A space-time network model based on improved genetic algorithm for airport taxiing scheduling problems

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Abstract

In order to reduce the flight delays and ease the airport congestion, a space-time network taxi scheduling model integrates the three types of conflicts was used. In the model, the aircraft taxiing schedule problem was transformed to multi-commodity network model, and the Genetic-annealing algorithm was designed to solve the problem. The simulation case showed that optimized schedule results significantly reduced the total taxiing time by 586 seconds of 17 flights compared with FCFS strategy and avoided the potential flight conflicts, which greatly improved airport operational efficiency. In addition, genetic-annealing algorithm weight out the standard genetic algorithm in convergence rate and solution efficiency.

Keyword: Airport Operation Control; Congestion hours; Taxi Scheduling; Genetic-annealing algorithm

1. Introduction

In recent years, there are an increasing number of flight delays related to the airport traffic control management. In the event of bad weather or air traffic flow control situation, the peak-hour of large hub airports congestion is worsening [1]. Therefore, the reasonable aircraft taxiing schedule is critical to increase the airport capacity and improve the efficiency of airport operations. To solve such problems, foreign scholars have made a series of researchers, which involve in a simple queueing model of busy airport departure operations [2], the method of genetic algorithm to solve taxiing schedule problem based on the conflict identification [3]. Some models taking into account the constraints like runway capacity, terminal configurations and takeoff queues [4] and so on. In addition, the mixed-integer programming models [5-6] for static taxiing schedule were also proposed by some scholars, which view the minimum dispatching time as the objective function and can be solved by using the method of sliding time window allocation algorithm. Chinese scholars focused on the heuristic algorithm of taxiing path[9], intelligent dispatching simulation[10]and dynamic path planning[11]. The research of home and abroad are mainly concerned about the planning and dispatching of static path. The airport route planning functions of the international advanced Surface Movement Guidance and Control System (A-SMGCS) are in the initial stage, which are mostly realized from the real-time automatic route calculation rather than the constant routing database. This paper takes the conflicts management in process of taxiing into account, which considers the taxiing time and the reasonableness of the routing. By designing the genetic-annealing algorithm, local optimum problems of single algorithm would be solved.

2. The space-time network model of taxiing

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The paper [8] proposed a taxiing dynamic space-time network model; the decision variables used in the model are defined as follows:

\[ E_{i,t}^w = 1, \text{if aircraft "w" waits at node "i" at period "t";} \]
\[ X_{i,j,t}^w = 1, \text{if aircraft "w" is routed from node "i" to node "j" at period "t";} \]

The Objective function is to minimize the taxiing time of all flights, so the objective function \( F \) is defined as the taxiing time of all flights:

\[
F(X, E) = \sum_{w \in W} \sum_{t \in T} p_w \left( \sum_{i,j \in A} t_y X_{i,j,t}^w + \sum_{i \in N} E_{i,t}^w \right) + \sum_{w \in W} \sum_{i \in N} r_{i}^{w} t_{i,w}^{w} \tag{1}
\]

Where \( p_w \) indicates the priority of flight \( w \) (under normal circumstances, give priority to international flights rather than domestic flights, scheduled flights rather than unscheduled flights); the average taxiing speed of the aircraft can be approximated as a fixed average. Then for each link \( i,j \), suppose \( t_y \) denotes the time required by the aircraft taxis on the link \( (i,j) \) at the average speed. Aircraft \( r_{i}^{w} \) denotes the estimated time required by the aircraft \( w \) which does not reach the destination at the end of the planning period \( "t" \) taxis from node "i" to the destination. Analyzed from the multi-commodity flow conservation constraints, the flow capacity constraints, and other side constraints, we can conclude the constraints:

**The flow conservation constraints at every node are:**

\[
E_{i,t}^w + \sum_{j \in F^i} X_{j,i,t-1}^w = E_{i,t+1}^w + \sum_{j \in F^i} X_{j,i,t+1}^w, \forall t, \forall i, \forall w \tag{2}
\]

where the sets \( F^i, T^i \) are defined as:

\[
F^i = \{ j \mid (i,j) \in A^i \}, \quad T^i = \{ j \mid (j,i) \in A^i \}, \quad \forall i \in N^i
\]

the aircraft at origin node which the flow conservation constraints need to take into account, \( o(w) \).aircraft “w” may wait or move at \( (o(w),t(w)) \):

\[
E_{o(w),t(w)}^w + \sum_{j \in F^i(o(w))} X_{o(w),j,t(w)}^w = 1, \forall w \in W \tag{4}
\]

at \( t = |T| \), all flights must be at some nodes:

\[
\sum_{i \in N^i} E_{i,t}^w = 1, \forall w \in W \tag{5}
\]

The flow capacity constraints at nodes“i” are defined as follows:

Capacity constraints at wait nodes \( N^W \):

\[
\sum_{w} e_w E_{i,t}^w \leq cap_{ni}, \forall t, \forall i \in N^{TH} \tag{6}
\]

Where \( cap_{ni} \) is the capacity of the node “i”, “\( e_w \)” is the surface space needed for aircraft “w” when it is waiting at a wait node.

