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On Robustness Paradox in Air Traffic Networks

Qing Cai, Sameer Alam, and Vu Duong

Abstract—Air traffic is operated in an air traffic network (ATN) environment. It is of great significance to improve the robustness of ATNs as they are frequently exposed to manifold uncertainties which can break down the functioning components of an ATN. Existing studies on improving the robustness of ATNs either rewire the links of a network or add more links to the network. In this paper we discover the robustness paradox phenomenon in ATNs. Specifically, we claim that the robustness of an ATN can be improved by removing some of its links. In order to determine the links whose removal can improve the robustness of a given ATN, we develop a bi-objective optimization model with one objective maximizing the network's robustness and the other one minimizing the number of links to be removed. We further apply and modify a non-dominated sorting genetic algorithm (NSGA-II) to optimize the developed model. In order to validate the effectiveness of the proposed idea, we carry out experiments on nine real-world ATNs. We also compare the modified NSGA-II algorithm against NSGA-III, and MODPSO, which are famous and efficient multiobjective evolutionary algorithms. Experiments indicate that NSGA-II outperforms the compared algorithms and that the robustness of an ATN indeed can be improved by just removing a small amount of its links. This work provides a new perspective for aviation decision makers to better design and manage ATNs.

Index Terms—Air transport, air traffic network, network robustness, multiobjective optimization

I. INTRODUCTION

AIR traffic profoundly changed the way we humans live in. According to International Air Transport Association (IATA) and International Civil Aviation Organization (ICAO), there is a growing trend in air traffic demand for the past decade, so will the coming one [1, 2]. Air traffic is contributing a great deal to the global economy [3, 4]. Note that air traffic is operated in an air traffic network (ATN) environment [5–7]. An ATN is composed of a set of nodes and a set of links with the nodes being entities like airports, navigation aids, etc., and the links the interactions between the nodes, like air routes, airways, etc [8]. In reality, ATNs frequently suffer from manifold perturbations such as bad weather, hurricane eruption, GPS signal interference, etc. It is therefore of great significance to ensure the robustness of ATNs to external/internal perturbations [9, 10].

The robustness of an ATN quantifies the ability of an ATN to withstand perturbations [11–13]. In the literature, researchers have developed a handful of metrics to estimate the robustness of an ATN [12, 14, 15] while the majority of them are based on network theory [16, 17]. When estimating the robustness of an ATN, it is assumed that the focal network is under attack

and its components (nodes and links) could break down as a result. Then the network theory based methods mainly gauge the robustness of an ATN in two ways, one is calculating the portion of surviving network components [18–20] and the other one is the spectral analysis of the Laplacian matrix corresponding to the focal ATN [16, 21]. In recent years, robustness evaluation of ATNs based on spectral analysis has received more attention as it is computationally friendly.

Researches on robustness estimation of ATNs have been well studied [21, 22]. Then a more appealing research problem is how to improve the robustness of a given ATN [21, 23, 24]. In line with this research, scientists have mainly devised two effective ways, one is to utilize network rewire mechanism and the other one is to add more links to a given ATN [25]. Network rewire mechanism aims to improve the robustness of an ATN by reconnecting their nodes. The rationale behind the rewire mechanism is that different network structures will lead to different network robustness properties [26–28]. For example, scale-free networks are robust to random attacks while multilayer networks with interdependencies are fragile to random failures [29]. Network rewire mechanism is helpful for robust ATN network structure design. As for the link addition strategy, it tries to improve the robustness of an ATN by adding more links to it. The rationale beneath this strategy is based on the fact that the most robust network is a clique network in which every node is linked to all the other nodes.

It should be pointed out that the network rewire and link addition mechanisms are not of practical use. The former leads to the redesign of the structure of an ATN which needs to consider many procedural and operational issues before proceedings, while the latter will make the already saturated ATN more congested. In this work we discover the robustness paradox phenomenon in ATNs. Putting it another way, we find that the robustness of an ATN can be improved by removing some of its links. The research finding is inspired by the Braess's Paradox which is a counter-intuitive phenomena frequently observed in ground traffic domain [30]. In order to mitigate congestion of urban traffic, an intuitive way is to pave new highways to dispatch the traffic flow. But it turns out that this measure can worsen the traffic. This counter-intuitive phenomena is named Braess's Paradox in honor of the great German discoverer Dietrich Braess.

