (2017) proposed a novel K+-isomorphism method to achieve K-anonymization state among subgraphs. Zhang *et al.* (2017) proposed an optimal cluster-based mechanism for load balancing with multiple mobile sinks. Chen *et al.* (2017) proposed an improved quaternion principal component analysis method for processing nonlinear quaternion signals. Wang *et al.* (2017) proposed a novel multi-watermarking scheme based on hybrid multi-bit multiplicative rules. Wang *et al.* (2017) proposed a back propagation neural network model by using solar radiation to establish the relationship. Ma *et al.* (2016) proposed an efficient overlapping community detection algorithm based on structural clustering. Zhang *et al.* (2017) proposed an optimal cluster-based mechanism for load balancing with multiple mobile sinks. Xiong *et al.* (2017) proposed a novel reversible data hiding scheme using integer wavelet transform, histogram shifting and orthogonal decomposition. Zhang *et al.* (2016) proposed an efficient algorithm to achieve k-barrier coverage by using 0-1 integer linear programming. Qu *et al.* (2016) proposed a multilevel pattern mining architecture to support automatic network management by discovering interesting patterns. The other algorithms are proposed to solve complex problems in recent years, such as krill herd algorithm and its improvements (Wang *et al.*, 2014, 2017; Guo *et al.*, 2014), cuckoo search algorithm (Deb *et al.*, 2016), evolutionary optimization algorithm (Derrac *et al.*, 2011, 2014; Wang *et al.*, 2017), butterfly optimization algorithm and its improvements (Wang *et al.*, 2014, 2016; Feng *et al.*, 2017), hybrid optimization algorithms (Wang *et al.*, 2016, 2013; Sáez *et al.*, 2014; Deng *et al.*, 2017b), metaheuristic optimization algorithms (Galar *et al.*, 2015; Deng *et al.*, 2017a; Wang, 2016) and so on.

The ACO algorithm is widely applied to solving the complex optimization problems. Because the ACO algorithm is easy to fall into local optimum and slow convergence speed, a lot of improved ACO algorithms are proposed by experts and scholars. Li and Li (2007) proposed an adaptive ACO algorithm, which used the information entropy to self-adaptively control the path selection and evolutional strategy. Li and Li (2013) proposed a self-adaptive ACO algorithm with changing parameters for solving time-cost optimization problems to assist the relevant construction management firm with their technological tool. Tuba and Jovanovic (2013) proposed a new improved ACO algorithm with novel pheromone correction strategy for the travelling salesman problem. Chen *et al.* (2013) proposed a fast two-stage ACO algorithm based on the scent pervasion principle to overcome the inherent problems of traditional ACO algorithms. Ghanbari *et al.* (2013) proposed a new cooperative ACO-genetic algorithm to construct expert systems with the ability to model and simulate fluctuations of energy demand under the influence of related factors. Qi and Li (2014) proposed a hybrid algorithm combining improved ACO algorithm with iterated local search and the exponential entropy to overcome the prematurity of ant colony algorithm for logistics distribution routing optimization. Juang *et al.* (2014) proposed a cooperative continuous ACO algorithm based on rules to address the accuracy-oriented fuzzy systems design problems. Wang *et al.* (2015) proposed a modified ACO approach based on several attractive mechanisms for network coding resource minimization. Mao *et al.* (2015) proposed an adapting ACO algorithm based on some strategies of local transfer, global transfer and pheromone update. Yang *et al.* (2015) proposed an improved ACO algorithm based on combining swarm intelligence with local search to improve the efficiency and accuracy of the algorithm. Bu *et al.* (2015) proposed a weighted max–min ant colony algorithm based on colony entropy and mean colony entropy to calculate each arc's increment based on its selected probability. Wang *et al.* (2016) proposed an improved ant colony system algorithm based on global heuristic mechanism. Huang and Yu (2017) proposed several novel hybrid ACO algorithms to resolve multi-objective job-shop scheduling problem with equal-size lot splitting. Yaralidarani and Shahverdi (2016) proposed an modified ACO based on some new ideas and innovations for the continuous inverse problem. Mavrovouniotis *et al.* (2017) proposed a memetic ACO algorithm based on a local search operator for a dynamic travelling salesman problem. Skinderowicz (2017) proposed an improved ant colony system based on simulated annealing to improve the solving efficiency.

It is very important to construct gate assignment models and solving methods for these models. In recent decades, some gate assignment models are constructed and some new or improved optimization algorithms are proposed to solve the gate assignment models. But these gate assignment models cannot better and comprehensively consider the various factors according to the actual airport operation demand, and these improved ACO algorithms still exist the slower convergence speed. Therefore, the deterministic robust gate assignment model is extended and a fast and effective ACO algorithm based on multi-strategies is proposed to solve the constructed gate assignment model.

3. Description of airport gate assignment problem

3.1 Description of gate assignment problem

The gate assignment is to assign the appropriate gates to the arrival and departure flights according to the layout of gates, the type of aircraft, the arrival and departure time of flights and so on. The goal is to ensure that the flight is normal and without delay. The gate assignment is one of main tasks of airport command center. It is a key to improve the airport capacity and the service efficiency by using the limited gates, achieving safe and efficient aircraft docking and ensuring the effective connections of passengers and goods. A reasonable assignment algorithm can relieve the tension condition of airport gates, ensure the safe and smooth operation of airport scene and improve the satisfaction of passengers. The gate assignment result determines the normal operation of airport, and the good gate assignment result is helpful to realize the perfect combination of safety and efficiency. From the view of the operation, the good optimization objectives will ultimately reflect the operating costs and benefits of airlines and airports and passenger satisfaction with the services. The service satisfaction for passengers is an important operation index in the civil aviation, and flight safety is the lifeline of civil aviation. From the perspective of operation and management, the shorter walking distance can make passengers with higher satisfaction. In real-time operation, it is very common to change arrival time and departure time of flights due to various reasons. For this situation, the gate assignment algorithm need to have a certain ability to handle dynamic changes in time and provide the margin for the real-time operation. That is to say, the optimization results should be robust.

