Enhancing the Robustness of Airport Networks By Removing Links

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***Abstract*—Air traffic is playing a leading role in the global economical growth. Air traffic is indispensable from airport networks which accommodate the traffic demands. Note that airport networks are confronted with intractable uncertainties such as severe meteorological conditions, random mechanical failures of aircraft instruments, terrorist attacks, etc., which give rise to the failures of the components of airport networks. It is of great significance to improve the robustness of airport networks to component failures as the failures can cause staggering economical losses. Existing works either employ network rewire mechanism or add more links to an airport network to enhance the robustness of the given network. In this paper, we provide a counter-intuitive way to enhance the robustness of airport networks. Specifically, we propose to remove links from a given airport network to improve its robustness in face of perturbations. To do so, we develop a single-objective genetic algorithm to locate the links of an airport network whose removal will increase its robustness. Experimental studies on six real-world airport networks validate the feasibility of the proposed research idea. This work provides a new perspective for aviation decision makers to manage airports and air routes, and therefore sheds new light towards robust airspace design.**

***Index Terms*—Air traffic, airport networks, network robustness, evolutionary computation**

I. Introduction

Air traffic facilitates not only our daily travel but also commodity delivery. According to the reports released by the International Civil Aviation Organization (ICAO) and the International Air Transport Association (IATA), an extremely large number of people travel through planes [1], [2], and a magnificent amount of freight are delivered via air traffic [3], [4]. Nowadays, more passengers and express companies have prioritised air traffic as their major choice for transportation. Air traffic is now contributing a great deal to the world globalization [5], [6].

As air traffic plays a critical role in the world economy, it is therefore of pertinent significance to ensure the reliability of air traffic [7], [8]. Note that air traffic is conducted through a complicated air transport system which involves a colossal amount of entities and amongst which is the airport. Air traffic is indispensable to airports which serve departures and arrivals for aircraft. In reality, airports frequently suffer from manifold perturbations like runway icing due to bad weather, GPS signal loss due to interference signals, airport closure due to terrorist attacks or persistently low visibility caused by volcano eruption or smog, etc [9], [10]. All these perturbations impact airports' operations, and as an outcome flight cancellations and delays occur which hurt all the aviation players [8], [11].

Note that for the sake of maximizing passenger flow so as to gain higher profit, airlines normally schedule the plan of an aircraft with multiple flight legs that travel between multiple airports [12]. As a consequence, airports "interact" with one another, forming the airport networks. When one airport suffers from perturbations, its capacity has been altered and departures from and arrivals at that airport are therefore affected [8], [11]. Those disturbances then propagate on the airport network through the connections between airports. In order to gauge how robust an air transport system is to external/internal perturbations, one of the most straightforward and effective ways is to model an air transport system as an airport network and then estimate its network robustness [13]–[15].

Robustness calculation for airport networks has been well studied [16]–[19]. Many metrics and methods have been developed to estimate the robustness of a given airport network, and among which is the eigenvalue of the Laplasian matrix corresponding to an airport network [20], [21]. The rationale behind this is that the eigenvalue has a positive correlation with the connectivity of a network in face of network component failures [20], [22]. Assisted with the eigenvalue metric, in the literature researchers have proposed a vast body of methods to improve the robustness of airport networks. Existing studies on the robustness enhancement of airport networks can be roughly categoried into two classes, viz., network rewire mechanism [23], [24] and link addition strategy [25], [26]. Network rewire mechanism aims to modify the structure of a network by rewiring (reconnect) the links but keeping the same degree distribution (the number of links attached to each node remains unchanged) of the focal network so as to achieve higher network robustness. Network rewire mechanism has proved as a potent instrument for improving a network's robustness and has been widely utilized in many domains. However, to rewire an airport network may not be of practical use since many routes have been in use for decades. Besides, rewiring an airport network needs to take into account operational and procedure factors before proceedings. Compared to network rewire mechanism, link addition strategy is more appealing as it does not profoundly change the structure of a given network. Link addition strategy improves the robustness of a network by

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adding extra links to the network. The basic principle behind this is in light of the fact that the most robust structure of a network is a clique structure [27] in which each node is linked to all the rest nodes. It should be well aware that construction of an airport network with clique structure is impossible in reality. Meanwhile, adding more links to an airport network could elicit air traffic congestion as current airport networks are already saturated.