For a given ATN, in order to locate the potential links whose removal can improve the network's robustness, we develop a bi-objective optimization model with one objective maximizing the network's robustness and the other one minimizing the number of removed links. We then introduce a multiobjective evolutionary algorithm named NSGA-II and partially redesign its critical operators so as to simultaneously optimize the proposed model. In order to validate the feasibility of the proposed research idea, we carry out experiments on eight real-

The authors are with the School of Mechanical & Aerospace Engineering, Nanyang Technological University, Singapore, e-mail: sameer-alam@ntu.edu.sg.

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world airport networks and one airway network. We also compare NSGA-II against other two multiobjective evolutionary algorithms termed as NSGA-III and MODPSO. Experiments indicate that the designed NSGA-II algorithm outperforms the comparison algorithms and the robustness of ATNs indeed can be improved by removing a small portion of their links. This work provides scientific supports for aviation decision makers for better air traffic management and robust airspace design.

The remainder of this paper is organized as follows. Section II presents preliminaries for better understanding of this work. Section III formulates the proposed research problem and Section IV delineates the designed algorithm to solve the proposed problem. Section V demonstrates the experiments and Section VI concludes the paper.

II. PRELIMINARY

A. Notations of Air Traffic Networks

An ATN can be denoted by a graph that is composed of a set of vertices and a set of edges [31]. A graph is mathematically denoted by $G = \{V, E\}$ with V and E respectively being the vertex and edge sets. A vertex $v_i \in V$ of G can represent an airport, a waypoint, a fix, etc., while an edge $e_{ij} \in E$ of G generally denotes the relationship between vertices i and j , e.g., route, airway, etc.

For a given network $G = \{V, E\}$, the relationships between the vertices can be depicted by its adjacency matrix $\mathbf{A}_{n \times n}$ with the cardinality $n = |V|$ being the number of vertices of G . Analogously, we use $m = |E|$ to denote the number of edges in G . The entry $a_{ij} \in \mathbf{A}$ denotes the relationship between vertices i and j .

B. Robustness Estimation of ATNs

Studies on network robustness have received enormous attention in the past decade [32–35]. In order to gauge the robustness of a given network in face of perturbations, scientists have developed a handful of robustness estimation methods [36, 37] which can be roughly categorized into the following two classes.

1) *Spectral Analysis Based Method*: Network spectral analysis estimates the robustness of a network based on its spectral features [16, 38]. Given a network G with $\mathbf{A}$ being its adjacency matrix. The degree of node v_i is calculated as $k_i = \sum_{j=1}^n a_{ij}$. We then define a diagonal matrix $\mathbf{D}$ with the i -th diagonal element being k_i . Then the Laplacian matrix $\mathbf{L}$ of network G is defined as

$$\mathbf{L} = \mathbf{D} - \mathbf{A} \quad (1)$$

Spectral analysis gauges the robustness of G by calculating the eigenvalues of $\mathbf{L}$. An eigenvalue λ of matrix $\mathbf{L}$ satisfies the relation $\mathbf{L}\mathbf{x} = \lambda\mathbf{x}$ with $\mathbf{x}$ being the eigenvector of $\mathbf{L}$. Among the n eigenvalues of $\mathbf{L}$, let λ_2 be the second smallest non-negative eigenvalue. Then researchers quantify the robustness of network G as λ_2 [21, 39]. The larger the value of λ_2 , the more robust the network is.

2) *Giant Component Based Method*: When a network is under attack, it may suffer from component (nodes and/or links) failures which could break up the network into pieces. Then the giant component (GC) based method estimates the robustness of the network by analyzing the giant one [29]. In the literature, the most widely utilized method is calculating the relative size of the GC [13, 32]. Specifically, when a network with n nodes breaks into pieces due to the removal of $1 - p$ fraction of nodes together with the links attached to them in face of attacks, then the robustness of the network, normally denoted by P^∞ , is calculated as

$$P^\infty = \frac{|\text{GC}|}{n} \quad (2)$$

where the symbol $|\cdot|$ denotes the number of nodes in the GC. Normally, the larger the value of P^∞ , the more robust a network is.

C. Multiobjective Evolutionary Algorithms

Many real-world problems are in principle optimization problems. Very often an optimization problem involves more than one objective that need to be optimized. If all the objectives are convex, then Lagrange operator can be introduced to merge all the objectives to construct a single objective optimization problem. However, if the objectives are concave, then canonical mathematical methods are mute to those concave optimization problems.

