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Study on an Airport Gate Reassignment Method and Its Application

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Abstract: Bad weather, mechanical failures, air control, and crew members of the discomfort health are very likely to cause flight delays. If these events occur, decision-makers of airport operation must rediscover the flight schedules through reassigning gates to these flights, delaying flights, and canceling flights. Therefore, it is important to study the recovery strategy with the feasibility and the least cost for delayed flights and to improve the airport operation efficiency. In this paper, a mathematical model of gate reassignment based on the objectives of the loss of passengers, airport operating, and airlines, and the most important index of disturbance value of the gate reassignment for delayed flights is constructed. Then, the genetic algorithm (GA) and ant colony optimization (ACO) algorithm are combined in order to propose a two-stage hybrid(GAOTWSH) algorithm, which is used to solve the constructed mathematical model of gate reassignment for delayed flights. The test data from the operations of the one airport is used to simulate and demonstrate the performance of the constructed mathematical model of gate reassignment for irregular flights. The results show that the proposed GAOTWSH algorithm has better optimization performance and the constructed gate reassignment model is feasible and effective. The study provides a new idea and method for irregular flights.

Keywords: gate reassignment; flight delays; two stage hybrid algorithm; optimization performance; disturbance

1. Introduction

With the rapid development of air transport, the gates have become one of the bottlenecks of airport resource operation. The gate assignment is to assign flights to the gates according to the certain rules and the flight schedule by the airport controller [1]. Airport resource operation is very complex, bad weather, aircraft failure, air control, crew members of their own discomfort health, and other reasons are very likely to cause flight delays. If the flight delays are not handled promptly and fast, it will affect the operation, revenue, decision-making efficiency, and passenger satisfaction, and so on of the whole airport, as well as the airlines [2]. When the flight delays occur, the airlines must adjust their flight schedules, such as delaying flights, canceling flights, resetting aircraft routes, reassigning crew members, or assembling new units and rearranging passengers, and so on. Therefore, the airport must be combined with the status of flight operation, on the basis of the original gate assignment schedule, the gates are constantly reassigned in order to ensure the efficiency of gates, reduce the operation cost of airlines, and improve the service level of the airport. Consequently, it is one of the important ways in how to study the recovery strategy with the feasibility and the least cost for the assignment of delayed flights in order to improve the airport operation efficiency.

These have greatly increased the probability of flight delays, and at the same time, the flight delays factors are complex and diverse. Airlines have their own reasons and non-airline reasons. Therefore, the flight delay is a worldwide problem that puzzles the air transportation. The flight delay does not only bring a lot of inconvenience to the passengers, but also causes the airlines to suffer economic losses, and seriously threatens the safety of the airport and the airspace. Over the past few decades, a lot of researchers and experts have proposed some methods to solve the problem of flight delays, such as linear programming, genetic algorithm, simulated annealing, particle swarm optimization algorithm, ant colony optimization algorithm, and other algorithms. Although these methods better solve the gate problem of delayed flights, take on relatively easy implementing and operation, the scheduling efficiency and solving accuracy are too low.

Genetic algorithms (GA) [3] is a metaheuristic inspired by imitating the processes that are observed during natural evolution. It is a parallel, random, and adaptive search method, it can avoid the local optimization result, but it exists in the relatively long calculation time, cannot guarantee the solution quality. Ant colony optimization (ACO) [4] is a metaheuristic inspired by imitating the behavior of real ants. It is a heuristic global optimization algorithm in essence, which has the characteristics of distributed computation, information positive feedback, and heuristic search. But it exists the longer search time, and is easy to appear the stagnation due to the found same solutions by all ants. Therefore, in this paper, on the basis of analyzing gates of airport, the operation management of the airport, and flight delays, an efficient optimization model of gate reassignment problem, which is based on the objectives of the loss of passengers, airport operating, and airlines, and the most important index of disturbance value of the gate reassignment for delayed flights is constructed. A new two-stage hybrid algorithm based on the GA and ACO (GAOTWSH) algorithm is proposed in this paper to solve the gate reassignment model for flight delays. An actual application case is used to test and verify the effectiveness of the constructed gate reassignment model and the proposed GAOTWSH algorithm.

The remainder of the paper is organized as follows. The related work is described in Section 2. A gate reassignment model is constructed in Section 3. In Section 4, the ant colony optimization algorithm is introduced and two stage hybrid algorithm is proposed. In Section 5, data simulation and analysis are introduced in detail. Finally, the conclusions are offered and future research direction is discussed in Section 6.

