A Multi-Objective Genetic Algorithm Based Optimum Schedule under Variety Capacity Restriction

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Abstract—Flight schedule influences the safe operation and profits of airlines, and also be restricted by air traffic capacity. In consideration of the complexity is a strict constraint of capacity and the different aircraft quantity of each en-route is a key element of traffic complexity, a matching model for the traffic flow and variety capacity based on the complexity is presented. And a novel flight schedule optimization method under variety capacity restriction is established. By defined an adjust cost and adjust number function of the flight bank construction for evaluating the planning strategy in each slot time, a multi-objective genetic algorithm is proposed to search Pareto solutions for flight schedule optimization model. Experimental results verify the effectiveness of the method as opposed to historical model.

Key words—traffic complexity; variety capacity; multi-objective genetic algorithm; air traffic flow management.

I. INTRODUCTION

With high-speed development of civil aviation, the phenomena of airspace resource shortage and air traffic flow congestion has frequently appeared. Allocating the arrival and departure time of hundreds of airlines scientifically can improve airport capacity utilization and also eliminate the congestion. Therefore the flight schedule planning has been considered as one of the most important strategy of air traffic flow management (ATFM) gradually.

The focus of flight schedule planning is the arrangement of the departure and arrival time slot. 2004, Gwiggner[1] analyzed the relations between time slots, capacity and real demand in ATFM, and indicated that the accurate flight schedule could improve current ATFM. 2007, Ding[2] established a compromise immune algorithm to achieve optimal schedule of airport flight arrival and departure according to the rule of flight priority and the limit of airport capacity. 2009, Ramanujam[3] proposed a statistical technique based on quantile regression, which is used for systematically analyzing arrival-departure capacity tradeoffs in multi-airport systems using observations of flight operations. 2012, Brinton[4] described the algorithms and methods by which the collaborative departure queue management could better achieve the integration and the synchronization of the airport surface operational plan and air traffic plan. 2013, Su[5] presented a modified mixed integer linear program for scheduling departure and arrival aircraft at airport runways in the form of deterministic optimization problem. 2013, Wang[6] proposed a multi-phase approach to solve the fleet assignment problem, and the objective was to minimize the cost by determining which type of aircraft should fly on each flight leg. 2015, Yan[7] established a flight scheduling model which considered the time slot allocation and variable demand, developed a heuristic algorithm to solve the problem instances with practical size. 2015, Zhang[8] proposed a reasonable queue of departure and arrival flights which focused on the Pareto optimization of departure flights. However, all of above researches are based on a same constraint which the capacity is a fix value and the sum of traffic flow should less than this value.

Unfortunately, the airspace capacity is influenced by multiple factors and it is considered as a various value, especially in the congested airspace. 2008, Klein[9] indicated that the airspace capacity is not a fixed value and considered an airspace sector capacity as a function of the geometric structure of traffic flows. 2014, Rafal[10] introduced a stochastic analytical model for generating probabilistic airport capacity predictions for strategic traffic flow planning which indicated that the variety of capacity could be caused not only by the uncertainty weather, but also by the complexity of traffic flow distribution. 2016, Chang [11] indicated that air traffic efficiency was heavily
influenced by multiple factors that result in capacity reduction, but he established an air traffic flow management model which just referred to weather-related uncertainty, but did not include other factors. Therefore, an optimization algorithm which the airspace capacity is influenced by the factors more than the weather should be proposed.

In this paper, by established the traffic flow and variety capacity matching model based on traffic complexity, the optimum flight schedule method under variety capacity restriction has been proposed. And the objects are the minimum the adjust cost and the minimum of adjust number of flights. A multi-objective genetic algorithm is proposed to search Pareto solutions for flight schedule optimization model. Experimental results verify the effectiveness of the method.

II. METHOD DESCRIPTION

A. Schedule plan strategy

In some time slots, the traffic flow may exceed the capacity. Therefore, it will cause some flight delay. In this schedule plan strategy, the above exceeding flight flow will be transferred to another time slots in which the flow is far less than the capacity by particular method, whichever is before or after this time slots. So this strategy can guarantee that flow in every time slots will not exceed the capacity.