In order to solve concave optimization problems with multiple objectives, scientists have developed a class of metaheuristic algorithms which are called multiobjective evolutionary algorithms (MOEAs) [40, 41]. that are inspired by the Darwinism. An MOEA works with a population of individuals each of which represents a feasible solution to a multiobjective optimization problem. Then the MOEA generates a new population of individuals using genetic operations including crossover and mutation or other kinds of heuristic operators. The MOEA iteratively implements the population regeneration process and the best solutions found so far by the MOEA are the optimal solutions to the problem to be optimized.

MOEAs have been well studied in the past decade and have found wide applications in diverse domains. Many MOEAs have been developed and representative MOEAs are NSGA-II [42], MODPSO [43], MOEA/D [41], NSGA-III [44], etc.

III. RESEARCH PROBLEM FORMULATION

A. Research Problem

This paper aims to investigate whether it is possible to improve the robustness of an ATN by removing some of its links instead of adding new ones or totally rewiring the network. Fig. 1 presents the concept diagram of the research problem investigated in this work.

For a given airport network like the toy network shown in Fig. 1, we estimate its network robustness based on spectral analysis. In this work we propose a bi-objective maximization model to locate the links of a given ATN whose removal can improve its robustness. A multiobjective evolutionary algorithm is designed to solve the proposed model. For the

Fig. 1. Concept diagram of the research problem studied in this work.

toy network shown in Fig. 1, the designed algorithm suggests a set of link removal choices each of which can improve the network's robustness. The middle part of Fig. 1 exhibits three new network structures corresponding to three choices (PS1, PS2 and PS3) suggested by the designed algorithm. We can see from the figure that the robustness of the new networks measured by the λ_2 metric are higher than that of the original one. In what follows we provide details for the formulation of our research problem.

B. Maximizing Network Robustness

Consider an ATN $G = \{V, E\}$. Let $\mathbf{A}$ be its adjacency matrix. In this work we adopt the λ_2 metric to gauge the robustness of a given network. Since we aim to remove a subset $E_0 \subset E$ to improve the robustness of G , we therefore propose to maximize the following objective:

$$\begin{aligned} \arg \max_{E_0} \quad & f_1(E_0) = \lambda_2 \\ \text{s.t.} \quad & \mathbf{L}_0 \mathbf{x} = \lambda_2 \mathbf{x} \\ & \mathbf{L}_0 = \mathbf{D}_0 - \mathbf{A}_0 \\ & \mathbf{A}_0 = \mathbf{A} \setminus E - E_0, E_0 \subseteq E \end{aligned} \quad (3)$$

where $\mathbf{L}_0$ is the Laplacian matrix of $\mathbf{A}_0$ and $\mathbf{A}_0$ is the surplus of $\mathbf{A}$ from which E_0 is removed.

C. Minimizing the Number of Removed Links

One thing should be pointed out that the structure of a real-world ATN is the outcome of collaborative efforts between

many aviation players. For example, an airway network was designed long time ago and its structure is still in use. Therefore, it is impractical to remove too many links from a given ATN. In light of this fact, we propose to minimize the number of removed links, and the following objective is to be minimized

$$\min f_2(E_0) = |E_0| \quad (4)$$

D. Proposed Multiobjective Optimization Model

Based upon the above formulated objectives, we in this paper aim to optimize the following model

$$\min \begin{cases} F_1 = 1/f_1(E_0) \\ F_2 = f_2(E_0) \end{cases} \quad (5)$$

Given a feasible solution (λ_2, E_0) to the above problem. Let λ'_2 be the robustness of the original ATN. If $\lambda_2 \geq \lambda'_2 \wedge E_0 \neq \emptyset$, then we prove that the robustness of the given ATN can be improved by removing its links contained in E_0 .

As an ATN normally contains many links, therefore there could be many choices of E_0 to improve a network's robustness. By simultaneously optimizing Eq. 5 we can obtain a serial of E_0 each of which is a feasible choice, and this is the merit for proposing a multiobjective optimization model to achieve the goal of this work.

IV. ALGORITHM DESIGN

A. Algorithm Overview

In order to solve the multiobjective optimization problem presented in Eq. 5, we here introduce the well studied NSGA-II algorithm and redesign its critical operators per the specific properties of the problem to be solved so as to work out the corresponding Pareto solutions. The framework of the introduced NSGA-II algorithm is provided in Algorithm 1.

In step 3 of Algorithm 1, an individual $\mathbf{p}_i$ represents a feasible solution to the optimized problem. The representation of an individual is described in subsection IV-B. Several key operations involved in step 5 of Algorithm 1 will be elucidated in the coming subsections.