2. Related Work

Flight delays have become a worldwide problem for airlines and travelers. A large number of flight delays not only bring economic losses to airlines and passengers, but also damage the reputation and competitiveness of airlines. Therefore, the gate assignment and reassignment problems have already been studied by many researchers and experts. Pan and Wey [5] proposed an efficient gate reassignment algorithm GRASS for inverter minimization in post technology mapping. Gu and Chung [6] proposed a genetic algorithm approach to solving the gate reassignment problem in order to efficiently find minimum extra delayed time solutions. Wong et al. [7] identified the causes, as well as the practical measurement of aircraft flight delays. The performance of air traffic management is measured by examining the technical delays and scheduled timetable delays, which are derived from a mathematical programming model. Lo et al. [8] proposed a model to predict the variation with time of the multipath delay for a jet aircraft or other broadband acoustic source in level flight with constant velocity over a hard ground. Yan and Tang [9] proposed a heuristic approach embedded in a framework that was designed to help the airport authorities make airport gate assignments that are sensitive to stochastic flight delays. The framework includes three components, a stochastic gate assignment model, a real-time assignment rule, and two penalty adjustment methods. Yan et al. [10] proposed a model that will assist in the reassignment of flights to common-use check-in counters following airport incidents. Yan et al. [11] proposed a reassignment model based on minimizing the number of gate changes for the purpose of helping airport authorities with flight-to-gate reassignments following temporary airport closures. Churchill et al. [12] proposed the examined the delay propagation in spatial and temporal terms. Two models, each incorporating different levels of fidelity and flexibility, are applied in an effort to examine this phenomenon. Eun and Bang [13] proposed the optimization problem and algorithm branch-and-bound algorithm with linear programming and Lagrangian dual decomposition for a decision-support tool for air-traffic control, which uses discrete delay times as optimization variables. Tang et al. [14] proposed a gate reassignment framework, and a systematic computerized tool, for repeatedly handling gate reassignments when given varied flight delay information. Maharjan and Matis [15] proposed a binary integer program based on minimizeing the total walking distance of those passengers either connecting or originating at an airport for the optimal reassignment of planes to gates in response to day-of flight delays. Tang [16] proposed a gate reassignment model to deal with temporary gate shortages and stochastic flight delays for the Taiwan Taoyuan airport. Yan et al. [17] proposed a gate reassignment model to consider both deterministic and stochastic flight departure/arrival times. A 0–1 integer programming technique is applied to formulate the model. Deshpande and Arikan [18] examined the impact of the scheduled block time that was allocated for a flight, a factor controlled by airlines, on on-time arrival performance. Li et al. [19] proposed a multi-objective programming model for airport gate reassignment based on the concept of disruption management to improve the efficiency of gate reassignment and to optimize the plan of gate reassignment. Wang et al. [20] proposed a real-time gate reassignment model based on the objective functions of minimizing the disturbance and penalty function in order to improve airport sources and service quality of travelers. ACO is presented to simulate and verify the effectiveness of the model. Farley et al. [21] proposed the algorithm basic reduction yare approach for flights, for minimizing the airline passenger trip delay. Wu et al. [22] studied the robust stability and stabilization problem of uncertain networked flight control system with random time delays. Radivojevic and Milbredt [23] proposed a decision support system tool based upon an examination made from the airlines' operational point of view and for determined prioritization strategy for use in the disruption management of the airline operation control centre. Montlaur and Delgado [24] compared different optimization strategies for the minimization of flight and passenger delays at two levels: pre-tactical, with on-ground delay at origin, and tactical, with airborne delay close to the destination airport. Zhang and Klabjan [25] proposed an efficient gate re-assignment methodology to deal with the disruptions, in which the objective function is to minimize the weighted sum of the total flight delays, the number of gate re-assignment operations, and the number of missed passenger connections. Yu et al. [26] proposed a novel heuristic approach to solve the integrated gate reassignment and taxiway scheduling based on considering the runway restriction, gate allocation, and taxiway conflict. Takeich [27] proposed the nominal flight time optimization strategies through the estimation/resolution of the delay accumulation, and discussed its feasibility. Marla et al. [28] proposed a novel approach addressing airline delays and recovery. The used mechanisms include aircraft swaps, flight cancellations, crew swaps, reserve crews, and passenger rebooking. Xu and Prats [29] proposed an approach to implement linear holding for flights that were initially subject to ground holding, in the context of Trajectory Based Operations for neutralizing additional delays raised from the lack of coordination between various traffic management initiatives and without incurring extra fuel consumption.

For solving methods of the gate assignment or reassignment, many researchers proposed a lot of solving methods in the past few decades, such as linear programming methods, numerical calculation methods, and intelligent algorithms. Genç et al. [30] proposed a method based on combining the benefits of heuristic approaches with some stochastic approaches. Gu and Sheng [31] proposed a regularization path algorithm for ν-support vector classification. Fu et al. [32] proposed an efficient multi-keyword fuzzy ranked search scheme. Xue et al. [33] proposed a self-adaptive artificial bee colony algorithm based on the global best candidate for solving global optimization problems.

Gu et al. [34] proposed an effective incremental support vector ordinal regression formulation based on a sum-of-margins strategy. Zhang et al. [35] proposed an optimal cluster-based mechanism for load balancing with multiple mobile sinks. Wang et al. [36] proposed a back propagation neural network model by using solar radiation to establish the relationship. Liu et al. [37] proposed a speculative approach for spatial-temporal efficiency with multi-objective optimization. Pan et al. [38] proposed an efficient motion estimation and disparity estimation algorithm for reducing the computational complexity. Xiong et al. [39] proposed a novel reversible data hiding scheme using integer wavelet transform, histogram shifting, and orthogonal decomposition. Kong et al. [40] proposed a belief propagation-based optimization method for solving task allocation problem. Chen et al. [41] proposed an improved quaternion principal component analysis method for processing nonlinear quaternion signals. Gu et al. [42] proposed a structural minimax probability machine for constructing a margin classifier. Wang et al. [43] proposed a novel multi-watermarking scheme based on hybrid multi-bit multiplicative rules. Zhang et al. [44] proposed a special model known as RELAX-RSMN with a totally unimodular constraint coefficient matrix to solve the relaxed 0–1 ILP rapidly through linear programming. Rong et al. [45] proposed a novel K+-isomorphism method to achieve the K-anonymization state among subgraphs. Ma et al. [46] proposed an efficient overlapping community detection algorithm based on structural clustering. Deng et al. [47] proposed a novel collaborative optimization algorithm for solving complex problems. Deng et al. [48] proposed an improved PSO algorithm for solving the gate assignment problem. Other solving methods are proposed [49–52].

After the domestic and international research findings of the gate reassignment are reviewed, most of the studies reassigned the delayed flights from the perspective of passengers under the determined flight information. But in the process of actual operation, the airport cannot obtain all of the departure and departure flight information in real time. The first-come first service algorithm is used to reassign the delayed flights to the gates in China. Although this algorithm is relatively easy to implement and operate, it exists with the low scheduling efficiency and it easily causes excessive delays. Therefore, on the premise of ensuring safety and obeying the capacity limitation of the whole airport, a gate reassignment model based on the objectives of the loss of passengers, airport operating, and airlines, and the most important index of disturbance value is constricted and a two stage hybrid algorithm based on GA and ACO algorithm is proposed in this paper to solve the constructed gate reassignment model.