The capacity of the ordinary nodes ( \( N^O \) ) and exit runway nodes ( \( N^{ER} \)):aircraft cannot stay waiting at these nodes:

\[
E_{i,t}^w = 0, \forall t < |T|, \forall i \in N^O \cup N^{ER} \tag{7}
\]

Apron node \( N^P \) and runway entrance node, the capacity of the node \( N^{AR} \) is 1:

\[
\sum_{w} E_{i,t}^w \leq 1, \forall t, \forall i \in N^P \cup N^{AR} \cup N^F \tag{8}
\]
The flow capacity constraints at other nodes:

$$\sum_w E^w_{ijt} + \sum_{j\in T(i)} X^w_{ijt-t_{p+1}} \leq 1, \forall i \in N^O \cup N^{AR} \cup N^F$$ (9)

Conflict constraints:
Conflict constraints of no node:

$$\sum_w E^w_{it} = 1 \quad \forall i \in N^O, \forall t$$ (10)

Conflict constraints of no link:

$$\sum_w (X^w_{ijt} + X^w_{ji}) = 1 \quad \forall i, j \in N^O, \forall t$$ (11)

3. Genetic-annealing algorithm

The space-time network model can be solved with the accurate algorithms such as Branch-and-Bound” (B&B) and Fix and relax (F&R), as NP hard problem, on the basis of drawing lessons from the natural selection and random search mechanism in the biological world, currently, the genetic algorithm is the universally effective method to solve this kind of optimization problems. However, because the traditional genetic algorithm has the problem of “premature convergence”, therefore, it is required to adopt the probability acceptance in the simulated annealing algorithm to make the objective function have better probing points, which facilitates to avoid that the search process falls into the local optimum [12]. There are mainly the following procedures when the space-time network is solved through the organic combination of the genetic algorithm and simulated annealing:

- **Encoding and decoding.** Each chromosome refers to a link on the taxiing route, under the condition that the average speed is constant, $t_w$ and $r_w^t$ can be calculated though encoding the chromosome.

Number the links of airport taxiway and runway, and one link consist of two airport nodes, and a chromosome consists of four genes, i, j, w and t, which respectively refer to node i and j as well as the t period of the w airplane, the genes shall be represented as binary code.

- **Calculation of the fitness function.** Take the objective function $f(x) = F(X,E)$ as the fitness value, where $t_w$, $r_w^t$, $X^w_{ijt}$ and $E^w_{it}$ can be obtained via chromosome representation.

- **Simulated annealing process.** Whether the generated new individual can replace its parent individual via the cross and variation operation of the genetic algorithm depends on the Metropolis acceptance principle of the simulated algorithm, and therefore, the individuals in the group can evolve gradually. Specifically speaking, at the temperature $T_k$, generate the new state $f$ from the current state $i$, their fitness are $f(x_i)$ and $f(x_2)$ respectively. Therefore, the acceptance probability of Metropolis is:

$$\exp\left\{-\left(f(x_i) - f(x_2)\right)/T_k\right\} > \text{rand}.$$

The flow chart of the genetic-annealing algorithm is shown as figure 1.
4. Simulation case

Select the arrival and departure flights of one runway of BCIA (Beijing Capital International Airports) at the busy hour in one day as the study objective, there are totally 17 flights arrival and departure in one hour, the flight schedule is shown as table 1.

