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Air route network optimization in fragmented airspace based on cellular automata

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Abstract Air route network optimization, one of the essential parts of the airspace planning, is an effective way to optimize airspace resources, increase airspace capacity, and alleviate air traffic congestion. However, little has been done on the optimization of air route network in the fragmented airspace caused by prohibited, restricted, and dangerous areas (PRDs). In this paper, an air route network optimization model is developed with the total operational cost as the objective function while airspace restriction, air route network capacity, and non-straight-line factors (NSLF) are taken as major constraints. A square grid cellular space, Moore neighbors, a fixed boundary, together with a set of rules for solving the route network optimization model are designed based on cellular automata. The empirical traffic of airports with the largest traffic volume in each of the 9 flight information regions in mainland China is collected as the origin-destination (OD) airport pair demands. Based on traffic patterns, the model generates 35 air routes which successfully avoids 144 PRDs. Compared with the current air route network structure, the number of nodes decreases by 41.67%, while the total length of flight segments and air routes drop by 32.03% and 5.82% respectively. The NSLF decreases by 5.82% with changes in the total length of the air route network. More importantly, the total operational cost of the whole network decreases by 6.22%. The computational results show the potential benefits of the model and the advantage of the algorithm. Optimization of air route network can significantly reduce operational cost while ensuring operation safety.

1. Introduction

In the period of 2011 to 2015, the average annual growth rates of the number of operations at the airport (in terms of takeoff and landing) and passenger throughput have reached to 9.4% and 10.2% respectively. It is foreseen that air transport in China will continue to grow at a high rate. The number of aircraft in 2020 is predicted to reach 4600, while the number of

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civil airports will be 270. By 2025, the global air traffic will continue to increase with an annual rate of 3%.[1] The rapid growth of air traffic demand will lead to serious problems in the air transportation system, such as airspace congestion, flight delay, etc. The effective utilization of air route network (ARN) resources is fundamental to solve these problems.

ARN is constructed by fixed nodes (including airports and boundary nodes), air route network nodes (ARNNs), and air routes. The spatial distribution and quantity of ARNNs determine the position, direction, segment lengths of the route segments, as well as air route network security elements. ARN plays an important role in transporting passengers and cargo.

Research in air traffic network mainly focuses on two aspects: complex analysis of airport network topology, and optimization of ARN topology structure.[2–4] Du et al.[2] have analyzed the Chinese airline network (CAN) as multi-layer networks and investigated its robustness. Cao et al.[4] have studied the topology structure of Chinese ARN and CAN based on complex network metrics such as average degree, average shortest path length, and clustering coefficient. A directed air-route network topology evolution method was proposed by Zhao et al.[5] for designing airspace to test ARN structure optimization. By merging and moving nodes, ARN costs are minimized under traffic control constraints. Based on a mesh fabric, Rivière[6] employed shortest path algorithm to optimize ARN. Cai et al.[7] developed a bi-level objective model and a memetic algorithm with push-pull operator to improve the evaluation indices. Optimization algorithms were developed for improving network capability, such as particle swarm optimization.[8,9] Jin et al.[10] built a multi-objective ARN optimization model based on ARN capacity, flight efficiency, and airspace safety, and proposed a multi-objective optimization algorithm based on comprehensive learning of particle swarm optimization and the Floyd-Walsh algorithm to solve the model. Chen[11] developed an ARN traffic flow model by proposing a single-objective particle swarm algorithm based on a betweenness guide and introducing a multi-objective particle swarm optimization algorithm for ARN capacity.

There are many prohibited, restricted, and dangerous areas (PRDs) in airspace, which makes ARN environment "fragmented". Fig. 1 shows PRDs in airspace in mainland China. Grey areas represent PRDs which are the major constraints for ARN optimization. Areas outside the grey areas can be used, which means that the available air-route network optimization space is discontinuous. Thus, PRDs must be considered when ARN is optimized. However, all the work mentioned above did not consider the fragment airspace environment. Zhao et al.[5] proposed a model based on the MAKLINK Graph method, using a multi-objective genetic algorithm based on fast non-dominated sorting to find solutions which avoids PRDs. Due to the limitations of the MAKLINK Graph method, it is applicable only to "convex" PRDs. Xu and Zhu[12] used a genetic algorithm to solve the ARN optimization model considering PRDs. The algorithm is however time-consuming. Wang and Gong[13] developed an ARN optimization model which avoids PRDs and introduced a new algorithm based on cellular automata (CA). The model comprehensively considered flight safety and cost constraints to optimize path length. In this work, it ignored segment traffic flows, focusing only on path length. Neither work described here considered ARN capacity, which could result in airspace congestion.

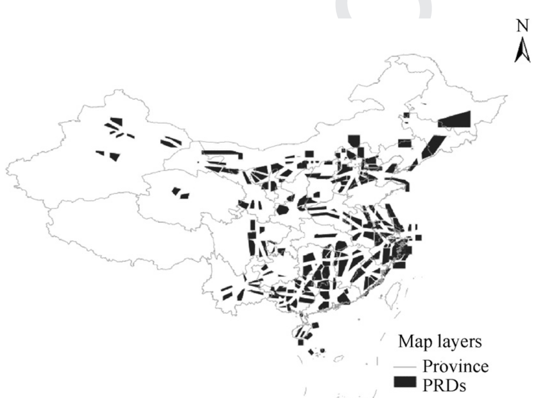

Fig. 1 Illustration of PRDs in China (PRDs are marked with grey).

This paper aims to optimize ARN structure in fragmented airspace. The objective is to minimize total operational cost. An ARN optimization model is developed considering constraints on different node configurations of ARN capacity, non-straight-line factors (NSLF), and the range of mobility of ARNN boundaries. A CA based algorithm is proposed to solve the model. To test the model, traffic flow of airports with the largest flow in each of the 9 flight information regions (FIR) is used as origin-destination (OD) demand. Computational results show the benefits of the model and the advantage of the algorithm.

2. ARN capacity model

ARN capacity is defined as the capability of an ARN to accommodate air traffic flow. ARN capacity can be divided into node capacity and segment capacity given certain conditions of airspace system structure, security restrictions, and operation regulations. At the design phase of an ARN, the following assumptions are made to investigate ARN capacity:

(1) An aircraft flies at a constant speed, and all aircraft have the same speed.
(2) Aircraft can be seen as a particle which flies along the center line of its route.
(3) Only the aircraft flying in the same direction in the same flight level are considered; horizontal separation must be maintained between flights.
(4) Continuous flow of aircraft is waiting to enter the route.

2.1. Route segment capacity

The route segment capacity C_s can be expressed as

$$C_s = 1/T_c \tag{1}$$

where T_c is the time interval between two consecutive aircraft. In average-speed model, let v be the average speed for all aircraft, L_d be the distance between two consecutive aircraft, and L_{min} be the minimum safety separation, and then we have

$$T_c = L_d/v \tag{2}$$