In order to provide a more feasible and much easier way to improve the robustness of airport networks, we in this paper suggest to achieve this goal by removing links from an airport network. In order to determine the links of an airport network whose removal will increase the robustness of the focal network, we develop a genetic algorithm to maximize the robustness of the focal network with respect to the eigenvalue. We carry out simulations on six real-world airport networks to validate the effectiveness of the developed algorithm. Experiments demonstrate that it is feasible to improve the robustness of airport networks by removing links. This work provides a new perspective for decision makers for better air traffic management and therefore sheds new lights towards robust airspace design.

The remainder of this paper is structured as follows. In what follows we provide the related backgrounds for better understanding of this work. Afterward, we formulate our proposed research problem and delineate in detail the designed algorithm for solving the formulated problem. Finally we present the experiments and conclude the paper.

II. Related Backgrounds

A. Airport Network Representation

Airports are critical infrastructures of air traffic [28]. Airports interact with each other by the flights traveling between them. It is straightforward and helpful to construct an airport network to capture the interacts between the airports [11]. An airport network in general is modelled as a graph which is composed of a set of nodes/vertices and links/edges. Mathematically, a graph is denoted by $G = \{V, E\}$. The symbols V and E respectively represent the node set and the link set.

For an airport network $G = \{V, E\}$, a node $i \in V$ denotes an airport. Generally, we use cardinalities $n = |V|$ and $m = |E|$ to respectively denote the number of airports and the number of links in G. Note that the physical meaning of a link $e_{ij} \in E$ may vary with respect to specific research purposes. In this study, we construct a link between airports i and j if there exist flights between those two airports.

B. Network Robustness Calculation

Complex networks in reality will inevitably suffer from versatile perturbations which cause failures to network components [29], [30]. In order to gauge how robust a network is in face of perturbations, the research on network robustness came into being and has received enormous attention in the past decade [31]–[34].

In the literature, a dozen of methods and metrics have been proposed to quantify the robustness of a network [20], [35]–[37]. Among existing avenues, network spectral analysis has proven as a potent tool for measuring the robustness of a complex network. Given a network G, let $\mathbf{A}$ be its adjacency matrix. The entry $a_{ij} \in \mathbf{A}$ denotes the interactions between nodes i and j. Typically, $a_{ij} = 1$, if there is an interaction between nodes i and j, and 0, otherwise. With all these, the Laplacian matrix $\mathbf{L}$ of network G can be formulated as

$$\mathbf{L} = \mathbf{D} - \mathbf{A} \tag{1}$$

where $\mathbf{D} = diag(d_1, d_2, ..., d_n)$ is a diagonal matrix with $d_i = \sum_{j=1}^{n} a_{ij}$ being the *i*-th diagonal element.

Let $\mathbf{x}$ be the eigenvector of $\mathbf{L}$. Therefore, we have $\mathbf{Lx} = \lambda\mathbf{x}$ where λ is the eigenvalue with respect to $\mathbf{x}$. As $\mathbf{L}$ is a square matrix, thus, it has maximumly n eigenvalues. Then researchers quantify the robustness of network G as λ_2 which is the second smallest non-negative eigenvalue [27], [38]. The larger the value of λ_2, the more robust the network is.

C. Evolutionary Algorithms

Many scientific and engineering problems are essentially optimization problems and in many cases, those problems are NP-hard. In order to find approximately optimal solutions within acceptable time, evolutionary algorithms (EAs) mainly inspired by Darwinism were developed and have been widely applied to solve diverse optimization problems that cannot be solved by canonical mathematical methods [39], [40].