B. Coding and Decoding Schema

How to code a chromosome is the key to link an MOEA with an multiobjective optimization problem. In this paper, we aim to remove some links from a given network G with m links to improve its robustness. Therefore, we code a chromosome $\mathbf{p}_i$ as follows:

$$\mathbf{p}_i = (p_i^1, p_i^2, \dots, p_i^m) \quad (6)$$

in which $p_i^j \in \{0, 1\}$ is a binary variable. If $p_i^j = 1$, then it means that the j -th link will be removed from network G .

Based on the above coding schema, we can easily decode $\mathbf{p}_i$ into a link set E_0 as

$$E_0 = \{j | p_i^j = 1, \forall j \in [1, m]\} \quad (7)$$

Given a chromosome $\mathbf{p}_i$ we then get the link set E_0 . By substituting E_0 into Eq. 5 we get the values of f_1 and f_2 .

Algorithm 1 Framework of the introduced NSGA-II algorithm**Input:** $\mathbf{A}_{n \times n}$ – adjacency matrix of an ATN G with m links**Output:** E_0^* – a set of subsets of the link set of G ; λ_2^* – robustness of G with E_0^* being removed.

- 1) Hyper-parameters settings of $psize$, pm , pc and $iter$;
- 2) Set $E_0^* = []$ and $\lambda_2^* = -\infty$;
- 3) $\mathbf{pop} = (\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_{psize})^T$; //initialize a population, see subsec IV-B
- 4) $[F_1, F_2] = \text{FitnessEvaluation}(\mathbf{pop}, \mathbf{A})$; //see Eq. 3
- 5) **For** $i = 1$ to $iter$, **do**
 - a) $[\mathbf{pop}, \mathbf{R}] = \text{NonDominatedSorting}(\mathbf{pop})$; //see subsec IV-C
 - b) $\mathbf{pop} = \text{CalcCrowdingDistance}(\mathbf{pop}, \mathbf{R})$; //see subsec IV-D
 - c) $\mathbf{pop}' = \text{GeneticOperation}(\mathbf{pop}, pc, pm)$; //create a new population, see subsec IV-E
 - d) $[F_1, F_2] = \text{FitnessEvaluation}(\mathbf{pop}', \mathbf{A})$;
 - e) $\mathbf{pop} = [\mathbf{pop}', \mathbf{pop}]$;
 - f) $[\mathbf{pop}, \mathbf{R}] = \text{NonDominatedSorting}(\mathbf{pop})$;
 - g) $\mathbf{pop} = \text{CalcCrowdingDistance}(\mathbf{pop}, \mathbf{R})$;
 - h) $\mathbf{pop} = \text{SortPopulation}(\mathbf{pop})$;
 - i) $\mathbf{pop} = \mathbf{pop}(1 : psize)$;
- 6) **end**
- 7) $[E_0^*, \lambda_2^*] = \text{ParetoSolutions}(\mathbf{pop})$;

C. Nondominated Sorting Operation

For multiobjective optimization, scientists conceived the concept called Pareto dominance to compare the quality of different solutions. Consider the following multiobjective minimization problem with k objectives

$$\min F(\mathbf{p}) = (f_1(\mathbf{p}), f_2(\mathbf{p}), \dots, f_k(\mathbf{p})) \quad (8)$$

where $\mathbf{p}$ represents the decision variables.

Given two solutions $\mathbf{p}_1$ and $\mathbf{p}_2$, then we say that $\mathbf{p}_1$ dominates $\mathbf{p}_2$, denoted by $\mathbf{p}_1 \prec \mathbf{p}_2$, if the following condition is satisfied

$$f_i(\mathbf{p}_1) \leq f_i(\mathbf{p}_2), \forall i \in [1, k] \quad (9)$$

A solution $\mathbf{p}_i$ is called a Pareto solution if there is no solution that dominates it. The set of all the Pareto solutions is called the Pareto optimal set, or Pareto set (PS) for short. The image of the PS in the objective space is called the Pareto front (PF), i.e., $\text{PF} = \{F(\mathbf{p}) | \mathbf{p} \in \text{PS}\}$.

Step 5a of Algorithm 1 categories all the individuals in the current population based on the Pareto dominance concept. All the Pareto solutions are designated as rank-1 solutions and are stored in the first reservoir of the variable $\mathbf{R}$, and rank-2 solutions (Pareto solutions in the population excluding the rank-1 solutions) are stored in the second reservoir of $\mathbf{R}$, and so on.