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Table 1 Flights Plan

<table>
<thead>
<tr>
<th>Aircraft</th>
<th>Type</th>
<th>A/D</th>
<th>Starting point</th>
<th>Departure time</th>
<th>Terminal point</th>
<th>Landing time</th>
<th>Apron</th>
</tr>
</thead>
<tbody>
<tr>
<td>J_1</td>
<td>B737-300</td>
<td>A</td>
<td>TAO</td>
<td>11:40:00</td>
<td>PEK</td>
<td>12:50:00</td>
<td>227</td>
</tr>
<tr>
<td>J_2</td>
<td>B737-800</td>
<td>A</td>
<td>WUX</td>
<td>10:55:00</td>
<td>PEK</td>
<td>12:50:00</td>
<td>238</td>
</tr>
<tr>
<td>J_3</td>
<td>A320</td>
<td>D</td>
<td>PEK</td>
<td>12:51:00</td>
<td>MNL</td>
<td>16:51:00</td>
<td>205</td>
</tr>
<tr>
<td>J_4</td>
<td>A340-300</td>
<td>A</td>
<td>CPH</td>
<td>04:20:00</td>
<td>PEK</td>
<td>12:52:00</td>
<td>219</td>
</tr>
<tr>
<td>J_5</td>
<td>B737-700</td>
<td>A</td>
<td>NNG</td>
<td>09:50:00</td>
<td>PEK</td>
<td>12:52:00</td>
<td>233</td>
</tr>
<tr>
<td>J_6</td>
<td>B737-300</td>
<td>D</td>
<td>PEK</td>
<td>12:53:00</td>
<td>TAO</td>
<td>14:50:00</td>
<td>227</td>
</tr>
<tr>
<td>J_7</td>
<td>B747-400</td>
<td>D</td>
<td>PEK</td>
<td>12:55:00</td>
<td>SFO</td>
<td>01:30:00</td>
<td>214</td>
</tr>
<tr>
<td>J_8</td>
<td>B737-300</td>
<td>A</td>
<td>WNZ</td>
<td>11:10:00</td>
<td>PEK</td>
<td>13:00:00</td>
<td>237</td>
</tr>
<tr>
<td>J_9</td>
<td>A330-200</td>
<td>A</td>
<td>DOH</td>
<td>06:15:00</td>
<td>PEK</td>
<td>13:20:00</td>
<td>210</td>
</tr>
<tr>
<td>J_10</td>
<td>B737-300</td>
<td>D</td>
<td>PEK</td>
<td>13:22:00</td>
<td>WNZ</td>
<td>17:01:00</td>
<td>237</td>
</tr>
<tr>
<td>J_11</td>
<td>B777</td>
<td>A</td>
<td>SIN</td>
<td>09:00:00</td>
<td>PEK</td>
<td>13:23:00</td>
<td>217</td>
</tr>
<tr>
<td>J_12</td>
<td>A340-300</td>
<td>D</td>
<td>PEK</td>
<td>13:25:00</td>
<td>CPH</td>
<td>01:20:00</td>
<td>219</td>
</tr>
<tr>
<td>J_13</td>
<td>B747-400</td>
<td>A</td>
<td>SFO</td>
<td>04:35:00</td>
<td>PEK</td>
<td>13:25:00</td>
<td>219</td>
</tr>
<tr>
<td>J_14</td>
<td>G4</td>
<td>A</td>
<td>CCU</td>
<td>09:30:00</td>
<td>PEK</td>
<td>13:40:00</td>
<td>601</td>
</tr>
<tr>
<td>J_15</td>
<td>B737-800</td>
<td>A</td>
<td>SZX</td>
<td>10:40:00</td>
<td>PEK</td>
<td>13:40:00</td>
<td>240</td>
</tr>
<tr>
<td>J_16</td>
<td>B777-200</td>
<td>D</td>
<td>PEK</td>
<td>13:50:00</td>
<td>SIN</td>
<td>22:25:00</td>
<td>217</td>
</tr>
<tr>
<td>J_17</td>
<td>B747-400</td>
<td>A</td>
<td>ORD</td>
<td>03:20:00</td>
<td>PEK</td>
<td>13:50:00</td>
<td>213</td>
</tr>
</tbody>
</table>

Set the parameter of genetic-annealing algorithm, iteration \( M = 300 \), population scale \( N = 100 \), the adjustment parameter of the variation probability \( P_m = 0.4 \), the initial temperature \( T_0 = 10 \), and the cooling coefficient \( \lambda = 0.95 \). The dispatching result after 300 iterations is shown as figure 2.

Fig 2 (a)Fitness comparison of GA; (b)GA-SA

Seeing from figure 2, it can be found that the average fitness tends to be a steady value when the iteration comes to the 37 by use of the single genetic algorithm, and the optimum solution can be obtained just at the 10 iterations after adding the annealing operator. The comparison between the calculation results of different algorithm is shown in table 2, compared to the standard genetic algorithm and B&B accurate algorithm [8], the genetic-annealing algorithm has the highest calculation efficiency. Compared to the scheme of First Come First Serve (FCFS), the whole dispatching time reduces by 586 seconds.
5. Conclusion

By use of the modelling thought of space-time network graph, this paper conducts the modelling for aircraft taxing dispatching process on airport surface, discretizes the continuous time, sets the dispatching time interval as the safe interval time exceeding all aircraft taxing and then avoids the node conflict and link conflict which take place in the peak hour. In order to solve the NP difficult problem for the multi-commodity flow model of the space-time network, the genetic-annealing algorithm is designed to solve the difficulty that the single algorithm is easy to fall into the local search. Though the simulation of flight taxing experiment in hub airports at the busy hour, it can be found that the scheme solved by the space-time network is superior to the static dispatching scheme which focuses on the dispatching thought of FCFS; therefore, the research result has a certain practical reference value.

Acknowledgements

This work was supported by the National Science Foundation of China (60979021) and by the Basic scientific research projects of the Central University of China (ZXH2010D010).

References