An EA approximates the global optimal solution(s) to an optimization problem with a population of chromosomes. Each chromosome is a feasible solution to the problem to be optimized. An EA iteratively generates the new population by harnessing genetic operators, viz., crossover and mutation. During each iteration, the EA saves the best solution found so far. After a given number of iterations, the EA takes the best solution discovered by the algorithm as the “global” best solution to the optimization problem.

III. Research Problem and Methodology

A. Research Problem

This paper aims to investigate if it is possible to improve the robustness of an airport network by removing 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 design a genetic algorithm to see if it is possible to remove some links from the given network to improve its robustness. For the toy network shown in Fig. 1, the designed genetic algorithm suggests that the link between nodes 2 and 6 can be removed and its robustness has been improved from 0.4374 to 1.3820. In what follows we will formulate our research problem and describe in detail the algorithm design.

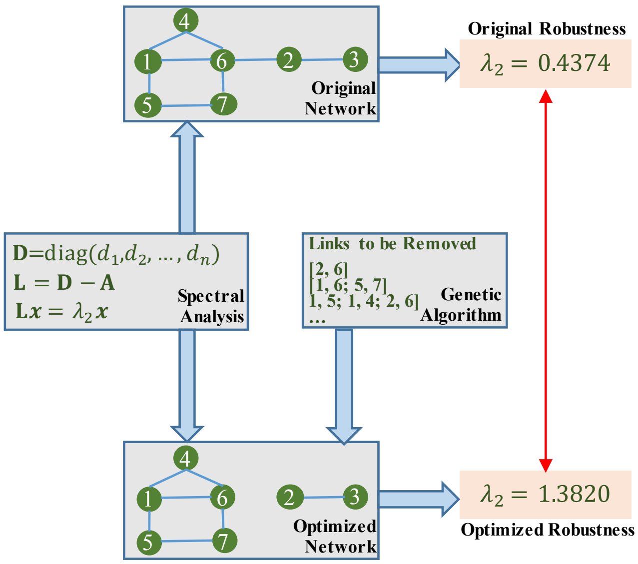


Fig. 1. Concept diagram of the proposed research problem.

B. Problem Modeling

In order to locate the links that can be removed to improve the robustness of an airport network, we therefore construct an optimization problem. Given an airport network $G = \{V, E\}$ with $\mathbf{A}$ being its adjacency matrix. Then we propose to solve the following maximization problem:

$$\begin{aligned} \arg\max_{E_0} \quad & \lambda_2 \\ s.t. \quad & \mathbf{L}_0\mathbf{x} = \lambda_2\mathbf{x} \\ & \mathbf{L}_0 = \mathbf{D}_0 - \mathbf{A}_0 \\ & \mathbf{A}_0 = \mathbf{A}\big|E - E_0, E_0 \subseteq E \end{aligned} \tag{2}$$

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 – a portion of its links – are removed.

By solving the above optimization problem we can get the subset E_0 with respect to the maximum value of λ_2. Let λ_2' be the second smallest non-negative eigenvalue of the Laplacian matrix corresponding to $\mathbf{A}$. Then we say that the robustness of the given airport network G can be improved by removing some of its links if the following condition is satisfied:

$$\lambda_2 \geq \lambda_2' \wedge E_0 \neq \emptyset \tag{3}$$

C. Algorithm Overview

As can be seen from Eq. 2, the formulated problem is a combinatorial optimization problem. In order to solve it properly, we here introduce and design a genetic algorithm (GA). The framework of the developed GA is provided in Algorithm 1.

In step 3 of Algorithm 1, the population $\mathbf{P}$ consists of $psize$ individuals each of which is also called a chromosome. Each chromosome represents a feasible solution to the problem to be optimized. In what follows we provide details for all the key steps of Algorithm 1.