3.2 Constraint conditions

According to the actual operation of airport and research literatures, and experts and scholars are invited to discuss and formulate the multi-objective optimization model of gate assignment problem and constraints. Therefore, the gate assignment needs to meet the following constraints.

3.2.1 Exclusive constraint. A flight must only be assigned one gate or apron. In its occupation time, the gate cannot serve other flights:

$$\sum_{\mathrm{k}=1}^{\mathrm{m}}(y_{ik}+g_{\mathrm{i}})=1 \tag{1}$$

where $y_{ik}=1$ indicates that the flight i is assigned to the gate k, and $g_i=1$ indicates that the flight i is assigned to the apron.

3.2.2 Matching constraint for flight-gate type. The flight can only be assigned to the gate that matches its own model. In general, the flight can be assigned to the greater gate or corresponding gate:

$$G_k \geq F_i \quad (y_{ik}=1) \tag{2}$$

G_k indicates the gate number, and F_i indicates the flight number.

3.2.3 Safety interval requirement. The interval between two adjacent flights at the same gate should be greater than or equal to the safety time interval, which is 5 min in here:

$$L_{\mathrm{ik}} - E_{jk} \geq 5 \quad Z_{ijk} = 1 \tag{3}$$

L_{ik} indicates the time when the flight i arrives at the gate k, E_{jk} indicates the time when the flight j leaves from the gate k , and Z_{ijk} indicates that flight i and flight j are the connecting flights. The flight i is earlier than the flight j to arrive at the gate k.

3.2.4 Priority constraint for gates. When the flight i arrived, it should be preferred to spark the gate, that the apron is selected and, finally, that the apron is considered to dock due to the unlimited use of apron:

$$F_{near} > F_{remote} > g_i \tag{4}$$

4. Construct an airport gate assignment model

A good airport gate assignment is conducive to achieve the perfect combination of safety and efficiency. Good optimization objectives will ultimately reflect the operation costs and benefits of airlines and airports, as well as passenger satisfaction. The gate assignment problem is a multi-objective combinatorial optimization problem. In general, from the view of passengers and airlines, it is necessary to reduce slide distance and waiting time on the ground to provide better services and save costs. From the view of the airport operating and control, the limited gate resources are reasonably balanced and efficiently used, and the boarding gates and remote gates are comprehensively considered to prevent the adverse effects of unexpected events in airport operations. Therefore, it is necessary to combine the existing research results of the gate assignment, the appropriate objectives are selected by the characteristics of the single objective. The appropriate research objective is selected, and the objective functions and the corresponding constraint conditions are determined. The service satisfaction for passengers is an important operation index, so the minimization passenger walking distance is selected as the optimization objective. The robustness realization is the balanced idle time for each gate, which also means the gate utilization balance, makes the personnel and equipment with the relatively balanced work time, ensures the smooth work progress and reduces the security risks caused by human factors. Therefore, the minimum variance of idle time for each gate is selected as the optimization objective. Because the apron is generally far away from the terminal, the flights need to rely on taxiing, this time will seriously affect the satisfaction of passengers. Therefore, the least number of flights at parking apron is selected as the optimization objective. In summary, the most balanced idle time, the shortest walking distances and the least number of flights at parking apron are selected as the optimization objectives for constructing a multi-objective optimization model in this paper.

4.1 The most balanced idle time

For each gate, if the idle time balance is poor, then this configuration is often unable to cope with these changes of arrival time and departure time. Under actual operation condition, the arrival time and departure time are changing due to the reasons of flow control, weather and so on. The minimum idle time variance for each gate is selected as the objective function, which is $\min \sum_{i=1}^{n} \sum_{k=1}^{m} (S_{\mathrm{ik}} - \mathrm{S})^2$. The expression can be simplified as $\min \sum_{i=1}^{n} \sum_{k=1}^{m} S_{\mathrm{ik}}^2$. So the objective function is described as follows:

$$\min F_1 = \min\left[\sum_{i=1}^{n}\sum_{k=1}^{m} S_{\text{ik}}^2 + \sum_{k=1}^{m} SS_k^2\right] \tag{5}$$

where n is total number of flights, m is total number of gates, S_{ik} is idle time before the flight i arrived at the gate j, SS_k is the idle time after all services are completed. That is to say, the difference value between the actual departure time and the scheduled departure time of the last flight.

4.2 The shortest walking distances of passengers

The distances between the different gate and check-in counters are given by constructing the travel matrix of passengers to determine the walking distances of passengers for distinguishing good gate or bad gate. The objective function is described as follows:

$$\min F_2 = \min\sum_{i=1}^{n}\sum_{k=1}^{m} q_{ik} f_{\text{k}} \text{y}_{ik} \tag{6}$$

where q_{ik} is the transferred number of passengers of flight i on the gate k. f_k is the walking distances of passengers for arriving at the gate k. $\text{y}_{ik} = 1$ is that the flight i is assigned to the gate k.

4.3 The least number of flights at apron

To improve the utilization rate of gates, reduce resource consumption of airport and improve the efficiency of airport, more flights are assigned to the gates. The number of flights on the gates are used to evaluate the assignment results. The objective function is described as follows:

$$\min F_3 = \min\sum_{\text{k}=1}^{\text{m}} g_{\text{i}} \tag{7}$$

where g_1 indicates whether the flight i is parked at the apron. When the flight i is assigned to the apron, the value is 1, otherwise the value is 0.

