The Optimization of Chinese Air Route Network with Cooperative Coevolving PSO

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Abstract. With the rapid development of Chinese air transportation, the performance of the Chinese air route network (ARN) becomes more and more important. Since the location of air route waypoints (ARWs) is crucial for the performance of ARN, we propose an ARW optimization model in this paper. In the model, the cooperative coevolving particle swarm optimization (CCPSO) is adopted to optimize the location of ARWs. The simulation results show that CCPSO can effectively decrease the total flight conflict coefficient and improve the performance of the Chinese ARN. Our work will be helpful to better understand and optimize the Chinese air route network.

Introduction

The air route is the real track that every flight travels from one airport to another. In the air route network (ARN), airports or air waypoints are nodes and links are denoted by the air route segments. Airports are the points that generate and absorb air traffic flow while air waypoints are the points that only transmit traffic flow without generating or absorbing any air traffic flow. There are two kinds of waypoints in ARN, one is the air route waypoints (ARWs) and the other is the crossing waypoints (CWs). An ARW is a navigation marker which keeps the pilots informed about the desired track [1,2], while a CW is a crossing point where two or more aircrafts may encounter with each other.

With the rapid development of air transportation, researchers and practitioners have pay great attention in past decades to improve the efficiency and safety of the air transportation system [3,4]. Different models aiming to optimize the performance of ARN have been proposed and some important aspects have been taken into account [5,6], such as flights efficiency, potential conflict and airspace capacity. Siddiquee [5] firstly presented a mathematical model to quantify various attributes of the air route network. Mehadhebi et al. [7] proposed an approach to minimize the total airline cost of the ARN. Zhou et al. [8] proposed a multi-objective optimization algorithm to minimize both airline costs and flight conflicts. Cai et al. [9] proposed a bi-objective optimization model to solve the crossing waypoint location (CWL) problems. Their approach not only reduces the total airline cost (TAC) but also decreases the total flight conflict coefficients (TFCC). Jin et al. [10] proposed a triple-objectives model to solve the CWL problems, where three key factors (flights efficiency, potential conflict and airspace capacity) are investigated.

Since the number of ARWs is larger than that of CWs, it is more difficult to optimize the location of ARWs. It is known that the cooperative coevolution (CC) algorithms [11-14] are suitable for solving large-scale optimization problems, and the particle swarm optimization (PSO) is an effective solution to solve complicated optimization problems. Thus, in this paper, we use the cooperative coevolving particle swarm optimization (CCPSO) to optimize the location of ARWs of the Chinese ARN.

The rest of this paper is organized as follows. Section 2 describes the CCPSO algorithm in detail. Section 3 presents the ARW optimization model based on the CCPSO. Section 4, simulation results and correspondent theoretical analysis are provided. Finally, we give the including remarks in section 5.

The CCPSO Algorithm

The CC algorithms can be regarded as automatic approaches to implement the divide-and-conquer strategy [11-14] and are quite effective for large-scale optimization problems. The particle swarm optimization (PSO) is a nature-inspired algorithm that has shown excellent performance in solving many real optimization problems. The CCPSO is a comprehensive optimization algorithm, where PSO and CC are incorporated together. The framework of CCPSO can be summarized as follows:

(1) Problem decomposition: A high-dimensional decision vector is decomposed into some smaller subcomponents. This is a dynamically grouping process, where the variables are selected randomly to form groups and a scheme is used to dynamically determine the size of the coevolving subcomponent variables.

(2) Subcomponent optimization: The algorithm of Cauchy and Gaussian PSO is used to optimize the subcomponents. In the algorithm, each swarm is located in a ring topology structure, which is potential to slow down the speed of convergence and maintains the diversity of population.

(3) Subcomponents coadaptation: Since interdependencies may exist between subcomponents, coadaptation is essential to capture such interdependencies during the optimization process. It is necessary to combine all subcomponents to a complete decision vector. The best individual from other subpopulations will be used when the objective function is calculated.