Algorithm 1 Framework of the proposed genetic algorithm

Input: $\mathbf{A}_{n\times n}$ – adjacency matrix of a network with m links
Output: E_0 – a subset of the link set E of $\mathbf{A}$

1) Hyper-parameters settings of $psize$, pm, pc and $iter$;
2) Set $E_0 = [\,]$ and $\lambda_2 = -\infty$;
3) $\mathbf{P} = (\mathbf{p}_1, \mathbf{p}_2, ..., \mathbf{p}_{psize})^T$; //initialize a population, see subsec III-D
4) $[E_0, \lambda_2] = \text{FitnessEvaluation}(\mathbf{P}, \mathbf{A})$; //see Eq. 2
5) $[E_0, \lambda_2] = \text{UpdateGlobalBest}(E_0, \lambda_2, \mathbf{P})$;
6) **For** $i = 1$ to $iter$, **do**
   a) $\mathbf{P} = \text{GeneticOperation}(\mathbf{P}, pc, pm)$; //create new population, see subsec III-E
   b) $[E_0, \lambda_2] = \text{FitnessEvaluation}(\mathbf{P}, \mathbf{A})$;
   c) $[E_0, \lambda_2] = \text{UpdateGlobalBest}(E_0, \lambda_2, \mathbf{P})$;
   d) $\mathbf{P} = \text{ElitismMechanism}(\lambda_2, \mathbf{P})$; //subsec III-F
7) **end**

D. Chromosome Representation

How to represent a chromosome is the key to bridge a GA with an optimization problem. In this paper we aim to delete some links from a given network G to improve its robustness. To do so, we represent a chromosome $\mathbf{p}_i$ as follows:

$$\mathbf{p}_i = (p_i^1, p_i^2, ..., p_i^m) \tag{4}$$

where m is the number of links of network G and $p_i^j \in \{0, 1\}$ is a binary variable. For a GA, p_i^j is also called the *j*-th gene of the *i*-th chromosome.

The above representation corresponds to a feasible solution to the problem formulated in Eq. 2. The *j*-th gene of chromosome $\mathbf{p}_i$ specifies whether the *j*-th link of G can be removed or not. Specifically, based on $\mathbf{p}_i$ we determine E_0 as