4.4 Non-quantized objective function

For the multi-objective optimization model of gate assignment, it is difficult to directly solve the multi-objective function and obtain a very satisfactory and feasible solution by simply adjusting the weighting factors. Therefore, the multi-objective optimization model of gate assignment need be non-quantized. The weighted method is simple and easy to operate and takes on high accuracy. This method determines the weight coefficient according to the importance of each objective. Therefore, the weighted method is used to non-quantize multi-objective optimization functions. The non-quantized process is described as follows:

The weight coefficients are set as $W_1 = 0.4$, $W_2 = 0.4$ and $W_3 = 0.2$. Suppose the function is $U = \sum_{\text{q}=1}^{3} W_{\text{q}} F_{\text{q}}$ ($F_{\text{q}}^0 = \max F_{\text{q}}$ (q = 1, 2, 3) and $F_{\text{q}}^0 \neq 0$). The non-qualified objective function is $U' = \sum_{\text{q}=1}^{3} \frac{W_{\text{q}} F_{\text{q}}}{F_{\text{q}}^0}$. In fact, it is difficult to determine F_1^0, F_2^0 and F_3^0, so the values of F_1^0, F_2^0 and F_3^0 need to be amended. A set of empirical values are selected to determine the values of F_1^0, F_2^0 and F_3^0. Suppose $\mu_1 = \frac{W_1}{F_1^0}$, $\mu_2 = \frac{W_2}{F_2^0}$ and $\mu_3 = \frac{W_3}{F_3^0}$, the final non-quantized objective function is described as follows:

$$F = \mu_1 \left[\sum_{i=1}^{n} \sum_{k=1}^{m} S_{\mathrm{ik}}^2 + \sum_{k=1}^{m} SS_k^2 \right] + \mu_2 \sum_{i=1}^{n} \sum_{k=1}^{m} q_{ik} f_{\mathrm{k}} y_{ik} + \mu_3 \sum_{\mathrm{k}=1}^{\mathrm{m}} g_{\mathrm{i}} \tag{8}$$

5. Ant colony optimization algorithm and its improvement

5.1 Ant colony optimization algorithm

ACO algorithm was proposed by Colorni *et al.* (1999). It is a metaheuristic inspired by the behavior of real ants in search for the shortest path to food sources. Ants tend to choose the paths marked by the strongest pheromone concentration. The ACO algorithm is an essential system based on agents that simulates the natural behavior of ants, including the mechanisms of cooperation and adaptation. It simulates the techniques used by real ants to rapidly establish the shortest route from a food source to their nest and vice versa without the use of visual information. The ACO algorithm consists of a number of cycles (iterations) of solution. In each iteration, a number of ants construct complete solutions by using heuristic information and the collected experiences of previous population of ants. These collected experiences are represented by using the pheromone trail, which is deposited on the constituent elements of a solution. The pheromone can be deposited on the components and/or the connections used in a solution depending on the solving problem. The flow of ACO algorithm is illustrated in Figure 1.

Ants are insects which live together. Because they are blind animals, they find the shortest path from nest to food with the aid of pheromone. The pheromone is the chemical material deposited by ants, which serves as the critical communication media among ants, thereby guiding the determination of the next movement. On the other hand, ants find the shortest path based on intensity of pheromone deposited on different paths. Generally, the intensity of pheromone and the length of the path are used to simulate ant system. Initially, n ants are randomly placed on m nodes. Then, in

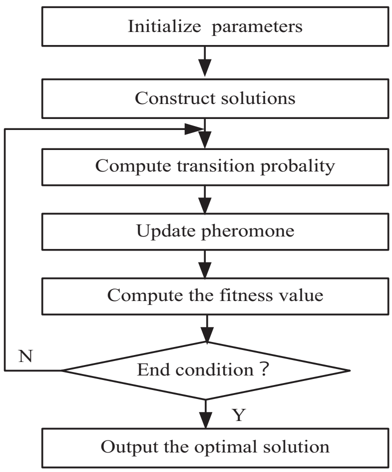

Figure 1.
The flow chart of the ACO algorithm

each construction step, each ant moves to a node it has not yet visited based on a probabilistic decision. When it completes a tour, it lays a substance called pheromone trail on the edges. In the ACO algorithm, we define a list of nodes which the k^{th} ant cannot choose as the next node. This list is called *Tabu k*, which includes all the customer nodes that have been visited by the k^{th} ant until the current state in addition to all the depots except the one which the current tour has been started from. Assume that there are n cities and m ants, at the same time assuming that the initial intensity of pheromone on each edge is set to a very small non-zero positive constant τ_0. In each cycle, each ant starts at a stochastic chosen city, then visits the other cities once and only once according to the transition rule based on the initial intensity of pheromone. When the ants complete the routes of one cycle, the length of one cycle will be computed. Then, the pheromone concentration will be updated by using pheromone update rule. The procedure of pheromone update rule is described as follow (Yang *et al.*, 2015; Bu *et al.*, 2015):

5.1.1 The transition rule. In the route, the k^{th} ant starts from city r, the next city s is selected among the unvisited cities memorized in J_r^k according to the following formula:

$$s = \arg\max_{u \in J_r^k} \left[\tau_i(r,u)^\alpha \cdot \eta(r,u)^\beta \right] if\, q \leq q_0 (Exploitation) \tag{9}$$

To visit the next city s with the probability $p_k(r,s)$:

$$p_k(r,s) = \begin{cases} \dfrac{\tau(r,s)^\alpha \cdot \eta(r,s)^\beta}{\sum\limits_{u \in J_r^k} \tau(r,u)^\alpha \cdot \eta(r,u)^\beta} & if\, s \in J_r^k \\ 0 & otherwise \quad if\, q > q_0 (Bias\ Exploitation) \end{cases} \tag{10}$$

In formula (10), $p_k(r,s)$ is the transition probability, $\tau(r,u)$ is the pheromone concentration between city r and city u in the i^{th} group, $\eta(r,u)$ is the length of the path from city r to city u, J_r^k is the set of unvisited cities of the k^{th} ant in the i^{th} group, the parameter α and β are the control parameters, q is a uniform probability [0, 1].