The ARW Optimization Model

Actually, the ARW location optimization problem is a high-dimension problem. The challenge of the location optimization of the ARWs is two-fold: first, a typical problem involves a large number of design variables; second, the objective function is non-differentiable. It is difficult to solve these problems by using traditional optimization algorithms [15-17], which suffer from the “curse of dimensionality”, i.e., the performance will deteriorate rapidly as the dimensionality of search space increases. In our ARW optimization model, we will adopt the CCPSO [14] algorithm to optimize the location of ARWs.

The target of the ARW optimization model is to optimize the location of ARWs within a limited airspace. Following the previous work [9], the mathematical formulation of the ARW optimization problem has three assumptions and principles:

(1) The ARN is defined as a planar graph, without considering aircrafts’ climbing or descending among different flight levels.

(2) The trajectory of each flight is always the shortest path in the ARN.

(3) Since the airport is a part of flight trajectory, we define the position of airports as one of the decision variables.

An ARW is a navigation marker whose longitude and latitude coordinates are determined by the ground navaids. Thus, the location of airports and ARWs can be represented as 2-dimensional vectors,

$$x^i_{min} \le x_i \le x^i_{max},\ \forall i \in \{1, \dots, n\},\quad y^i_{min} \le y_i \le y^i_{max},\ \forall i \in \{1, \dots, n\}, \qquad (1)$$

where x_i and y_i represent the location of ARW i.

Objective: The objective can be measured by the total flight conflict coefficient (TFCC). Here, the TFCC is a reference value indicating how “dangerous” the network is. Generally, the larger the total flight conflict is, the higher the flight conflicting risk is.

$$\min \mathrm{TFCC} = \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq k}}^{T_i} \sum_{k=1}^{T_i} \frac{f_{ji} \cdot f_{ki} \cdot S}{V \cdot \cos(\frac{\alpha^i_{jk}}{2})}\ , \qquad (2)$$

where f_{ji} is the traffic flow from node j to node i, and f_{ki} is the traffic flow from node k to node i; $a^i_{jk} \in [0,\pi]$ is the included angle between air routes ji and ki; S is the horizontal separation standard (km) of air traffic control, and V is the average cruising speed (km/h) of flights.

Constraint: The flight efficiency, which can be calculated by the total airline cost (TAC) of flights.

$$\min \mathrm{TAC} = \sum_{i=1}^{m+n} \sum_{j=1}^{m+n} f_{ij} \cdot d_{ij}, \qquad (3)$$

where f_{ij} is the traffic flow from node i to node j, d_{ij} is the Euclidean distance between node i and node j.

In the optimization procedure, new path will be searched once the location of ARWs is changed, and the Floyd algorithm is used to search the new shortest path for each flight.

Results and Analysis

The data used in the paper are provided by the Air Traffic Management Bureau (ATMB) of China. The Chinese ARN contains 207 airports and 1499 waypoints. Here, we need to optimize 3412 decision variables. Since the ARW optimization problem is a high-dimension and complicated problem, we use the set of G={500, 1000, 1500, 2000} to determine the size of the groups. The maximum number of fitness evaluations (FEs) is set to 10000, and the results over 10 independent runs are recorded. Table 1 shows the real value of the TFCC and TAC.

Table 1

	TAC0	TFCC0
Value	2.397e+09	4.308e+08

The original values of the TAC and TFCC.

Firstly, we do experiment to find how the value of TAC is changed when the TFCC value goes from 0.1*TFCC0 to 10*TFCC0. The values of TAC for 10 runs are shown in Table 2. From Table 2, one can see that the changes between the TAC values are not obvious. Thus it is reasonable to set the TAC as the constraint and set the value of it within 0.1*TAC0 and 10*TAC0.