$$E_0 = \{j \big| p_i^j = 1, \forall j \in [1, m]\} \tag{5}$$

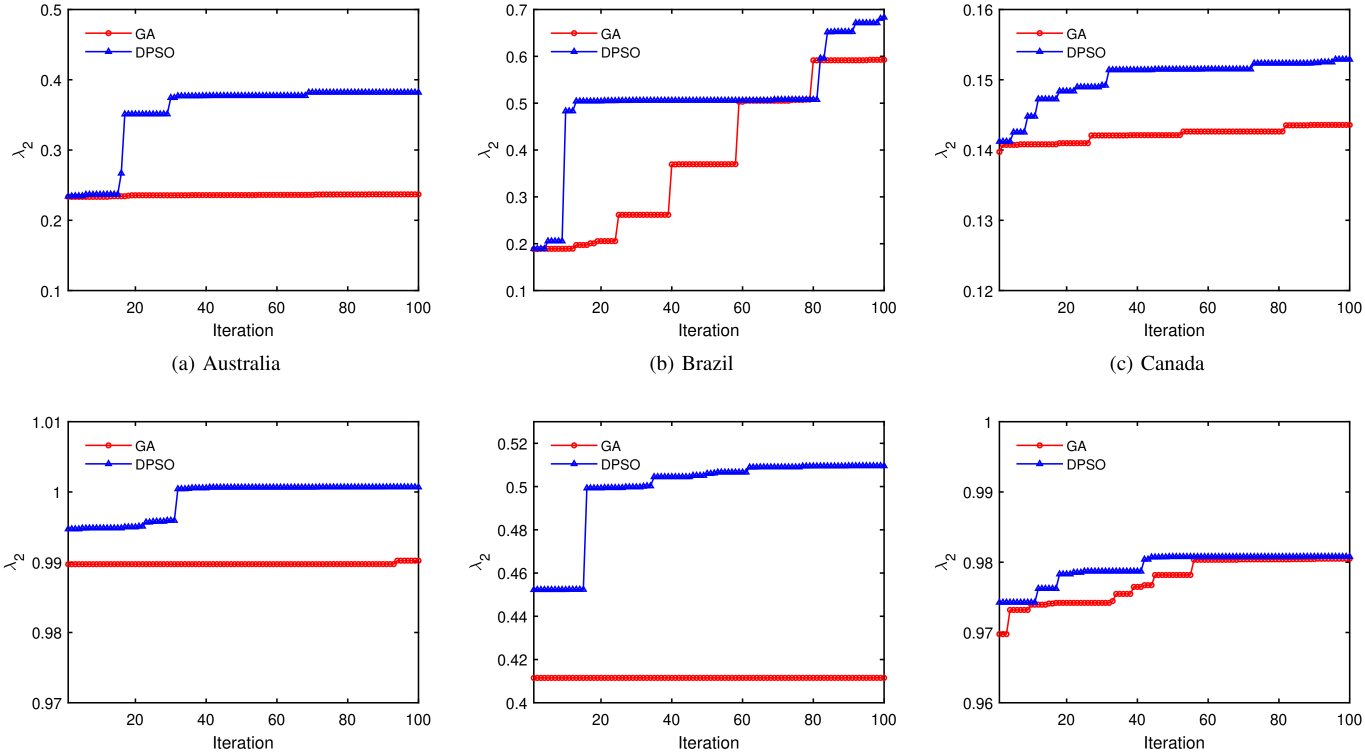
Substituting E_0 into Eq. 2 we get the value of λ_2 and per the condition formulated in Eq. 3 we then get to know whether E_0 is indeed the set of links whose removal will increase the robustness of the original network G.

E. Genetic Operation

The genetic operation as shown in step 6a of Algorithm 1 is to generate a new population. The genetic operation consists of two operators, viz., crossover and mutation.

Single Point Crossover) The crossover operator is implemented pairwise. For a pair of chromosomes $\mathbf{p}_i$ and $\mathbf{p}_j$, in this paper we adopt single point crossover operation. Specifically, we first randomly select a position r between 1 and m. Then we swap the genes of $\mathbf{p}_i$ and $\mathbf{p}_j$ starting from the position r with a given crossover probability pc. As a consequence, we generate two new chromosomes $\mathbf{p}_i'$ and $\mathbf{p}_j'$.

Single Point Mutation) For chromosomes $\mathbf{p}_i'$ and $\mathbf{p}_j'$ we then carry out single point mutation operation. Specifically, for $\mathbf{p}_i'$ and $\mathbf{p}_j'$ we randomly select one gene from each chromosome with a probability pm and change its value.



(a) Australia (b) Brazil (c) Canada (d) China (e) Europe (f) India

Fig. 2. Best values of λ_2 found by GA and DPSO when applied to the airport networks. The values of λ_2 are drawn with respect to the iteration number.

F. Elitism Mechanism

Note that GA is a stochastic method. In order to improve its searching ability, we introduce an elitism mechanism. For a given population $\mathbf{P}$, the elitism mechanism first locates all the worst individuals $\mathbf{p}_i$ that have the smallest fitness value. If the best individual of $\mathbf{P}$ is worse than the historically best individuals, then the elitism mechanism replaces the worst individuals in $\mathbf{P}$ with the historical ones.

IV. Experimental Study

A. Airport Network Datasets

In the experiments we carry out case studies on six real-world airport networks which are abstracted from the Open-Flight dataset [41]. Table I lists the basic properties of the studied airport networks.