5.1.2 The pheromone update rule. To improve the solution, the pheromone trails must be updated. Trail updating includes local updating and global updating. The local trail updating formula is given as follow:

$$\tau(r,u) = (1-\rho)\tau(r,s) + \sum_{k=1}^{m} \Delta\tau_k(r,s) \tag{11}$$

In the formula (11), ρ $(0 < \rho < 1)$ is the pheromone trial evaporating rate. $\Delta\tau_k(r,s)$ is the amount of pheromone trail added to the edge(r, s) by ant k between time t and t + Δt in the tour. It is given as follows:

$$\Delta\tau_k(r,s) = \begin{cases} \dfrac{Q}{\sum L_k} & (\mathrm{r}, s) \in \pi_k \\ 0 & otherwise \end{cases} \tag{12}$$

where Q is a constant parameter, and L_k is the distance of the sequence π_k toured by ant in Δt.

5.2 Improved ant colony optimization algorithm

5.2.1 Improvement of the number of ants. In the basic ACO algorithm, the ants can only perform a pheromone update after a search period is completed. For all passed paths by ants, poor solutions are obtained on some paths. Due to the increased pheromone, this solution could become false optimal solutions. When the optimal solution has not still appeared, the pheromone of this path becomes smaller and smaller due to the evaporation, so far as to be ignored. In the next search, the selection probability of this path with the optimal solution is smaller and smaller, which results in a large number of invalid search, so that the operation speed is reduced. In this paper, the ant colony collaborative strategy is used to improve the basic ACO algorithm. The ant colony collaborative strategy dynamically assigns the number of ants according to the number of gates m. A total of $k \times m$ ants is assigned according to the solving problem. One solution for this problem is collaboratively found by using ants with k populations. In each iteration, the passed path by ants with optimal population is only updated for the pheromone increment, which can will avoid the rapid convergence to the local optimal solution.

5.2.2 Improved formula and range of pheromone update. To reduce the effect of the basic ACO algorithm for poor path, in a short time, the difference of pheromone amount between the excellent path and other path is increased to guide the ACO algorithm to converge to the optimal path and accelerate the convergence speed. The formula (12) is rewritten as follows:

$$\Delta\tau_{\mathrm{ij}}^{\mathrm{k}}(\mathrm{t}) = \frac{Q}{2^{L_{\mathrm{k}}(\mathrm{t}) - \mathrm{BestSolution}}} \tag{13}$$

The new pheromone update rule can quickly increase the pheromone amount on excellent paths, and it is not obvious to increase the pheromone amount on poor paths. After a number of iterations are executed, there will be some differences of the pheromone amount on the excellent path and the poor path, which is helpful to eliminate the interference of the poor path, greatly accelerate the convergence speed and is conducive to quickly converge to the optimal value.

The limited range of pheromone update is given as follows:

$$\tau_{\mathrm{ij}} \in [\tau_{\mathrm{min}}, \tau_{\mathrm{max}}] \tag{14}$$

When the pheromone is updated, the pheromone concentration on each edge is limited to the interval$[\tau_{\mathrm{min}}, \tau_{\mathrm{max}}]$. If there is $\tau_{\mathrm{ij}} < \tau_{\mathrm{min}}$, then let $\tau_{\mathrm{ij}} = \tau_{\mathrm{min}}$. If there is $\tau_{\mathrm{ij}} > \tau_{\mathrm{max}}$, then let $\tau_{\mathrm{ij}} = \tau_{\mathrm{max}}$. The initial pheromone is set as the upper bound of its range, that is $\tau_{\mathrm{ij}}(0) = \tau_{\mathrm{max}}$.

6. A novel airport gate assignment method

6.1 Airport gate assignment model

The most balanced idle time, the shortest walking distances of passengers and the least number of flights at apron are considered as the objective functions to construct an efficient multi-objective optimization model of gate assignment problem. This optimization model takes on multi-objective and multi-constraint. The mathematical model of gate assignment and the corresponding constraint conditions are described as follows:

$$F = \mu_1\left[\sum_{i=1}^{n}\sum_{k=1}^{m} S_{\mathrm{ik}}^2 + \sum_{k=1}^{m} SS_k^2\right] + \mu_2\sum_{i=1}^{n}\sum_{k=1}^{m} q_{ik}f_{\mathrm{k}}\mathrm{y}_{ik} + \mu_3\sum_{\mathrm{k}=1}^{\mathrm{m}} g_{\mathrm{i}} \tag{15}$$

s.t:

$$\sum_{k=1}^{m}(y_{ik}+g_{\mathrm{i}})=1 \tag{16}$$

$$G_k \geq F_i \quad (y_{ik}=1) \tag{17}$$

$$L_{\mathrm{ik}}-E_{jk} \geq 5 \quad Z_{ijk}=1 \tag{18}$$

$$F_{near} > F_{remote} > g_i \tag{19}$$

6.2 Solving flow and steps of gate assignment model

For the actual airport gates and flights, the gate assignment belongs to NP-hard problem. It has complex constraints and larger scales. Therefore, it is difficult to solve this model to obtain the accurate optimal solution in the effective time by using the branch definition or other traditional integer programming and so on. And the general intelligent algorithms are also difficult to obtain the optimal solution for meeting requirements. So the designed ICQACO algorithm is used to solve the optimization model of airport gate assignment to obtain the satisfactory gate assignment result. The solving flow of the optimization model of airport gate assignment is shown in Figure 2.

The specific solving steps are described as follows:

- *Step 1*: Input the information of gates and flights and record the relations between flights and conflicts in the form of a matrix.
- *Step 2*: Initialize parameters. These parameters include the size of population (k), the maximum number of iterations (NC_{max}) and the current iteration (NC = 1), the number of ants (m) according to the number of gates, the initial pheromone (c), the

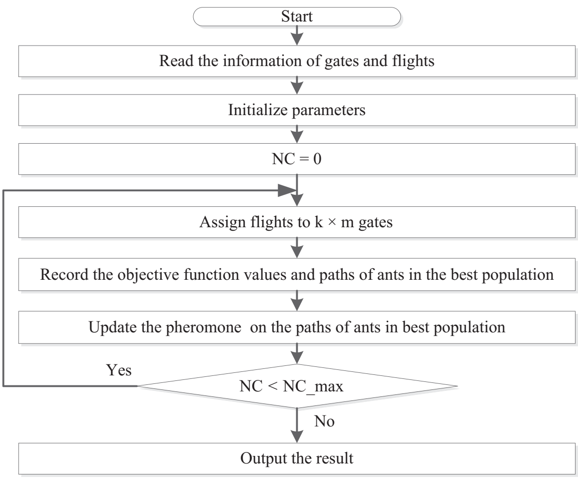

Figure 2.
Solving flow of the optimization model of airport gate assignment

pheromone evaporation coefficient (ρ), the pheromone factor (α) and heuristic factor (β), pheromone amount (Q) and so on.