Table 2

The number of runs	TAC
1	2397286149
2	2397285921
3	2397286033
4	2397285687
5	2397285668
6	2397285808
7	2397285727
8	2397285803
9	2397285964
10	2396971249

The value of TAC over 10 runs.

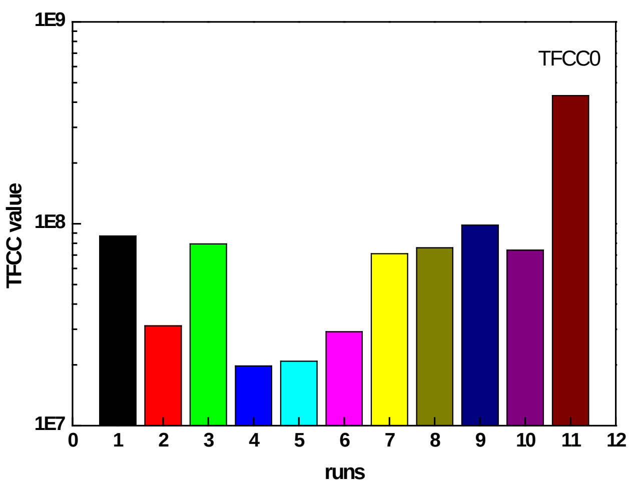

Fig.1 The value of TFCC under CCPSO.

Table 3

	TFCC
best	1.972e+07
median	7.105e+07
mean	5.869e+07
std.	2.993e+07

The best, median, mean and std. value of TFCC under CCPSO.

The results of TFCC over 10 independent runs are shown in Fig.1. Compared with the original value TFCC0, we can see that the TFCC values over 10 independent runs are obviously smaller than that of TFCC0. In Table 3, the best, median and mean values of TFCC over 10 independent runs are also displayed. This shows that the mean value of TFCC is also smaller than that of TFCC0. Fig. 2 shows the mean, best and median TFCC value as a function of FEs, one can see that the value of them all decreases with the increment of FEs. Especially, in the case of “best”, we can drop the value of TFCC to 6.602e+07 by running only 2500 FEs. These results indicate that the CCPSO is an effective algorithm to solve the ARW location optimization problem.

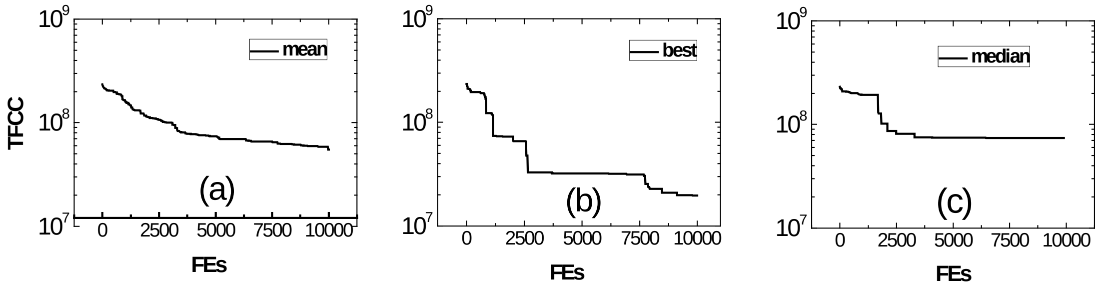

Fig.2 (a) The mean TFCC value as a function of FEs. (b) The best TFCC value as a function of FEs. (c) The median TFCC value as a function of FEs.

Conclusion

To summarize, we have proposed a novel ARW optimization model by adopting the CCPSO algorithm, which aims to solve the air route waypoint location optimization problem. In the model, the total flight conflict coefficient (TFCC) is the objective and the total airline cost (TAC) is considered as the constraint. Experiment results demonstrate that the CCPSO algorithm is feasible and effective to solve the large-scale ARWs location optimization problem. In the future, we will use the CCPSO algorithm to optimize the location of crossing waypoints (CWs) in the Chinese air route network.

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