3. Construct a Gate Reassignment Model

3.1. Gate Reassignmet Modeling for Delayed Flights

In the actual operation of the airport, due to some uncertain factors, such as bad weather, mechanical failures, air control, and crew members of the discomfort health, some flights are delayed. In this time, the airport need to quickly and dynamically adjust the subsequent flights in order to meet the actual needs. In addition to the scientific, fair and reasonable optimization adjustment can meet the multi-stakeholder needs of the airlines, airports, and passengers, so as to maximize the service level and efficiency of the civil aviation. However, in most of the papers for the flight delays, the two aspects of airlines and passengers loss are considered, the increased costs of airport operating do not take into account in most of papers. Therefore, this study does not only take into account the loss of airlines and passengers, but also takes into account the increased costs of airport operating. Under different conditions, the weights of the three factors may be different. For example, when the flight delay time is longer, the loss of passengers should be mainly taken into account. Therefore, the weight of passengers is increased in order to reflect the characteristics of public infrastructure industry. Based on the anlaysis, in this paper, the gate reassignment for delayed flights mainly considers the loss of passengers, airport operating, and airlines, which are minimized as the objective function, and the most important index of disturbance value for the gate reassignment for delayed flights is regarded as the objective function in order to construct the gate reassignment model for delayed flights. The disturbance value indicates the planned gate assignment to equal to the gate reassignment.

(1) The objective function of the least weighted sum of the loss of passengers

$$f_1 = \min\sum_{i=1}^{m}\sum_{j=1}^{n}[T_i \times P_i \times \sqrt[3]{((RA_i - A_i) \times x_{ij}/60)^2}/29 + S_i \times T_i \times (RA_i - A_i) \times x_{ij} + C_i \times y_i] \quad (1)$$

(2) The objective function of the least weighted sum of the cost of airport operating

$$f_2 = \min[H_i \times T_i \times (RA_i - A_i) \times x_{ij} + D_i \times y_i] \quad (2)$$

(3) The objective function of the least weighted sum of the economic loss of airlines

$$f_3 = \min[g_k \times (RA_i - A_i) \times x_{ij} + E_i \times y_i] \quad (3)$$

$$\begin{aligned} F_1 = \min \sum_{i=1}^{m}\sum_{j=1}^{n}\{ & w_1 \times [T_i \times P_i \times \sqrt[3]{((RA_i - A_i) \times x_{ij}/60)^2}/29 + S_i \times T_i \times (RA_i - A_i) \times x_{ij} + C_i \times y_i] + \\ & w_2 \times [H_i \times T_i \times (RA_i - A_i) \times x_{ij} + D_i \times y_i] + w_3 \times [g_i \times (RA_i - A_i) \times x_{ij} + E_i \times y_i]\} \end{aligned} \quad (4)$$

(4) The objective function of the most important index of disturbance value for the gate reassignment for delayed flights

$$F_2 = \sum_{i=1}^{n} zd_i \quad (5)$$

where m is the number of gates, n is the number of flights, A_i is the planned arrival time of the ith flight, D_i is the planned departure time of the ith flight, RA_i is the actual arrival time of the ith flight, RD_i is the actual departure time of the ith flight, S_i is the loss of each passenger of the ith flight in unit time, C_i is the increased loss of each passenger of the canceled ith flight (8 h), D_i is the increased loss of airport of the canceled ith flight (8 h), E_i is the increased loss of airport of the canceled ith flight (8 h), H_i is the recovery cost of each passenger of the ith flight (including compensation, resettlement fees, transfer fees and so on), $TD_{\max}$ is the maximum delay time, T_i is the number of passengers of the ith flight, P_i is the price of the ith flight, w_1, w_2 and w_3 are the weights of passengers, airport and airline. g_i is delay cost of the ith flight in unit time (70 for large flight, 50 for medium flight and 30 for small flight).

In the gate reassignment model, x_{ij}, zd_i and y_i are 0–1 variables, which are defined as follows.

$$x_{ij} = \begin{cases} 1 & \text{The } i\text{th flight is reassigned to the } j\text{th gate} \\ 0 & \text{Otherwise} \end{cases}$$

$$zd_i = \begin{cases} 1 & \text{The } i\text{th flight is assigned to the planned gate} \\ 0 & \text{Otherwise} \end{cases}$$

$$y_i = \begin{cases} 1 & \text{The } i\text{th flight is canceled} \\ 0 & \text{Otherwise} \end{cases}$$

The constructed objective function can better ensure the planned gate assignment, least reassign the gates, reduce unnecessary trouble for passengers and staff, and meet the needs of real-time operation of the airport. This objective function is alsothe first satisfied target function in real-time assignment.

3.2. Linearize the Gate Reassignment Model

Set the weighting factor of v_1 $(0 \le v_1 \le 1)$ and v_2 $(0 \le v_2 \le 1)$. Suppose the objective function is $Z = \sum_{q=1}^{2} v_q F_q$. For the two different objective functions of F_1 and F_2, the values of actual objective function of F_1 and F_2 are not easily determined, and the difference between the value of actual objective function of F_1 and the value of actual objective function of F_2 could be very huge. Therefore, it is difficult to obtain the satisfied optimal solution by simply adjusting the weighting factors. In this paper, the objective functions of F_1 and F_2 are linearized as follow.

$$F_{\max 1} = \max\{|F_1|\} \text{ and } F_{\max 1} \neq 0 \tag{6}$$

$$F_{\max 2} = \max\{|F_2|\} \text{and } F_{\max 2} \neq 0 \tag{7}$$

$$Z' = \sum_{q=1}^{2} v_q F_q / F_{\max q} \tag{8}$$

In the actual process, it is difficult to simply determine the $F_{\max 1}$ and $F_{\max 2}$. Therefore, for the values of the $F_{\max 1}$ and $F_{\max 2}$, it is necessary to select a set of empirical values, and finally the objective function eventually linearized as follow.

$$Z' = \frac{v_1}{F_{\max 1}} \times F_1 + \frac{v_2}{F_{\max 2}} \times F_2 \tag{9}$$

4. Two Stages Hybrid Algorithm

4.1. GA

Genetic algorithms (GA) [3] is a class of population-based stochastic search techniques that solves problems by imitating processes observed during natural evolution. It is based on the principle of the survival and reproduction of the fitness. GA continually exploits new and better solutions without any pre-assumptions, such as continuity and unimodality. GA is provided as the parallel iterative algorithm with a certain learning ability, which repeats evaluation, selection, crossover, and mutation after initialization until the stopping criteria are reached. It has been widely applied to many complex optimization problems, such as function optimization, multi-objective optimization, traveling salesmen problem, and so on. GA shows its merits for optimization problems; especially as it is propitious to the problems of multiple optimum solutions. A real-coded GA is a genetic algorithm representation that uses a vector of floating-point numbers instead of 0's and 1's for implementing chromosome encoding. With some modifications of the genetic operators, the real-coded GA has a better performance than the binary-coded GA for traveling salesman problem. The crossover operator of a real-coded GA is performed by the borrowing concept of convex combination. Searching process of the GA is shown in Figure 1.