- *Step 3*: Read data. The arrival time of the first flight is used as the start time of gate, the end time of gate is the departure time of the last flight.
- *Step 4*: For the ant j^{th} (j = 1,2,3,. . ., m) in the i^{th}(i = 1,2,3,. . ., k) population, the next flight is selected according to the formula (10). If there does not have flight to be placed in the ant j, the j++ is executed.
- *Step 5*: If all ants do not have flights to dock, go to Step 6. Otherwise continue to execute Step 4.
- *Step 6*: Calculate the objective function values of ants in each population. Record the best function values and path at the moment. Update the pheromone on the paths of ants in best population according to formula (11)-(13).
- *Step 7*: Execute $NC = NC + 1$. If there is $NC > NC_{\max}$, go to Step 5. Otherwise output the optimal result and the solving process is end.

7. Data simulation and analysis

7.1 Experimental environment

The experiment environment is described as follows: the Pentium IV, 2.40 GHz, 2.0 GB RAM, Win 7 and MATLAB 2010b. The initial parameters of the ACO algorithm, the CPACO algorithm and ICQACO algorithm are selected after thorough testing. In the simulation experiments, the alternative values were tested and modified for some functions to obtain the most reasonable initial values of these parameters. These selected values of the parameters take on the optimal solution and the most reasonable running time of these algorithms to efficiently complete the problem solving. Therefore, according to the simulation experiment result, related references and the actual operation demand of airport, the selected values of these parameters of the ACO algorithm, the CPACO algorithm and ICQACO algorithm are described as follows. $k = 20$, $NC_{\max} = 200$, $m = 30$, $c = 1$, $\rho = 0.2$, $\alpha = 2$, $\beta = 3$, $Q = 0.1$.

7.2 Experimental data

The experimental data set is obtained from Guangzhou Baiyun airport of China. It is an actual flight schedule data for one day. In all, 30 available gates and 212 flights are used to test and verify the effectiveness of the ICQACO algorithm and multi-objective optimization model of gate assignment in this paper. And the walking distances of passengers are less than 950 m, which is regarded as the boarding gate. These gates are divided into large gates, medium gates and small gates, and the information of gates are shown in Table I. The information of flights are shown in Table II.

7.3 Experimental results and analysis

To demonstrate the effectiveness of the ICQACO algorithm for solving complex optimization problem, the ICQACO algorithm is used to solve the multi-objective function of gate assignment. A minimum interval time T = 5 min between two consecutive flights to the same gate is set to avoid the conflict. The experiments were carried out for ten consecutive simulations. One of the experimental results is selected to further analyze and study. The gate assignment results for the constructed multi-objective function are shown in Table III and Figure 3, the corresponding Gantt chart is shown in Figure 4.

No. of gate	Walking distances of passengers	Type of gate	No. of gate	Walking distances of passengers	Type of gate
1	190	Small	16	115	Large
2	260	Medium	17	215	Medium
3	400	Large	18	535	Small
4	333	Small	19	235	Large
5	384	Medium	20	170	Large
6	135	Large	21	585	Large
7	440	Small	22	500	Medium
8	150	Medium	23	450	Medium
9	975	Large	24	920	Large
10	960	Large	25	1,000	Large
11	1,050	Large	26	426	Medium
12	270	Large	27	265	Small
13	230	Medium	28	1,300	Large
14	580	Medium	29	1,250	Large
15	1,100	Large	30	1,200	Large

Table I. The information of gates

No. of flight	Arrival time	Departure time	Passengers	Type of flight
1	2015-07-26 00:05:00	2015-07-26 07:15:00	482	Large
2	2015-07-26 00:10:00	2015-07-26 07:30:00	273	Medium
3	2015-07-26 00:35:00	2015-07-26 06:10:00	261	Medium
4	2015-07-26 00:35:00	2015-07-26 05:55:00	116	Medium
5	2015-07-26 00:40:00	2015-07-26 07:00:00	244	Medium
6	2015-07-26 00:45:00	2015-07-26 06:40:00	312	Large
7	2015-07-26 00:55:00	2015-07-26 08:30:00	340	Large
8	2015-07-26 01:00:00	2015-07-26 06:45:00	198	Medium
9	2015-07-26 01:00:00	2015-07-26 08:30:00	184	Medium
10	2015-07-26 01:10:00	2015-07-26 06:55:00	494	Large
11	2015-07-26 01:15:00	2015-07-26 07:15:00	19	Small
12	2015-07-26 01:20:00	2015-07-26 07:45:00	443	Large
13	2015-07-26 01:20:00	2015-07-26 08:30:00	457	Large
14	2015-07-26 01:25:00	2015-07-26 06:30:00	398	Large
15	2015-07-26 01:40:00	2015-07-26 08:10:00	49	Small
16	2015-07-26 01:50:00	2015-07-26 02:35:00	131	Medium
17	2015-07-26 02:00:00	2015-07-26 02:50:00	168	Medium
18	2015-07-26 02:00:00	2015-07-26 03:00:00	340	Large
19	2015-07-26 04:50:00	2015-07-26 05:50:00	68	Small
20	2015-07-26 04:55:00	2015-07-26 08:50:00	361	Large
21	2015-07-26 05:00:00	2015-07-26 08:00:00	53	Small
22	2015-07-26 05:40:00	2015-07-26 09:00:00	327	Large
23	2015-07-26 05:45:00	2015-07-26 07:40:00	247	Medium
24	2015-07-26 06:00:00	2015-07-26 08:20:00	390	Large
25	2015-07-26 06:20:00	2015-07-26 08:30:00	358	Large
26	2015-07-26 06:20:00	2015-07-26 08:00:00	452	Large
27	2015-07-26 06:15:00	2015-07-26 09:10:00	445	Large
28	2015-07-26 06:50:00	2015-07-26 10:10:00	167	Medium
211	2015-07-26 23:50:00	2015-07-27 01:50:00	128	Medium
212	2015-07-26 23:55:00	2015-07-27 09:10:00	307	Large