TABLE I
PROPERTIES OF THE TESTED AIRPORT NETWORKS. SYMBOL $\langle k \rangle$ DENOTES THE AVERAGED DEGREE, AND λ_2' IS THE ROBUSTNESS 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

Note that each constructed airport network is unweighted. Putting it another way, we construct a link between two airports 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. Experimental Settings

In the experiments we compare the designed GA against a discrete particle swarm optimization (DPSO) algorithm [42]. The DPSO algorithm utilizes the same individual representation scheme as that of GA. The settings of the hyper-parameters for the GA and the DPSO algorithm are provided as follows:

1) GA – $psize = 100$; $iter = 100$; $pc = 0.9$; $pm = 0.1$;
2) DPSO – $psize = 100$; $iter = 100$; $c_1 = 1.496$; $c_2 = 1.496$; $w = 0.729$.

Note that the parameter settings are based on experience. We do not tune all the parameters and see their impact on the final results. This is because that the main purpose of this paper is to validate whether the proposed research idea is feasible or not.

C. Fitness Comparison

For each tested network, we apply GA and DPSO to maximize Eq. 2. During each iteration we record the best value of λ_2 found by each algorithm. Fig. 2 demonstrates the corresponding results on the tested airport networks.

As can be seen from Fig. 2 that the DPSO algorithm performs better than GA with respect to the best value of λ_2. As GA and DPSO are stochastic algorithms, each independent run of GA or DPSO could yield different results. Since the results shown in Fig. 2 are the outcome of one run of each algorithm, we therefore further compare the two algorithms by running each algorithm for 30 independent times.

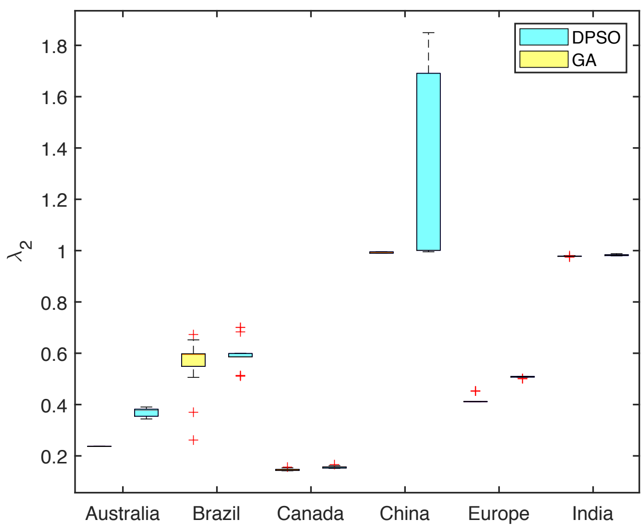


Fig. 3. Box plot of the best values of λ_2 found by GA and DPSO for 30 independent runs on each studied airport network.

Fig. 3 displays the box plot of the best values of λ_2 obtained by GA and DPSO through 30 independent runs. We can clearly see from Fig. 3 that the values of λ_2 obtained by the DPSO algorithm through 30 independent runs on China airport network vary a lot which indicates that the DPSO algorithm is unstable. This is mainly due to the stochastic nature of the algorithm. The box plot results indicate that for the six tested networks, DPSO outperforms GA in terms of the maximum objective value.

D. Link Removal Comparison

The above experiments demonstrate that DPSO can obtain higher fitness values than GA does. For each airport network we record the best solutions (λ_2 and E_0) found by DPSO and GA during the 30 independent runs. Table II summarizes the statistical results.

By comparing Table II and Table I, we can see that the robustness of the studied airport networks have been increased by removing links from the networks. Although results shown in Figs. 2 and 3 indicate that the DPSO algorithm yields solutions with higher objective values, Table II reveals that the solutions yielded by the DPSO algorithm need to remove more links from an airport network than that obtained by GA does to increase the network's robustness.