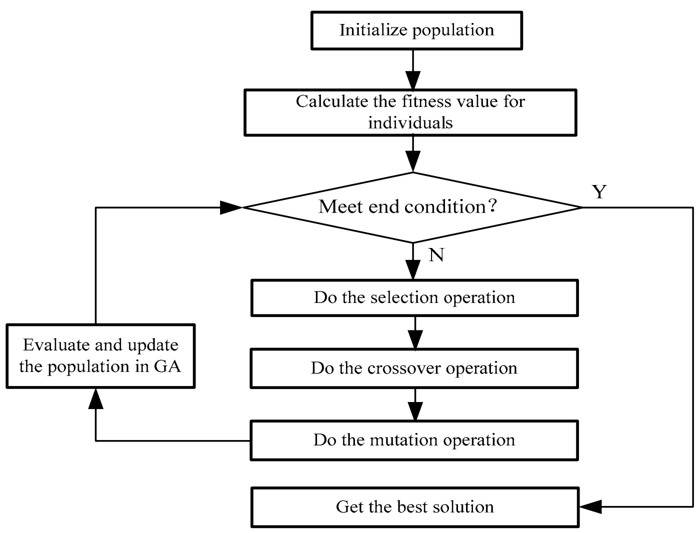

Figure 1. Searching process of the genetic algorithms (GA).

4.2. ACO Algorithm

ACO algorithm was proposed by Dorigo [4]. It is a metaheuristic that is inspired by the behavior of real ants in search of 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 that is based on agents that simulate the natural behavior of ants, including the mechanisms of cooperation and adaptation. It simulates the techniques that are employed 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 solving problem. The flow of ACO algorithm is illustrated in Figure 2.

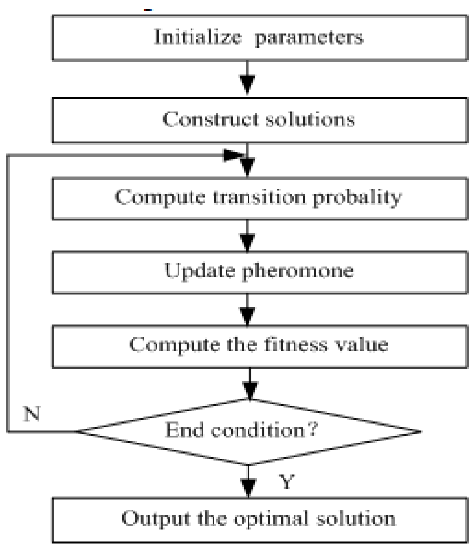

Figure 2. The flow chart of the ant colony optimization algorithm.

Ants are insects that live together. Since they are blind animals, they find the shortest path from nest to food with the aid of pheromone. The pheromone is the chemical material that is deposited by ants, which serves as the critical communication media among ants, thereby guiding the determination of the next movement [29]. On the other hand, ants find the shortest path based on intensity of pheromone that is deposited on different paths. Generally, the intensity of pheromone and the length of the path are used to simulate the ant system. Initially, n ants are randomly placed on m nodes. Then, in 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 that the *k*th ant cannot choose as the next node. This list is called Tabuk, which includes all of the customer nodes that have been visited by the *k*th ant until the current state in addition to all of the depots except the one that 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, and 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 intensity of pheromone will be updated by using the pheromone update rule. The procedure of pheromone update rule is shown as follows:

(1) The transition rule

In the route, the kth 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:

$$s = \underset{u \in J_r^k}{\arg\max}[\tau_i(r,u)^\alpha \cdot \eta(r,u)^\beta] \text{if } q \leq q_0 \text{ (Exploitation)} \tag{10}$$

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

$$p_k(r,s) = \begin{cases} \dfrac{\tau(r,s)^\alpha \cdot \eta(r,s)^\beta}{\sum\limits_{u \in J_r^k} \tau(r,u)^\alpha \cdot \eta(r,u)^\beta} & \text{if } s \in J_r^k \\ 0 & \text{otherwise} \end{cases} \quad \text{if } q > q_0 \text{ (Bias Exploitation)} \tag{11}$$

In two formulas, $p_k(r,s)$ is the transition probability, $\tau(r,u)$ is the intensity of pheromone between city r and city u in the ith 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 kth ant in the ith group, the parameter α and β are the control parameters, q is a uniform probability [0, 1].

(2) The pheromone update rule

In order 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 by:

$$\tau(r,u) = (1-\rho)\tau(r,s) + \sum_{k=1}^{m} \Delta\tau_k(r,s) \tag{12}$$

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 $t + \Delta t$ in the tour. It is given by:

$$\Delta\tau_k(r,s) = \begin{cases} \dfrac{Q}{\sum L_k} & (\mathrm{r},s) \in \pi_k \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