Based on flight bank theory, the all-day flight schedule of an airport can be divided into several flight banks, and each flight has arrival flight bank and departure flight bank. Flight flow of one flight bank cannot exceed the capacity. In this schedule plan strategy, each flight bank is 4 hours long and 4 time slots. The adjusted flights should be transferred in this flight bank. Then the 4-hour flight schedule can be optimum, which means the all-day flight schedule reach optimum under this adjusted method.

B. Flow-capacity matching model based on traffic complexity

The goal of traffic flow management is to ensure that the traffic flow cannot exceed the capacity. However, the different aircraft quantity of each en-route is a key element of traffic complexity. Also traffic flow proportion results in variety airspace capacity. Therefore, varying quantity has important influence on the coupling relationship between capacity and flow.

In this paper, capacity can be converted to a varied value which is restricted by the maximum rule workload value. Different traffic complexity means that different arrival and departure flow proportion produce different workload. And this workload is chosen to better describe the coupling relationship between flow and capacity. Traditional capacity-flow matching model is only based on quantity. A novel capacity-flow matching model based on traffic complexity is presented as followed:

\[
\sum_{k} \alpha_k \cdot C \cdot \frac{f_k}{F} + \sum_{j} \left( \beta \cdot C^2 \cdot \frac{f_j}{F} \right) - W = 0, F \leq C \tag{1}
\]

Where \( f_k \) is the flow of air corridor; \( \alpha_k \) and \( \beta \) are weight which reveals the influence of the traffic flow quantity to workload; \( C \) is the airspace capacity; \( F \) is the total traffic flow. \( f_i \) is the corresponding flow of entrance point \( i \); \( f_j \) is the corresponding flow of departure point \( j \); \( W \) is the maximum rule workload.

C. Adjust cost function

When planning a new flight schedule, cost is the most concerned point. As mentioned above, when the flow in one time slot exceeding the capacity, it can be transferred to another time slots. The acceptance of airline to different adjust time has obvious distinction, and different degree of acceptance represent various adjust cost. Therefore, adjust cost is defined. Fig.1 shows the relation between adjust cost and adjust time.

In this fig, adjust cost is relatively less which means airline could accept this adjustment when adjust time is less than \( t_1 \). With the growth of adjust time, the growth rate of adjust cost is increasing significantly. When adjust time reach to \( t_2 \), the growth rate of adjust cost reach the maximum. After this point, the growth rate of adjust cost begins to fall. Until the adjust time reach to \( t_3 \), the increase of adjust time nearly has almost no influence on the adjust cost.

![Fig.1. Relation between adjust cost and adjust time](image)

Based on the relation between adjust cost and adjust time. The adjust cost function is as follows:

\[
FAC = \begin{cases} 
\xi_0 t_1^2 & t < t_1 \\
\xi_1 t_1^2 + \xi_2 t + \left( \xi_3 - \xi_2 \right) t_1^2 - \xi_3 t_1 & t \geq t_1 
\end{cases} \tag{2}
\]

Where \( FAC \) is the flight adjust cost; \( \xi_0 \) is adjust cost coefficient which depends on the airline; \( t_1 \) is the key adjust time which can make adjust cost growth rate reach to the maximum.

III. MULTI-OBJECTIVE OPTIMIZATION FOR FLIGHT SCHEDULE MODEL

A. Related hypothesis

Because the factors which affect schedule plan strategy are too many, following hypotheses are presented before modeling:
1. The maximum rule workload is 80% of controller’s work time;
2. The flight adjustment is only in one flight bank;
3. The capacity of sector in any time slot can be represented by known traffic flow functions;
4. The time of same type of flight spend flying between each two fixed point is same and fixed;
5. This model doesn’t consider the flight schedule plan which has specific type selection, and every flight flies in constant speed;
6. The forecast of estimated time of arrival is accurate

Hypothesis 1 ensures the capacity can be calculated by adjust cost functions action, 2,4,6 are proposed in order to simplify the model, and 3,5 are deterministic hypotheses of the model. In this paper these factors are not considered in order to increase the simplicity of computation here.