We can observe from Table II that the GA yields more optimal solutions (reflected by $\#E_0$) than the DPSO does. This is due to the intrinsic nature of GA and DPSO. GA employs the genetic operators which help in better exploitation, while DPSO harnesses particle status update equations which contribute to better exploration. Although DPSO can yield solutions with higher objective function values, this does not necessarily mean that DPSO outperforms GA. This is because that the solutions obtained by DPSO suggest to remove more links from an airport network which may not be realistic.

TABLE II
STATISTICS OF THE BEST SOLUTIONS FOUND BY DPSO AND GA FOR 30 INDEPENDENT RUNS. $\#E_0$ IS THE NUMBER OF OPTIMAL SOLUTIONS, AND MIN$|E_0|$ IS THE MINIMUM NUMBER OF REMOVED LINKS WITH RESPECT TO ALL THE OPTIMAL SOLUTIONS.

Reigion	GA			DPSO		
	λ_2	$\#E_0$	min$\|E_0\|$	λ_2	$\#E_0$	min$\|E_0\|$
Australia	0.2378	1	11	0.3904	1	12
Brazil	0.6730	1	19	0.7005	1	19
Canada	0.1563	1	22	0.1661	1	26
China	0.9960	4	51	1.8494	1	70
Europe	0.4527	2	108	0.5103	1	255
India	0.9807	2	7	0.9881	1	10

E. Network Structure Comparison

The best solutions presented in Table II suggest that the robustness of an airport network can be improved by removing links. Since GA requires less link removal to improve a network's robustness, we therefore take the results generated by GA as the final output. In what follows we compare the original airport network structures against those being optimized by GA with respect to their robustness.

For better visualization, here we only analyze the Australian and Indian airport networks as these two networks are smaller in size than the remaining four networks. As shown in Table II that GA respectively needs to remove 11 and 7 links from the Australian and Indian airport networks to improve their robustness, we therefore in Fig. 4 exhibits the original airport network structures and the structures obtained by removing the corresponding links from the original networks.

Note that the positions of the nodes of the networks displayed in Fig. 4 are exactly based on their real GPS coordinates. Fig. 4 demonstrate that some of the removed links are associated with several hub nodes (the red nodes of the Australian airport network and the purple nodes of the Indian airport network). If a hub airport suffers from perturbations, then many flights will be affected. If some routes/links attached to a hub airport are removed, then the hub airport becomes less centralised and therefore perturbations to that airport may impact relatively less flights.

One may notice from the bottom panel of Fig. 4 that after removing the link between the red nodes, one node becomes isolated. On one hand, the solutions obtained by GA may not be the global optima due to the stochastic nature of GA. On the other hand, the node isolation does not necessarily mean that flights between those two airports are permanently cancelled. In order to minimize economical losses in face of perturbations occurred to airports, airlines can cancelled flights within a time window and will resume in the near future when the perturbations disappear.