Table II. The information of flights

Gates	The no. of flights												Total no.
1	140	168	191	204									4
2	126	170											2
3	95	125	152	178									4
4	69	148	190	203									4
5	5	127	141	181									4
6	65	94	151	177	183	198							6
7	54	91	124										3
8	13	61	118	138	169	185	199						7
9	8	55	119	158									4
10	52	90	117	145	160	166	176	200	208				9
11	14	50	71	89	132	146	165	186	194				9
12	6	47	87	110	139	175	193	205					8
13	7	135	157	179									4
14	46	70	85	116	142	159	167						7
15	18	53	81	103	114	131	150						7
16	28	63	80	171									4
17	9	44	86	112	134	174	186	202					8
18	17	29	84	106	133	154							6
19	12	36	48	68	92	109	137	156	164	180	209		11
20	26	34	42	66	82	105	120	184					8
21	25	40	56	73	98	123	149	163	173	207	212		11
22	27	43	62	79	101	122	155	196					8
23	24	38	60	78	93	111	128	187					8
24	23	35	49	75	104	147	182	192	206				9
25	10	32	41	59	67	83	102	113	136	153	162	197	12
26	22	39	64	76	100	115	143	211					8
27	21	33	45	74	99	195							6
28	20	37	57	72	88	107	130	144	161	189			10
29	2	31	51	77	97	108	121						7
30	19	30	58	96	129	172	201						7
The apron	1	3	4	11	15	16	188						7

Table III.
The gate assignment results

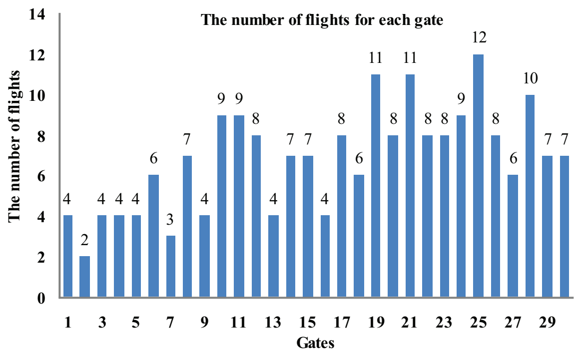

Figure 3.
The number of flights for each gate

As can be seen from Table III, Figures 3 and 4, for 30 gates and 212 flights, there are 205 flights, which are assigned to 30 gates, and there are only 7 flights, which are assigned to the apron. The assigned rate for 212 flights is 96.7 per cent to 30 gates. The assigned result is more ideal in this airport. And the gate assignment based on the constructed optimization model of gate assignment and ICQACO algorithm does not appear

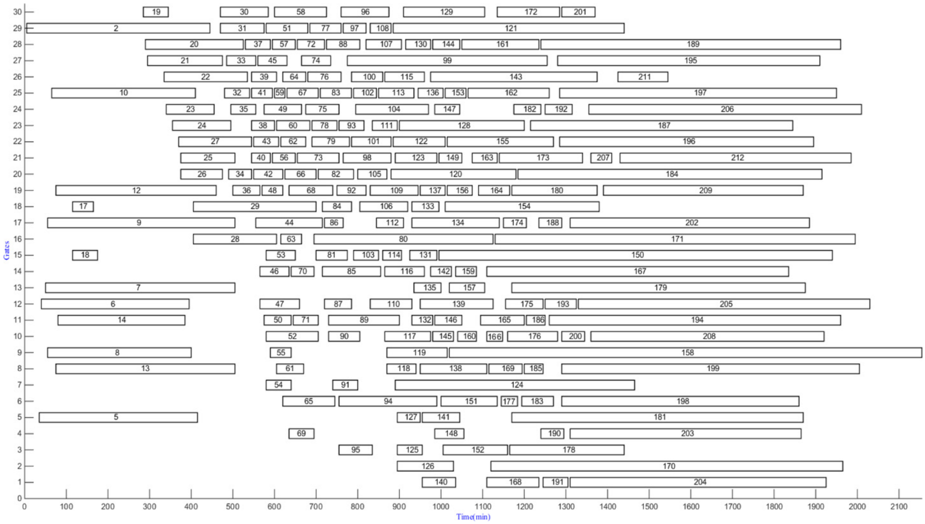

Figure 4. The Gantt chart of gate assignment result

idle gates. The assigned flights for each gate are relatively average. The more flights are assigned to Gate 10, Gate 11, Gate 19, Gate 21, Gate 24, Gate 25 and Gate 28. The Gate 25 is assigned 12 flights. The most flights are assigned to this gate. The Gate 2 is only assigned two flights. The least flights are assigned to this gate. As is known to all from Table III, Figures 3 and 4, the airport operation safety is regarded as the inflexibility constraint condition for gate assignment method, the constructed multi-objective optimization model of gate assignment based on the objectives of the most balanced idle time, the shortest walking distances of passengers and the least number of flights at apron can improve the utilization efficiency, balanced idle time of gates and satisfaction degree of passengers. The designed ICQACO algorithm can effectively solve the multi-objective optimization model of gate assignment problem. The designed ICQACO algorithm takes on better optimization performance for solving complex optimization problem.