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

4.3. Two Stages Hybrid Algorithm

4.3.1. The Idea of Two Stages Hybrid Algorithm

Genetic algorithm (GA) is an adaptive random search method that is based on natural selection and genetic theory. It recombines feasible solutions in the multidimensional space to improve the trajectory or tendency of the solution by maintaining a set of feasible solutions for reaching the optimal solution. The GA has the advantages of global optimization, strong robustness, and overall optimization for solving complex problems, but it has poor performance for solving large-scale or large scale multivariable solution tasks. ACO has the characteristics of distributed computing and positive feedback mechanism, shows strong robustness and heuristic search, and takes on the higher efficiency for solving combinatorial optimization problems. But it contains a longer calculation time, slow convergence speed, and it is easy to fall into local optimum. The uniform distribution of initial pheromone causes the blindness of initial pheromone distribution and a slow convergence in the early stage. Therefore, in order to comprehensively use the respective characteristics of GA and ACO algorithm and realize the complementary advantages and increase the value of information, a two stage hybrid(GAOTWSH) algorithm based on GA and the ACO algorithm is proposed to solve the gate reassignment problem for flight delays. The whole process of GAOTWSH algorithm is divided into two stages. In the first stage, the basic GA is improved to propose an adaptive GA in order to improve the solving range of GA. The evolution rate of each iteration of the adaptive GA is set in order to avoid still iterate and waste a lot of time when the adaptive GA is reduced over a period of time. The advantage of the adaptive GA is used to solve the gate reassignment problem for flight delays and obtain a sub-optimal solution after a certain number of iterations are executed (called rough search). In the second stage, the obtained sub-optimal solution is used to adjust the initial distribution of pheromone of ACO algorithm in order to improve the searching speed. Then, the advantages of the parallelism, positive feed back, and high precision solution of ACO algorithm are used for the gate reassignment problem for flight delays in order to complete the solving of the gate reassignment problem for the whole flight delays (called fine search). Therefore, in solving the gate reassignment problem of flight delays, the time efficiency of the proposed GAOTWSH algorithm is better than the ACO algorithm, and the accuracy and efficiency of the proposed GAOTWSH algorithm are better than the GA. It can be said that the proposed GAOTWSH algorithm is a complementary algorithm. The fundamental purpose of the proposed GAOTWSH algorithm is to let the GA and ACO algorithms overcome their weaknesses and to fully use the respective advantages and characteristics for improving the convergence speed and the accuracy in the process of solving the gate reassignment problem. The goal is to reduce the airport losses, minimize passenger losses and disappointments and fuel consumption of airlines, and to obtain the best gate reassignment results.

4.3.2. The Flow of the Proposed GAOTWSH Algorithm

According to the idea of two stage hybrid algorithm, the flow of the proposed GAOTWSH algorithm based GA and ACO algorithm is shown Figure 3.

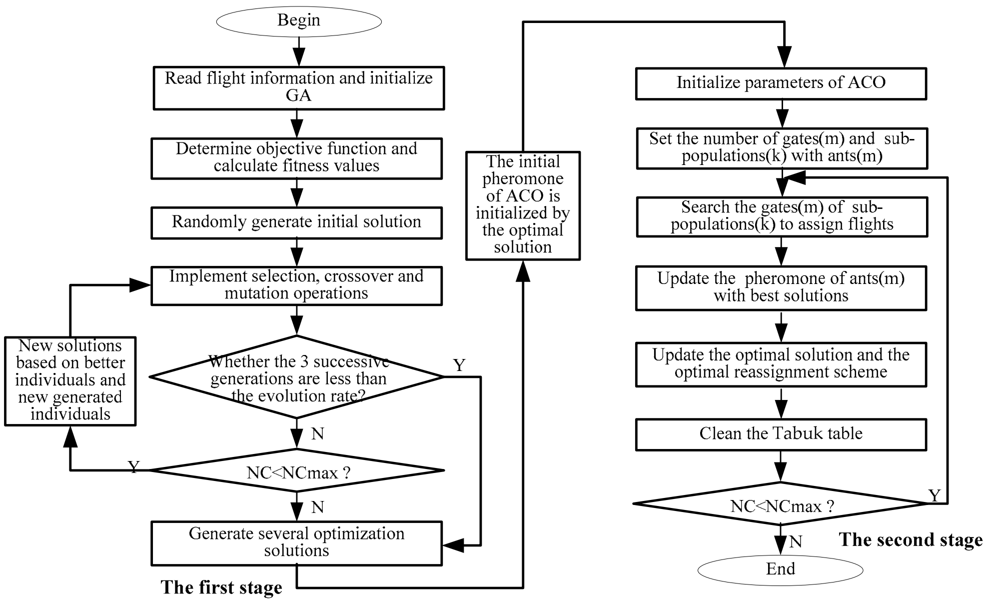

Figure 3. The flow of the new two-stage hybrid algorithm based on the GA and ACO (GAOTWSH) algorithm.

4.3.3. The Steps of the Proposed GAOTWSH Algorithm

According to the idea of two stage hybrid algorithm, the steps of the proposed GAOTWSH algorithm based GA and ACO algorithm is described as follows.

Step 1. Read flight information and initialize the parameters of GA.
Step 2. The initial solution is randomly generated. The selection factor, crossover factor and mutation factor are obtained according to the elitist strategy and the offline ranking selection method.

Step 3. Implement selection operation, crossover operation and mutation operation.

Step 4. Determine whether the three successive generations are less than the evolution rate, and the number of iterations is larger than the maximum iterations. If the three successive generations are less than the evolution rate and the number of iterations is larger than the maximum iterations, then continue Step 5. Otherwise go to Step 3.

Step 5. The several optimization solutions are generated by suing adaptive GA, then the optimization solutions are used to initialize the initial pheromone concentration of ACO algorithm.

Step 6. The parameters of ACO algorithm are initialized. The number of gates and sub-populations and ants are set according to the number of flight delays. The unvisited nodes are filled in the Tabuk table.

Step 7. The optimal solutions of ants are searched by using ACO algorithm.

Step 8. The pheromone concentrations of the ACO algorithm are updated, and the Tabuk table is cleaned.

Step 9. Determine whether the number of iterations reaches the maximum number of iterations. If the number of iterations reaches the maximum number of iterations, the continue Step 10. Otherwise go to Step 7.

Step 10. Obtain the optimal solution and the optimal scheme of the gate reassignment.