B. Parameter definition

- \( W \): Maximum rule workload;
- \( C \): Flight capacity of a sector;
- \( F \): Flight flow of a sector;
- \( f_i \): Set of flights which enter the sector through point \( k \);
- \( T \): Running time of sectors, divide into \( j \) time slot, and every time slot is \( \tau \) min;
- \( P \): Set of entry and exit point, \( p \in P \);
- \( f^\prime \): Subsequent flights of Flight \( f \);
- \( \xi \): Adjust cost coefficient which depends on the airline;
- \( t_{ip}^{\text{out}} \): Expected crossing point time of flight \( f_{ip} \) which enter through point \( P \);
- \( t_{ip}^{\text{in}} \): Actual crossing point time of flight \( f_{ip} \) which enter through point \( P \);
- \( t_{ip}^{\text{out},P} \): Time that flight \( f \) leaves sector through point \( P \);
- \( t_a \): Adjust time of flight which exceed the capacity;
- \( t_f \): Duration of a flight bank;
- \( t_s \): Adjust time which can make adjust cost growth rate reach to the maximum;

C. Objective function

The first goal of the model is to make the adjust cost as small as possible. The adjust cost in the model refers to the adjust time. Different adjust time will not only cause the various adjust cost also the different adjust cost growth rate. Here, optimization objective is to minimize the total adjust cost after reprogramming the flight schedule, as follows:

\[
\text{Min}\{\text{FAC}\} = \begin{cases} 
\text{Min}\{\xi, t^2\} & t < t_s \\
\text{Min}\{\xi, t^2 + \xi f + (\xi_i - \xi) t_s^2 - \xi_i t_s\} & t \geq t_s 
\end{cases} \quad (3)
\]

The second objective of the model is to minimize the adjust number. Each adjust flight has corresponding adjust cost, though each one has its distinction, the smaller adjust number can effectively reduce the total adjust cost.

\[
\text{Min}\{\text{FAQ}\} = \sum q_i \quad (4)
\]

Where \( FAQ \) is total flight adjust quantity; \( q_i \) is the adjust quantity in \( i \) time slot.

D. Model constraint

1. Capacity constraint

At a specified time \( \lambda \), the quantity of flights in the sector must be less than the capacity of the sector. Based on the flow-capacity matching model, that is:

\[
\sum_{k} \lambda_{k} \cdot f_{k} + \sum_{j} \left(\beta_{j} \cdot f_{j}\right) \leq W \quad (5)
\]

Generally, the value of \( \lambda \) is 1 hour; The capacity constraint in the model is that the flight flow of this sector cannot exceed the capacity generated by flow of each air corridor and the maximum rule workload which usually takes 80% of the working time.

2. Flight characteristic constraint

The time of flight \( f \) fly out of the sector, the time through the air corridor and the flight time of the flight \( f \) in the sector, as follows:

\[
t_{ip}^{\text{out}} = t_{ip}^{\text{in}} + f_{ip} \quad (6)
\]

3. Adjust time constraint

The adjust time of schedule plan strategy cannot exceed the flight bank which is four hours long based on the flight bank theory, for the flight which exceed the capacity should be transferred in one flight bank, as follows:

\[
t_a \leq t_{f} \quad (7)
\]

IV. SIMULATION AND DISCUSSION

Multi-Objective Genetic Algorithm (MOGA) is generally developed on the basis of simple genetic algorithm, which can be directly weighed between multiple objectives. MOGA based on non-dominated solution set can obtain the Pareto optimal solutions with multiple uniform distribution, and without prior knowledge, which is suitable for making decision under the situation of different route structure and flight traffic flow. The NSGA-II algorithm has some advantages in the search efficiency and search results, and has better robustness.