To further analyze the optimization performance of the ICQACO algorithm for solving multi-objective optimization model of gate assignment, the basic ACO algorithm and the CPACO algorithm based on improved control parameters (Yang *et al.*, 2015) are selected to solve the constructed multi-objective optimization model of gate assignment in here. The experiments were carried out for ten consecutive simulations. The experiment results are shown in Table IV and Figure 5.

Table IV is experimental results by using ACO algorithm, CPACO algorithm and ICQACO algorithm. Figure 5. is comparison result of optimal solution value by using ACO algorithm, CPACO algorithm and ICQACO algorithm. As can be seen from Table IV and Figure 5, for the simulation results of ten consecutive simulations, the least optimization value is 0.4000 at the 96^{th} iteration, and the average optimization value is 0.4105, and the average iterations are 103.3 iterations by using the basic ACO algorithm. The least optimization value is 0.3945 at the 48^{th} iteration, the average optimization value is 0.3999 and the average iterations are 98.9 iterations by using the CPACO algorithm. The least optimization value is 0.3821 at the 24^{th} iteration, the average optimization value is 0.3953 and the average iterations are 92.6 iterations by

No.	ACO algorithm Operation time (s)	Iterations	Optimal solution value	CPACO algorithm Operation time (s)	Iterations	Optimal solution value	ICQACO algorithm Operation time (s)	Iterations	Optimal solution value
1	33.2	110	0.4181	579.3	87	0.4053	633.6	74	0.3994
2	36.1	35	0.4057	564.8	48	0.3945	652.1	24	0.3821
3	36.1	120	0.4043	607.3	75	0.4029	659.2	42	0.3974
4	35.0	59	0.4290	604.9	136	0.3984	681.3	176	0.3955
5	35.4	34	0.4105	597.2	63	0.4021	673.0	98	0.3979
6	34.7	60	0.4284	574.4	94	0.3973	672.1	106	0.3924
7	35.8	96	0.4000	610.5	74	0.4000	664.7	107	0.3999
8	34.5	188	0.4044	569.9	157	0.4006	664.2	135	0.3975
9	34.2	187	0.4033	589.1	120	0.3972	660.2	49	0.3915
10	33.7	144	0.4010	577.6	135	0.3985	665.0	115	0.3994
Average value	34.87	103.3	0.4105	587.5	98.9	0.3999	662.54	92.6	0.3953

Table IV. The experimental results

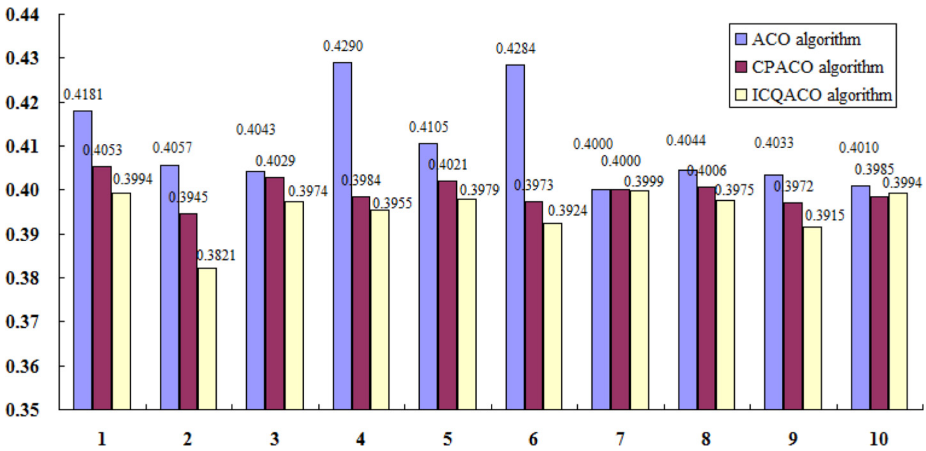

Figure 5. Comparison of optimal solution value

using the ICQACO algorithm. The average optimization value and iterations of the designed ICQACO algorithm are better than the average optimization value and iterations of the basic ACO algorithm and the CPACO algorithm for solving the multi-objective function of gate assignment. And the average optimization value and iterations of the CPACO algorithm are better than the average optimization value and iterations of the basic ACO algorithm for solving the multi-objective function of gate assignment. But the average operation time of the basic ACO algorithm is 34.87 s, the average operation time of the CPACO algorithm is 587.5 s and the average operation time of the designed ICQACO algorithm is 662.54 s. The average operation time of the designed ICQACO algorithm is the most times than the average operation time of the designed ICQACO algorithm. The average operation time of the CPACO algorithm is more times than the average operation time of the basic ACO algorithm. Although the designed ICQACO algorithm uses more time cost to solve the constructed multi-objective optimization model of gate assignment, the solution quality of the designed

ICQACO algorithm has been improved by comparing the solution qualities of the basic ACO algorithm and the CPACO algorithm. The designed ICQACO algorithm can obtain the best convergence efficiency and the best optimization ability for solving gate assignment problem by sacrificing the operation time. The designed ICQACO algorithm takes on the ability to escape the local minimum value and improve the global search ability.

The Wilcoxon signed-rank test is a non-parametric statistical hypothesis test used when comparing two related samples, matched samples or repeated measurements on a single sample to assess whether their population mean ranks differ (i.e. it is a paired difference test). It can be used as an alternative to the paired Student's *t*-test, *t*-test for matched pairs or the *t*-test for dependent samples when the population cannot be assumed to be normally distributed. A Wilcoxon signed-rank test is a nonparametric test that can be used to determine whether two dependent samples were selected from populations having the same distribution. From the view of statistical point, the test is safer because it does not assume normal distributions. The Wilcoxon test assumes continuous differences, so they should not be rounded to one or two decimals because this would decrease the power of the test in the case of a high number of ties. The test results of Wilcoxon signed ranks are shown in Table V.

Table V shows the R^+, R^- and p-values computed for all pairwise comparisons concerning ICQACO algorithm (the p-values have been computed by using SPSS Statistics software). As can be seen from Table V, the ICQACO algorithm shows a significant improvement over the basic ACO algorithm and the CPACO algorithm.