D. Crowding Distance Calculation

Note that NSGA-II is a stochastic searching algorithm. In order to improve diversity of the population, researchers

developed the crowding distance mechanism. It is regarded that a solution with a larger crowding distance is better than a solution with a small one.

Step 5b of Algorithm 1 calculates the crowding distance for each solution in each rank in the current population. For a solution $\mathbf{p}_i$ in a given rank as stored in $\mathbf{R}$, its crowding distance is calculated as

$$\sum_{j=1}^k |f_j(\mathbf{p}_{i-1}) - f_j(\mathbf{p}_{i+1})| \quad (10)$$

where $\mathbf{p}_{i+1}$ and $\mathbf{p}_{i-1}$ are the neighboring solutions of $\mathbf{p}_i$. In case $\mathbf{p}_i$ is a corner solution, its crowding distance is set to be infinite.

E. Genetic Operators

Step 5c of Algorithm 1 is to generate a new population utilizing the genetic operation. The genetic operation consists of two operators, viz., crossover and mutation.

Single Point Crossover) The crossover operator is implemented pairwise. For a pair of individuals $\mathbf{p}_i$ and $\mathbf{p}_j$, we generate two new individuals $\mathbf{p}'_i$ and $\mathbf{p}'_j$ in the following way:

$$\begin{aligned} \mathbf{p}_i &= (p_i^1, p_i^2, \dots, p_i^m) \rightarrow \mathbf{p}'_i = (p_i^1, p_i^2, \dots, p_j^{rd}, \dots, p_i^m) \\ \mathbf{p}_j &= (p_j^1, p_j^2, \dots, p_j^m) \rightarrow \mathbf{p}'_j = (p_j^1, p_j^2, \dots, p_i^{rd}, \dots, p_j^m) \end{aligned} \quad (11)$$

where rd is a random integer between 1 and m . The above single point crossover operation is conducted with a given crossover probability pc .

Single Point Mutation) For individuals $\mathbf{p}'_i$ and $\mathbf{p}'_j$ we then carry out single point mutation operation. Specifically, we randomly alter one element of $\mathbf{p}'_i$ and $\mathbf{p}'_j$ with a given mutation probability pm .

In the literature, some scientists employ multi-point operations (there are multiple rd in Eq. 7) for certain problem solving. In this work, we only adopt single point operations since they are much easier to implement than the multi-point operations.

V. EXPERIMENTAL STUDY**A. ATN Datasets**

In the experiments we carry out case studies on eight real-world airport networks and one airway network. The airport networks are obtained from the OpenFlight dataset [45], while the airway network is the network for the Singapore airspace. Table I lists the basic properties of the studied ATNs.

In this study, we only consider unweighted networks. When constructing an airport network, we connect two airports with an edge as long as there are flights that fly between them. We are not considering the weights of the links of a network as the traffic demand varies from day to month.

B. Parameter Settings

In the experiments we compare the introduced NSGA-II algorithm against other two algorithms, i.e., NSGA-III [44]

Fig. 2. Pareto fronts obtained by NSGA-II when applied to the nine studied ATNs.

TABLE I
PROPERTIES OF THE NINE TESTED ATNS. THE SYMBOL $\langle k \rangle$ REPRESENTS
THE AVERAGE DEGREE OF A NETWORK.

Region	n	m	$\langle k \rangle$	λ_2'
Australia	113	227	4.0	0.1646
Brazil	127	374	5.9	0.1228
Canada	205	436	4.3	0.0919
China	178	1402	15.7	0.9871
Europe	566	5101	18.0	0.4115
India	72	199	5.5	0.9587
Russia	115	356	6.2	0.6469
USA	583	2852	9.8	0.0812
Singapore	198	274	2.8	0.0308

TABLE II
HYPER-PARAMETER SETTINGS OF THE THREE ALGORITHMS.

Algorithm	Hyper-parameters
NSGA-II	$psize = 100$; $iter = 100$; $pc = 0.8$; $pm = 0.3$
NSGA-III	$psize = 100$; $iter = 100$; $pc = 0.8$; $pm = 0.3$; $ns = 30$
MODPSO	$psize = 100$; $iter = 100$; $c_1 = 1.496$; $c_2 = 1.496$; $w = 0.729$; $ns = 30$

and MODPSO [43]. Table II lists the settings of all the parameters involved in each algorithm.

Note that the parameter settings for each algorithm are based on experience. In the experiments we fix those parameters as what are provided in Table II. The main reason is that we are more interested in the research problem instead of the impact

of the parameters.