5. Case Analysis

5.1. Experimental Data and Environment

A domestic airport is selected as study case in this paper. 100 available gates for 500 flights are used to test and simulate. The pre-assigned flight schedule came from the actual assigned schedule under the normal landing condition, and there are the total of 147 delayed flights according to the flight timetable. The information of flights is shown in Table 1. The 100 available gates include 60 boarding gates and 40 remote boarding gates. These remote boarding gates are large gates. The 60 boarding gates include 36 large gates, 22 medium gates and two small gates. The information of gates is shown in Table 2.

Table 1. The information of flights.

Code	Price	Passengers	Type	Planed Arrival Time	Planed Departure Time	Actual Arrival Time	Actual Departure Time	Delayed Time (m)	Pre-Assigned Gate
1	3565	256	Medium	2015-7-26 6:00:00	2015-7-26 8:20:00	2015-7-26 6:00:00	2015-7-26 8:20:00	-	19
2	3058	606	Large	2015-7-26 6:00:00	2015-7-26 14:30:00	2015-7-26 6:00:00	2015-7-26 14:30:00	-	54
3	2483	298	Medium	2015-7-26 6:20:00	2015-7-26 8:00:00	2015-7-26 6:20:00	2015-7-26 8:00:00	-	17
4	1173	378	Large	2015-7-26 6:55:00	2015-7-26 9:10:00	2015-7-26 6:55:00	2015-7-26 9:10:00	-	21
5	1248	298	Medium	2015-7-26 7:50:00	2015-7-27 2:50:00	2015-7-26 7:50:00	2015-7-27 2:50:00	-	1
6	3022	606	Large	2015-7-26 7:55:00	2015-7-26 9:50:00	2015-7-26 7:55:00	2015-7-26 9:50:00	-	34
7	2249	378	Large	2015-7-26 8:15:00	2015-7-27 3:00:00	2015-7-26 8:45:00	2015-7-27 3:00:00	30	53
8	974	312	Large	2015-7-26 8:20:00	2015-7-26 9:20:00	2015-7-26 8:20:00	2015-7-26 9:20:00	-	37
9	3079	362	Large	2015-7-26 8:25:00	2015-7-26 10:05:00	2015-7-26 9:00:00	2015-7-26 10:05:00	35	93
10	1248	98	Small	2015-7-26 9:10:00	2015-7-26 10:10:00	2015-7-26 9:10:00	2015-7-26 10:10:00	-	55
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
500	1421	378	Large	2015-7-26 23:55:00	2015-7-27 9:10:00	2015-7-26 23:55:00	2015-7-27 9:10:00	-	27

Table 2. The information of gates.

Code	Type	Attribute	Started Time	Closed Time
1	Large	Boarding	2015-7-26 6:00	2015-7-26 23:59
2	Medium	Boarding	2015-7-26 6:00	2015-7-26 23:59
3	Large	Boarding	2015-7-26 6:00	2015-7-26 23:59
4	Large	Boarding	2015-7-26 6:00	2015-7-26 23:59
5	Large	Boarding	2015-7-26 6:00	2015-7-26 23:59
6	Large	Boarding	2015-7-26 6:00:	2015-7-26 23:59
7	Large	Boarding	2015-7-26 6:00	2015-7-26 23:59
8	Medium	Boarding	2015-7-26 6:00	2015-7-26 23:59
9	Medium	Boarding	2015-7-26 6:00	2015-7-26 23:59
10	Large	Boarding	2015-7-26 6:00	2015-7-26 23:59
⋮	⋮	⋮	⋮	⋮
60	Medium	Boarding	2015-7-26 6:00	015-7-26 23:59
61	Large	Remote	2015-7-26 6:00	015-7-26 23:59
⋮	⋮	⋮	⋮	⋮
100	Large	Remote	2015-7-26 6:00	015-7-26 23:59

The experiment environment is the Intel Core i3-4005U, 1.70 GHz, 12.0 GB RAM, Wind 10, and Matlab 2014a (MathWorks Company, Natick, MA, USA). In order to demonstrate the optimization performance of the proposed GAOTWSH algorithm, the GA and ACO algorithm are selected to solve the constructed gate reassignment model. The initial parameters of the GA, ACO algorithm, and GAOTWSH algorithm are selected after thorough testing. In the simulation experiments, the alternative values were tested and modified for some functions in order 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. So the selected values of these parameters are described in Table 3.

Table 3. Parameters of the three algorithms.

Parameters	GA	ACO	NGASAH
Population size (m_1)	100	-	100
Ants (m_2)	-	100	100
Iteration time ($T_{\max}$)	100	100	100
Initial crossover probability (p_c)	0.90	-	0.90
Initial mutation probability (p_m)	0.05	-	0.05
Pheromone factor (α)	-	2.0	2.0
Heuristic factor (β)	-	4.0	4.0
Initial concentration τ_{ij}	-	1.5	1.5
Evaporation coefficient (ρ)	-	0.80	0.80
Pheromone amount (Q)	-	100	120

5.2. Experimental Results

Suppose that a minimum interval time T = 5 min between two consecutive flights to the same gate is required to avoid conflict. The experiments were carried out for 30 consecutive simulation to solve the constructed gate reassignment model for flight delays. Random 10 times simulation results are selected to study and analyze in here. For 500 irregular flights, the gate reassignment results are shown in Table 4.

Table 4. The gate reassignment results.

Gate	Total Number	Gate	Total Number	Gate	Total Number	Gate	Total Number
1	4	16	8	31	4	46	7
2	2	17	8	32	5	47	8
3	11	18	9	33	3	48	6
4	13	19	11	34	6	49	5
5	9	20	5	35	3	50	8
6	9	21	12	36	8	51	6
7	15	22	12	37	7	52	2
8	3	23	3	38	4	53	7
9	3	24	9	39	7	54	11
10	9	25	11	40	6	55	3
11	17	26	3	41	4	56	7
12	10	27	9	42	4	57	4
13	12	28	3	43	5	58	2
14	9	29	4	44	9	59	10
15	6	30	6	45	4	60	9

As can be seen from Table 4, for 60 boarding gates, 40 remote boarding gates and 500 flights, there are 419 flights, which are assigned to 60 gates, there are 54 flights, which are assigned to the apron and there are only 27 flights that are canceled. The reassigned rate for 500 flights is 94.6% and the canceled rate for 500 flights is only 5.4%. The gate reassignment result based on the constructed mathematical model using the proposed GAOTWSH algorithm does not appear idle gates, and the reassigned flights for each gate are relative uniformity. As is known from Table 4, the constructed mathematical model of gate reassignment based on the objectives of the loss of passengers, airport operating and airlines, and the most important index of disturbance value is reasonable and effective. The proposed GAOTWSH algorithm can effectively solve the constructed mathematical model of gate reassignment problem. The proposed GAOTWSH algorithm has better optimization performance in solving the mathematical model of complex problem.