A. Solving algorithm design

1. Chromosome encoding

This model focuses on the scheduled number of arrive and departure aircrafts, rather than the flight time, so the flight is not chosen as the gene. If the flight is selected as the gene, the number of flights in a long time can lead to a large number of genes, which resulting in a slow calculation speed, which is not conducive to the solution of the algorithm. Since the flight schedule is generated after the
number of each slot is determined, so flight schedule can be obtained by calculation through schedule plan strategy. The number of time slots is limited, thus the number of arrive and departure aircrafts of each slot is chosen as the gene which can reduce the number of variables and increase the calculation speed.

In this paper, the number of arrive and departure aircrafts is used as the gene, that is, in the above model the real value is used in the process of encoding. The numbers of slots are used as the gene, and arranged in a fixed order which corresponding for the gene of different slots. For example, for a sector, there are four slots, and the number of arrive and departure is separate:

Serial number: 1,2,3,4,5,6,7,8 (one hour corresponding to two number, the first for arrive, the second for departure )
Chromosome 1: 7,13,13,6,14,7,14,8(corresponding to the arrive and departure number of each slot separately)
Chromosome 2: 8,12,14,4,15,6,5,15

(2) Calculation of the objective function

In this model, the economic efficiency and the stability of the strategy are considered, which the economic target is characterized by the adjust cost and the stability target is characterized by the adjust number.

The economic objective is the minimum adjust time, so the fitness function for the target of the economy is as follows:

$$EC = \sum_{p \in P} \sum_{k \in K} FAC_{gp} + \varepsilon \cdot \sigma$$

(8)

Where $\varepsilon$ is a small positive number, which ensuring the fitness function meaningful, when the adjust cost is 0, the value in this paper is 1; $\sigma$ is the penalty function, the individual that causing flow over capacity may still occur after control the transfer interval, thus the penalty function is introduced to make the fitness of the individual 0 that does not meet the constraints, $\sigma$ is represented as follows:

$$\sigma = \begin{cases} 1, & \text{if } W_c \leq W_{slot} \\ 0, & \text{if } W_c > W_{slot} \end{cases}$$

(9)

The stability target is the minimum adjust number in each time slot, so the fitness function for the stability target is as follows:

$$SC = \sum_{p \in P} \sum_{k \in K} FAQ_{gp} + \varepsilon \cdot \sigma$$

(10)

(3) Algorithm flow and genetic operators

Fig.2 is the algorithm flow chart of the NSGA-II algorithm to solve the model.

Firstly, the initial population of the flight number in each slot is generated. An initial population is generated by the method of generating random numbers based on the encoding method, and the population size is 20. In order to ensure that the initial population of each individual is the initial feasible solution, that is to ensure that the 20 individuals to meet the workload constraints.

Then the population is not-dominated classified, all non-dominated solutions of the current population are divided into the same level, and mark them Level 1, then remove them from the population and find out the new non inferior solutions in the remaining individuals, and then mark them Level 2.

Next, genetic operations are continuously conducted. Genetic manipulation of NSGA-II algorithm includes three basic genetic operators: selection, crossover and mutation.

The selection operation of the population $P_g$: Firstly, according to the non-dominant classification of the population, the $N_p$ can be divided into several levels, and the each level value of the individual $j$ is defined as $m(j) = 1,2,3,..., j = 1,..., N_p$. Then, the fitness of each chromosome is calculated, the fitness of the individual $j$ can be calculated as follows:

$$f_{ga}(j) = \frac{1}{1 + m(j)}$$

(11)

Finally, the expected value method is used to determine the selected individuals, and the population size of the selected operation is still $N_p$.

The selection operation of the population $R_g$: based on the non-dominant classification of the population $R_g$, the set of hierarchical sequence sets are respectively represented as $\lambda_1, \lambda_2, \lambda_3, \cdots$. If the number of individual $\lambda_i$ is greater than $N_p$, then the crowding distance is calculated, and according to the crowding distance, individuals are ranked. If the number of individual $\lambda_i$ is equal to $N_p$, then $P_{g+1}$ is made up of $\lambda_i$ directly. If the number of individual $\lambda_i$ is less than $N_p$, then add individuals from the collection of $\lambda_i$, if still not enough, then add individuals from the collection of $\lambda_i$. And so on, the individuals in the same collection are sorted according to the crowding distance until $P_{g+1}$ has contained $N_p$ individuals. Among them, the crowding distance refers to the local crowding distance between each individual and the same level of two individuals.