C. Pareto Front Comparison

For each tested ATN, we apply the designed NSGA-II algorithm to optimize Eq. 5 and get the Pareto solutions. Fig. 2 exhibits the PFs obtained by NSGA-II. We can clearly see from Fig. 2 that the designed NSGA-II algorithm can output a set of solutions to each tested network.

For each PF, except the corner solution with $|E_0| = 0$, each of the rest Pareto solution corresponds to a subset E_0 of the

Fig. 3. Pareto fronts obtained by the three algorithms when applied to the nine studied ATNs. Each PF is obtained through 30 independent runs.

link set of an ATN G . We further compare the PFs obtained by NSGA-II against those obtained by NSGA-III and MODPSO.

For each algorithm, we run it for 30 independent times for each tested network. We then merge all the Pareto solutions and work out the final PS for each network. Fig. 3 demonstrates the PFs obtained by NSGA-II, NSGA-III, and MODPSO for 30 independent runs. We can clearly observe from Fig. 3 that the PSs on the PFs obtained by NSGA-II are better than those yielded by NSGA-III and MODPSO since NSGA-II can either output more PSs or the majority of PSs generated by NSGA-II dominate those produced by NSGA-III and MODPSO.

D. Network Structure Comparison

Since NSGA-II outperforms the rest two algorithms, we therefore choose five Pareto solutions with minimum $|E_0|$ excluding the one with $|E_0| = 0$ and two Pareto solutions with maximum $|E_0|$ from each PF obtained by NSGA-II. We

compare those seven solutions in terms of λ_2 and the results are summarized in Table III.

We can observe from Table III that the robustness of the ATNs of Australia, Brazil, Canada, Russia and Singapore can be greatly improved by just removing several links from each of the corresponding network. When the number of removed links reaches around 40, the robustness of all the tested ATNs can be significantly improved.

Fig. 4 and Fig. 5 respectively display the structures of the Australian and Brazilian ATNs with respect to different link removal situations. For the Australian ATN, its original network robustness is $\lambda'_2 = 0.1646$. As can be seen from the above figure, the robustness of the Australian ATN can be significantly improved by removing less than 6 links. When the number of removed links surpasses 30, its robustness reaches $\lambda_2 = 0.9161$, which is almost four times higher than its original one. Similar phenomenon also happens to the Brazilian ATN.

Note that when the number of removed links reaches a

TABLE III
SUMMARY OF SEVEN PARETO SOLUTIONS FOUND BY NSGA-II WHEN APPLIED TO EACH TESTED NETWORK.

Region	λ'_2	PS1		PS2		PS3		PS4		PS5		PS6		PS7	
		λ_2	$ E_0 $	λ_2	$ E_0 $	λ_2	$ E_0 $	λ_2	$ E_0 $	λ_2	$ E_0 $	λ_2	$ E_0 $	λ_2	$ E_0 $
Australia	0.1646	0.1852	1	0.2345	2	0.2366	3	0.2607	4	0.3512	5	0.9161	35	0.9168	36
Brazil	0.1228	0.1691	1	0.1907	2	0.5098	3	0.5930	4	0.6505	5	0.8392	57	0.8408	69
Canada	0.0919	0.1416	1	0.1423	2	0.1478	3	0.1497	4	0.1510	5	0.2884	31	0.2922	98
China	0.9871	0.9897	1	0.9950	2	0.9960	3	1.0005	4	1.0006	5	1.6973	33	1.6974	34
Europe	0.4115	0.4116	1	0.4116	2	0.4116	3	0.4117	4	0.4117	5	0.5107	18	0.5108	19
India	0.9587	0.9675	1	0.9743	2	0.9774	3	0.9789	4	0.9818	5	1.9003	22	1.9005	23
Russia	0.6469	0.7159	1	0.7657	2	0.7832	3	0.8043	4	0.8197	5	0.9094	15	0.9096	16
USA	0.0812	0.0823	1	0.0829	2	0.0824	3	0.0839	4	0.0844	5	0.2460	948	0.2463	950
Singapore	0.0308	0.0417	1	0.0430	2	0.0443	3	0.0453	4	0.0462	5	0.2137	129	0.2254	131

Fig. 4. Structures of the Australian ATN with respect to different link removal situations together with their corresponding robustness measured by λ_2 .