5.3. Result Comparison and Analysis

In order to demonstrate the optimization performance of the proposed GAOTWSH algorithm, the GA and ACO algorithm are selected to solve the constructed gate reassignment model. The comparison result for solving the constructed objective function is shown in Table 5 and Figure 4. The comparison result of running time for solving the constructed objective function is shown in Table 6 and Figure 5. The process of iteration for solving the constructed objective function is shown in Figure 6.

Table 5. The comparison result for solving the constructed objective function.

Methods	Index	1	2	3	4	5	6	7	8	9	10	AVG
GA	Iteration	71	71	60	49	61	72	70	66	72	71	66.3
	Optimal value	1.885	1.904	1.881	1.907	1.925	1.901	1.895	1.873	1.873	1.923	1.896
ACO	Iteration	128	187	180	156	98	175	120	117	137	182	148
	Optimal value	1.431	1.459	1.476	1.467	1.444	1.434	1.477	1.485	1.489	1.467	1.431
GAOTWSH	Iteration	155	137	182	89	183	110	98	163	163	153	143.3
	Optimal value	1.164	1.191	1.175	1.199	1.179	1.185	1.192	1.187	1.207	1.201	1.188

Table 6. The comparison result of running time.

Methods	1	2	3	4	5	6	7	8	9	10	AVG
GA	134.3	129.2	127.6	126.8	127.2	127.2	128.7	128.1	127.2	126.3	128.3
ACO	164.6	166.3	164.2	174.1	162.4	162.2	163.3	169.2	162.8	164.8	165.4
GAOTWSH	183.6	175.1	175.6	171.1	176.1	172.4	168.9	172.3	169.1	169.8	173.4

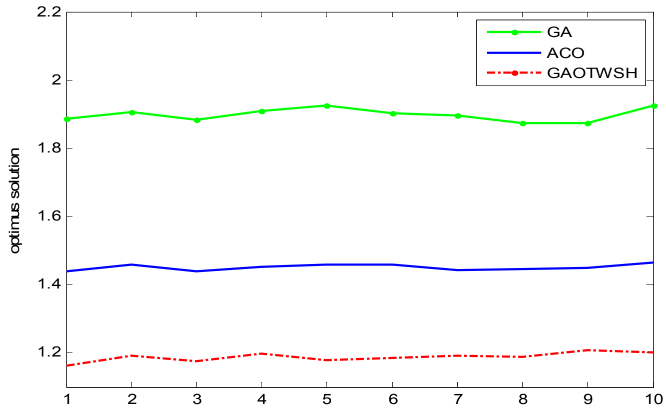

Figure 4. The comparison for solving the constructed objective function.

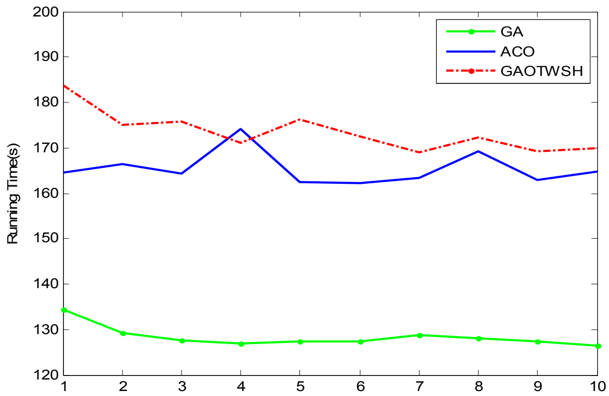

Figure 5. The comparison of running time for solving the constructed objective function.

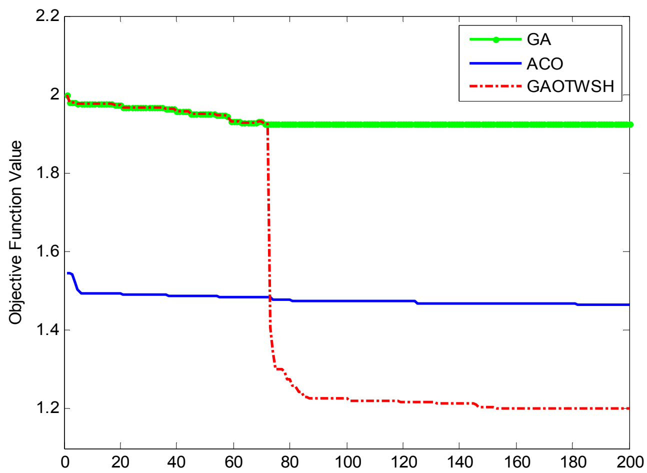

Figure 6. The process of iteration for solving the constructed objective function.

As can be seen from Tables 5 and 6, Figures 4–6, the optimal value and the average optimal value of the objective function is 1.873 and 1.896, and the least running time and average running time is 126.3 s and 128.3 s by using the GA, respectively. The optimal value and the average optimal value of the objective function is 1.431 and 1.463, and the least running time and average running time is 162.2 s and 165.4 s by using the proposed ACO algorithm, respectively. The optimal value and the average optimal value of the objective function is 1.164 and 1.188, and the least running time and average running time is 168.9 s and 173.4 s, by using the proposed GAOTWSH algorithm, respectively. As is known from Tables 5 and 6, Figures 4–6, the optimal value and the average optimal value of the objective function by using the proposed GAOTWSH algorithm are the least optimization value than the optimal values and the average optimal values of the objective function by using the GA and ACO algorithms. The experiment results show that the proposed GAOTWSH algorithm can obtain the least optimization value; it has better optimization performance in solving the gate reassignment problem. But, the least running time and average running time by using GA is the least time. The proposed GAOTWSH algorithm need more time to solve the gate reassignment problem due to two hybrids running.