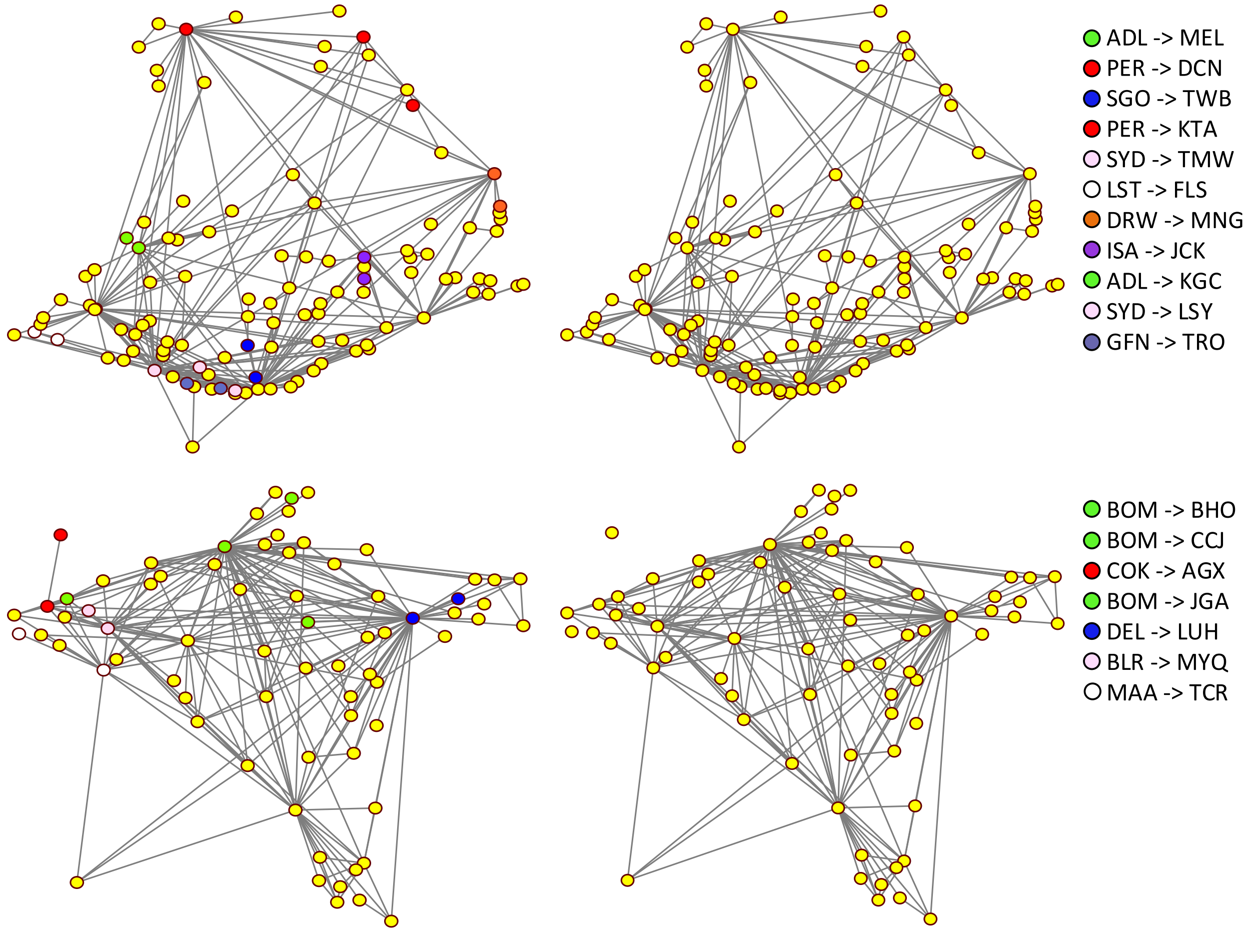


Fig. 4. Comparisons between the original airport network structures (left panel) and those optimized by GA (right panel) with respect to λ_2. The upper and bottom panels respectively exhibit the network structures of the Australian and Indian airport networks.

V. Conclusion

Airport networks inevitably suffers from internal/external perturbations which gives rise to the dysfunction or unavailability of airports that will elicit staggering traffic delays and economical losses. How to improve the robustness of an airport network in face of perturbations is of pertinent significance to aviation industry. Existing studies on improving the robustness of airport networks either apply network rewire strategy or argument a network by adding in more links. In this study we provided a more realistic and much easier way to achieve this goal. Specifically, we proposed to improve the robustness of an airport network by removing some of its "redundant" links. To do so, we developed a genetic algorithm to locate those links by maximizing the second non-negative eigenvalue of the Laplacian matrix for a given airport network. Experiments on real-world airport networks had been carried out and the feasibility of the proposed idea had been validated. This work provides a new perspective towards robust airspace design.

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