Fig. 5. Structures of the Brazilian ATN with respect to different link removal situations together with their corresponding robustness measured by λ_2 .

certain value, a given ATN can be fragmented as some nodes are isolated due to the link removal. This phenomena can be seen from the last subfigures of Figs. 4 and 5. For one thing, a decision maker does not need to choose such Pareto solutions from the PF yielded by the NSGA-II algorithm. Each single run of the designed NSGA-II algorithm can generate a set of solutions. Aviation decision makers therefore can

choose a preferred solution from the PF based on specific air traffic conditions for better air traffic management. For another thing, even such fragmentation is inevitably for some special situation, the link removal operation could be provisional. Decision makers can resume routes between airports when the perturbations occurred to an ATN disappear.

Fig. 6. Robustness of the original ATNs and the optimized networks to random node failures with respect to the GC based method. An optimized network refers to the remaining part of a given ATN from which links specified by a Pareto solution are removed. For a given network, $1 - p$ fraction of nodes are randomly removed and the values of P^∞ are drawn as a function of p .

E. Network Robustness Validation

The above experiments indicate that the robustness of an ATN measured by eigenvalue can be improved through link removal. In the following subsection we will further estimate the robustness of ATNs using the GC based method.

1) Robustness of ATNs to Random Node Attack

For a tested ATN, each of the seven Pareto solutions recorded in Table III corresponds to an optimized ATN from which some links are removed. Here we estimate the robustness of the original ATNs and the optimized networks to random node failures using the GC based method.

For a given network, we randomly remove $1 - p$ fraction of nodes from the network and calculate the value of P^∞ with p ranging from 0 to 1 at an interval of 0.01. For p with a given value we implement the random removal process for 30 independent runs and get the average value of P^∞ . The

robustness of the original ATNs and the optimized networks to random node failures are demonstrated in Fig. 6.

In Fig. 6, the red lines represent the robustness of the original ATNs, while the lines with symbols correspond to the robustness of the optimized networks with respect to Pareto solutions PS1-PS7. It is obvious that the robustness of the optimized networks with respect to Pareto solutions PS1-PS5 are very close to the robustness of the original ATNs, while the robustness of the optimized networks with respect to Pareto solutions PS6 and PS7 deviate a lot from the robustness of all the ATNs except those for China and Europe.

2) Robustness of ATNs to Target Node Attack

Since ATNs could suffer from target attacks, here we continue to estimate the robustness of ATNs in face of target node attacks. In order to quantify the importance of a network node so as to determine the order of the nodes to be attacked, scientists have developed a handful of node centrality metrics.

Fig. 7. Robustness of the original ATNs and the optimized networks to target node attacks with respect to the GC based method. The nodes of a network are sorted based on their degrees and are removed from highest degrees to lowest ones.

Regarding network robustness calculation, the two most widely utilized centrality metrics are degree centrality and betweenness centrality [15].

For the tested ATNs and their optimized networks, we estimate their network robustness under target node attacks based on degree centrality and betweenness centrality. The corresponding results are respectively summarized in Fig. 7 and Fig. 8.

As can be seen from Fig. 7 and Fig. 8, except for the Singapore airway network, the robustness of the optimized networks with respect to Pareto solutions PS1-PS7 are very close to the robustness of their original ATNs when the networks are under target node attacks.

F. Discussion

Note that the robustness curves drawn in Figs. 6, 7 and 8 are too close to distinguish them. In order to better compare them,

we further calculate the network robustness using the area based method. Specifically, the area based method quantifies the robustness of a network by calculating the area below the robustness curve that is obtained by using the GC based method.

For each of the robustness curves drawn in Figs. 6, 7 and 8, we calculate the area (R_A) under the robustness curve and confined by the x-y axis. The area based robustness of the networks are recorded in Table IV.

We can observe from Table IV that except for Singapore airway network, the values of R_A for the optimized networks are very close to those of the original ATNs when the networks are under random node attacks. When it comes to target attacks, the values of R_A highlighted in bold in Table IV indicate that the optimized networks are more robust than their original networks. All the above results indicate that when an ATN suffers from perturbations, its robustness measured by the

Fig. 8. Robustness of the original ATNs and the optimized networks to target node attacks with respect to the GC based method. The nodes of a network are sorted based on their betweenness centralities and are removed from highest centralities to lowest ones.

eigenvalue is greatly improved by removing a small fraction of its links while its robustness quantified by the GC based method also may increase.

VI. CONCLUSION

Air traffic networks, such as airport networks and airway networks, are critical to air traffic. Note that ATNs inevitably suffers from manifold internal/external perturbations. An ATN can be vulnerable in face of perturbations as its components can break down due to the perturbations. In order to improve the robustness of an ATN to perturbations, scientists mainly adopt network rewire mechanism or add more links to an ATN. Note that these two kinds of methods are impractical for real-world ATNs.