In order to further analyze the optimization performance of the proposed GAOTWSH algorithm, the objective function of the loss of passengers, airport operating and airlines, and the objective function of the disturbance value of the gate reassignment for delayed flights are, respectively, selected to study and analyze here. The comparison result of the disturbance value is shown in Table 7 and Figure 7, the comparison result of the loss of passengers, airport operating, and airlines is shown in Table 8 and Figure 8.

Table 7. The comparison result of the disturbance value.

Methods	1	2	3	4	5	6	7	8	9	10	AVG
GA	460	460	462	462	474	465	473	462	461	465	464.4
ACO	344	345	344	355	349	344	351	346	345	347	347
GAOTWSH	204	213	215	219	219	207	214	220	216	219	214.6

Table 8. The comparison result of the loss of passengers, airport operating and airlines.

Time	1	2	3	4	5	6	7	8	9	10	Average
GA	3.849	3.848	3.839	3.785	3.891	3.881	3.796	3.859	3.833	3.715	3.829
ACO	3.046	3.046	3.046	3.046	3.046	3.046	3.046	3.046	3.046	3.046	3.046
GAOTWSH	3.072	3.017	3.072	3.018	3.072	3.072	3.016	3.015	3.072	3.072	3.050

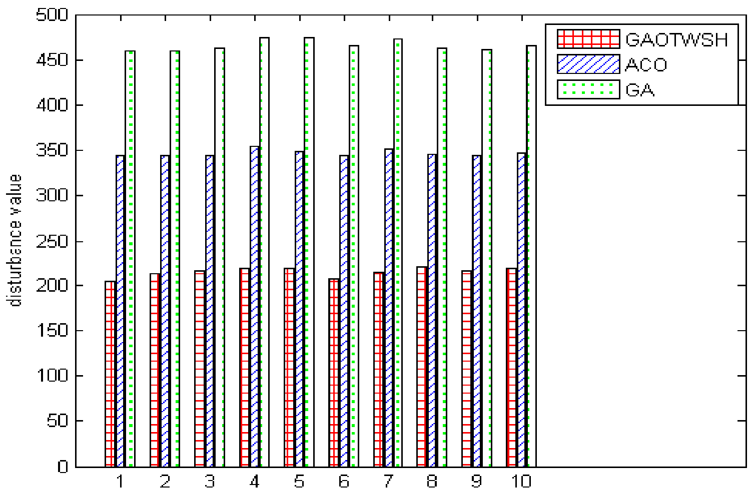

Figure 7. The comparison result of the disturbance value.

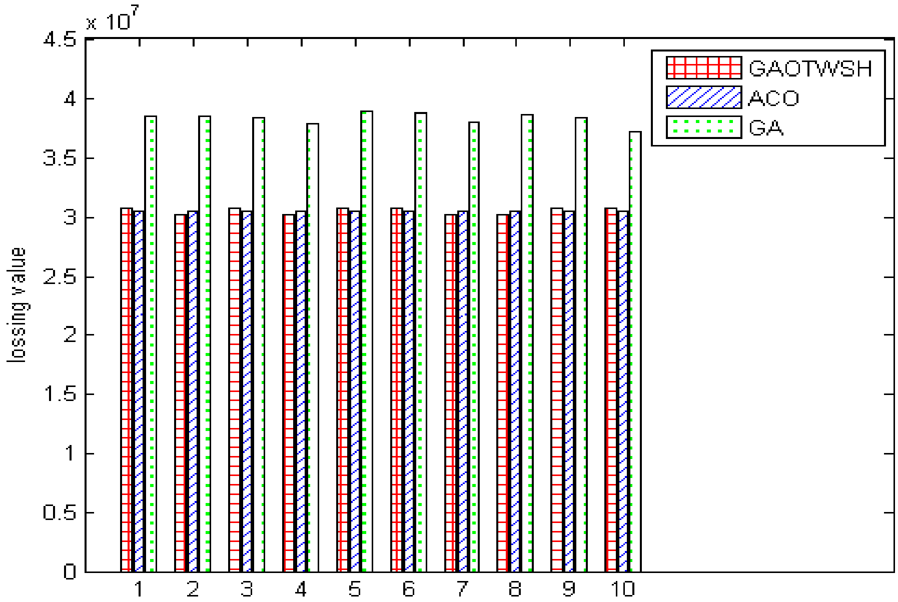

Figure 8. The comparison result of the loss of passengers, airport operating and airlines.

6. Conclusions and Future Work

For the flight delays caused by bad weather, mechanical failures, and air control, a gate reassignment model based on the objectives of the loss of passengers, airport operating, and airlines, and the disturbance value is constructed in order to really describe the actual airport operation condition. A two stages hybrid(GAOTWSH) algorithm based on combining the GA and ACO algorithm is designed to solve the constructed gate reassignment model for irregular flights. In order to effectively demonstrate the optimization performance of the GAOTWSH algorithm in solving the gate reassignment model, the test data with 500 flights (147 delayed flights), 60 boarding gates and 40 remote boarding gates from the operations of the one domestic airport is selected. 419 flights are assigned to 60 gates, 54 flights are assigned to the apron, and 27 flights are canceled. The reassigned rate is 94.6% and the canceled rate is only 5.4%. The optimal value and the average optimal value of the objective function is 1.164 and 1.188 by using the proposed GAOTWSH algorithm, respectively. Therefore, the results show that the proposed GAOTWSH algorithm takes on better optimization performance and the constructed gate reassignment model is feasible and effective.

Because the constructed gate reassignment model is considered as a less objective function, the more objectives need to be analyzed and studied in the next work to us. The proposed GAOTWSH algorithm should further be deeply studied and improved in order to reduce the time complexity.

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Author Contributions: Wu Deng conceived and designed the experiments; Bo Li performed the experiments; Huimin Zhao analyzed the data.

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