In this paper, single point crossover is used. Firstly, the individual is randomly paired and a crossover point is set up randomly in the individual string. According to the crossover probability $p_c$, parts of chromosome in two individuals are exchanged at the intersection of each two individuals, thus resulting in two new individuals. At the same time, whether the newly generated two individuals meet the corresponding constraints should be determined, if satisfied, the next step continues, otherwise, the new individuals are recreated.

Considering the value of the crossover probability $p_c$, then select the individual with high fitness to the population $P_{g+1}$.

Finally, the calculation speed.
it differs from the general genetic algorithm (Population of general genetic algorithm is approaching convergence when it evolving to the late generation), the NSGA-II algorithm needs to keep population diversity from the beginning to the end to meet the requirements to update the obtained non-dominated solutions, so the values tend to be larger. This paper selects the crossover probability $p_c$ as 0.8.

![Flow chart of the NSGA-II algorithm](image)

In this paper, basic mutation operation is used. Under the premise of meeting the mutation probability $p_m$, an individual is selected randomly and its encoding of gene position is changed. At the same time, whether the newly generated individual meet the constraints is determined, if satisfied, the next step continues, otherwise, the new individuals are recreated. In order to meet the requirements of the diversity of the NSGA-II algorithm, the mutation probability $p_m$ is 0.1.

The termination condition of the genetic algorithm can be realized by satisfying the fitness value or the maximum evolutionary generation. The termination condition of NSGA-II algorithm is generally adopted to set the maximum evolutionary generation.

**B. Example analysis**

Kunming terminal sector is classified to be 2 classifications in which one is used to enter and the other used to leave. Four hours of flight schedule is chosen and divided into 16 time slots to be original data to prove the schedule plan strategy which presented in this paper. Each time slot is 15 minutes long.

NSGA-II algorithm is used to solve the above model, calculation parameters is as follows: The number of individuals is set to 20, the maximum genetic generation is 100, the length of chromosome is 8, the use of the generation gap is 0.8, the crossover probability is 0.8 the mutation probability is 0.1. Calculation and analysis of the model with the NSGA-II algorithm is shown in Fig 3, Fig 4 and Fig 5 by the use of MATLAB.
Fig. 4 shows that when focusing on the adjust cost target. In this fig, the blue line represents flight of entrance in the 16 time slots and the red line represents the flights of departure in the time slots. Meanwhile, the green line graph represents the capacity of one time slot generated by the flight number of two points. The adjust cost can be calculated by the adjust cost function, and it is 96. Meanwhile, the adjust number is 48. In conclusion, it satisfies that flow cannot exceed the capacity, and minimize the adjust cost.

Fig. 5 shows that when focusing on adjust number target. In this situation, the capacity of each time slot is more than the adjustment which focuses on the adjust cost. It also can be willing to accept by airline. The adjust cost in this situation is 172. Meanwhile, the adjust number is only 16. In conclusion, the adjust cost and adjust number cannot reach superior in the meantime.

V. CONCLUSIONS AND DISCUSSION

The plan of flight schedule is the most common part in airline's routine work. Flight schedule has impacts on the safe operation and profits of airlines. However, it is not so effective in complex traffic flow. In consideration of the complexity is a strict restriction of capacity and the different aircraft quantity of each en-route is a key element of traffic complexity, traffic flow proportion result in variety airspace capacity. By established the traffic flow and capacity matching model based on traffic complexity, a novel method has been developed. And the objects are the minimum the adjust cost and the minimum of adjust number of flights. A Multi-Objective Genetic Algorithm is proposed to search Pareto solutions for multi-objective optimization model. Experimental results verify the effectiveness of the method.

Based on the results for one real traffic scenarios presented here, it can be concluded that the model computes Flight Schedule Plan strategy which is more reliable for the current traffic and efficiently reduce the adjust cost and adjust number, as opposed to historical model. Thus, this Flight Schedule Plan strategy model should aid the airlines in planning new flight schedule.

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