In this paper, we discovered the robustness paradox in ATNs. Specifically, we found that the robustness of an ATN

can be improved by removing some of its links. For a given ATN, in order to locate the links whose removal can improve its network robustness, we proposed a biobjective optimization model with one objective maximizing the network's robustness and the other one minimizing the number of removed links as it is infeasible to remove a large amount of links from an ATN. This paper then introduced a well studied multiobjective optimization evolutionary algorithm named NSGA-II and redesigned some of its critical components to optimize the proposed model.

Experiments on several real-world ATNs had been carried out. Comparisons of the designed NSGA-II algorithm against other two algorithms named NSGA-III and MODPSO were done. The experiments indicated that NSGA-II outperforms the other two algorithms and that the robustness of an ATN indeed can be improved by removing a small portion of its links. As each single run of the designed NSGA-II algorithm

TABLE IV
AREA BASED ROBUSTNESS (R_A) OF THE TESTED ATNs AND THEIR OPTIMIZED NETWORKS WITH RESPECT TO THREE NODE ATTACK STRATEGIES.

R_A		Australia	Brazil	Canada	China	Europe	India	Russia	USA	Singapore
random	org	0.3773	0.4015	0.3645	0.4624	0.4398	0.4224	0.4255	0.3794	0.3034
	PS1	0.3710	0.3937	0.3605	0.4606	0.4389	0.4187	0.4211	0.3785	0.2964
	PS2	0.3659	0.3836	0.3602	0.4585	0.4385	0.4125	0.4187	0.3772	0.2929
	PS3	0.3576	0.3775	0.3558	0.4566	0.4380	0.4076	0.4164	0.3763	0.2913
	PS4	0.3523	0.3784	0.3553	0.4548	0.4375	0.4039	0.4137	0.3775	0.2877
	PS5	0.3442	0.3759	0.3559	0.4527	0.4368	0.3996	0.4109	0.3762	0.2860
	PS6	0.2773	0.3121	0.2924	0.4326	0.4331	0.3327	0.3871	0.2863	0.0370
	PS7	0.2753	0.3065	0.2459	0.4310	0.4324	0.3283	0.3849	0.2856	0.0370
degree	org	0.0696	0.1061	0.0798	0.1509	0.1710	0.0722	0.1013	0.0662	0.1136
	PS1	0.0653	0.1058	0.0776	0.1500	0.1705	0.0709	0.1005	0.0661	0.1118
	PS2	0.0648	0.1019	0.0774	0.1496	0.1700	0.0702	0.0996	0.0657	0.1097
	PS3	0.0635	0.0984	0.0702	0.1493	0.1695	0.0694	0.0983	0.0653	0.1103
	PS4	0.0573	0.0953	0.0760	0.1492	0.1691	0.0687	0.0961	0.0663	0.1099
	PS5	0.0559	0.0941	0.0762	0.1486	0.1692	0.0688	0.0953	0.0651	0.1100
	PS6	0.0406	0.0769	0.0601	0.1411	0.1660	0.0659	0.0896	0.0362	0.0155
	PS7	0.0405	0.0729	0.0495	0.1409	0.1661	0.0649	0.0891	0.0362	0.0151
betweenness	org	0.0629	0.1053	0.0860	0.1358	0.1536	0.0783	0.1054	0.0590	0.1542
	PS1	0.0602	0.1016	0.0823	0.1356	0.1534	0.0806	0.1047	0.0586	0.1592
	PS2	0.0577	0.0984	0.0821	0.1364	0.1532	0.0828	0.1017	0.0576	0.1565
	PS3	0.0553	0.0939	0.0747	0.1358	0.1530	0.0806	0.1010	0.0566	0.1561
	PS4	0.0544	0.0939	0.0798	0.1357	0.1523	0.0814	0.1009	0.0586	0.1535
	PS5	0.0526	0.0931	0.0805	0.1356	0.1522	0.0822	0.0993	0.0569	0.1524
	PS6	0.0403	0.0789	0.0587	0.1266	0.1501	0.0678	0.0903	0.0380	0.0168
	PS7	0.0402	0.0738	0.0508	0.1265	0.1500	0.0687	0.0898	0.0379	0.0166

can produce a set of solutions, aviation decision makers thus can have multiple choices for better air traffic management.

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