The single objective function [equation (6)] and the multi-objective function [equation (8)] are further studied and analyzed to explain the significance of multi-objective function in solving gate assignment. In this paper, the objective of the shortest walking distances of passengers is selected to deeply study. The designed ICQACO algorithm is used to solve the optimization model of gate assignment. These parameters in the designed ICQACO algorithm are the same as those of the previous selection. The experimental results are shown in Table VI and Figure 6.

As can be seen from Table VI and Figure 6, for the walking distances of passengers and the simulation results of ten consecutive simulations, the airport operation safety is regarded as the inflexibility constraint condition for gate assignment method. For the multi-objective function, the least optimization value is 24,040,465 at the 122*th* iteration, and the average optimization value is 2,6017,444 and the average iterations are 120.1 iterations. For the single objective function, the least optimization value is 23,549,610 at the 145*th* iteration, and the average optimization value is 23,988,838 and the average iterations are 80.4 iterations. The average operation time for the multi-objective function is 511.65 s, and the average operation time for the single objective function is 513.55 s. On the basis of the analysis and comparison, it can be seen that the optimization result of the multi-objective gate assignment is worse than that of single objective gate assignment in the objective of the walking distances of passengers. Because the objectives of the most balanced idle time, the shortest walking distances of passengers and the least number of flights at apron are comprehensively considered to

Index	Comparison	R^+	R^-	p-value
1	ICQACO algorithm versus ACO algorithm	0	55	0.005034
2	ICQACO algorithm versus CPACO algorithm	2	53	0.009344

Table V. The test results of Wilcoxon signed ranks

Table VI.
The experimental results

Experimental no.	Multi-objective function Operation time(s)	Iterations	Optimal value	Single objective function Operation time(s)	Iterations	Optimal value
1	503.8	11	25,994,519	520.6	145	23,549,610
2	509.3	74	25,657,351	516.3	52	23,871,067
3	510.2	192	26,728,652	519.3	85	24,004,320
4	515.2	101	25,331,140	514.3	15	24,405,231
5	525.7	156	27,443,929	516.2	26	23,933,342
6	506.8	178	27,261,241	509.8	160	23,994,052
7	504.4	122	24,040,465	501.8	87	24,381,330
8	513.9	74	25,657,351	511.7	34	24,060,431
9	505	192	26,728,652	511.8	97	23,781,039
10	522.2	101	25,331,140	513.7	103	23907960
Average value	511.65	120.1	26,017,444	513.55	80.4	23,988,838

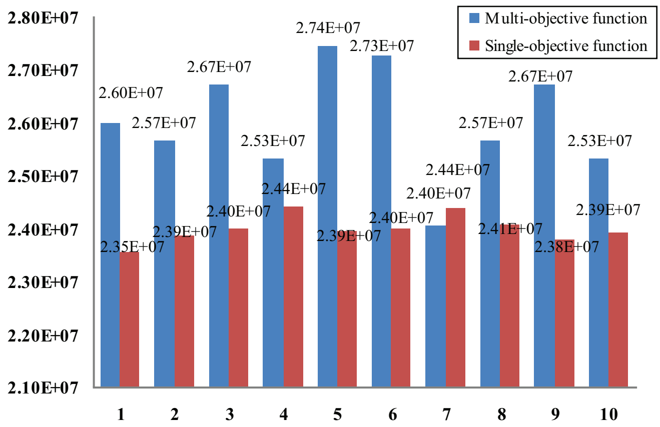

Figure 6.
The comparison of walking distances of passengers

construct the multi-objective optimization model of gate assignment to improve the overall operation capacity of the whole airport. So it is very meaningful to study multi-objective optimization model of gate assignment problem by using new intelligent optimization algorithms.

8. Conclusion and future work

The gate assignment is an important work in the operation and management of airport system. With the rapid development of civil aviation, the airport gate assignment is becoming more and more important. The gate resources are reasonable and effectively assigned, which has become a common problem for large and medium-sized airports under ensuring the safety. In this paper, on the basis of analyzing characteristics of gate assignment and flights, the most balanced idle time, the shortest walking distances of passengers and the least number of flights at apron are considered as the optimization objectives to construct an efficient multi-objective optimization model for airport gate assignment. However, it is difficult to directly solve the multi-objective function and obtain a very satisfactory and feasible solution by simply adjusting the weighting factors. Therefore, the multi-objective optimization model of gate assignment needs to be non-quantized, and the weighted method is used to non-quantize multi-objective optimization functions. Because the gate assignment belongs to NP-hard problem, the designed ICQACO algorithm based on the ant colony collaborative strategy and the formula and range of pheromone update strategy is used to solve the constructed optimization model of airport gate assignment to obtain the satisfactory gate assignment result. The experimental data set with 30 available gates and 212 flights from Guangzhou Baiyun airport of China is used to test and verify the effectiveness of the designed ICQACO algorithm and multi-objective optimization model of gate assignment problem. And the basic ACO algorithm and CPACO algorithm are selected to solve the optimization model of gate assignment to demonstrate optimization performance of the ICQACO algorithm. The average optimization value and iterations of the designed ICQACO algorithm is better than the average optimization value and iterations of the basic ACO algorithm and the CPACO algorithm in solving the multi-objective function of gate assignment. The simulation calculation results show that the designed ICQACO algorithm can obtain the best convergence efficiency and the best optimization ability for solving gate assignment problem by sacrificing the operation time. The designed ICQACO algorithm takes on the ability to escape the local minimum value and improve the global search ability. And the gate assignment results show that the gate assignment model and method can balance the idle time of gates and improve the satisfaction degree of passengers. This study provides some references for the airport operation management.

Because the designed ICQACO algorithm exists higher time complexity, it need more time to solve the gate assignment problem. So the designed ICQACO algorithm need to further be deeply studied. And the multi-objective optimization model of gate assignment is only considered three objectives. The more objectives need to be analyzed and studied in the next work to us.

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