Analysis and Optimization of airline networks: A Case Study of China

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We study the spatial form of the networks of the 20 largest domestic airlines by analyzing their edge set, degree and betweenness distributions, clustering coefficients and network diameter, and discover that the whole Chinese domestic airline network is not a scale-free but a small-world network. We analyze each network with two different metrics (i) *fitness*: we minimize the diameter of networks, and maximize the passenger flow for each edge; (ii) *robustness*: we compute the change in average path length after removing predetermined hubs and account for the scale of network disintegration. Finally, we compare the robustness of the network of different airlines and find that some small domestic airlines have very good robustness properties. Chinese airline topologies vary from pure stars to scale-free graphs to graphs with uniform dense clusters and scale-free branches to remote destinations.

Keywords: airline networks, topology, fitness, robustness

1. Introduction

The structure of the airline network, like other transportation infrastructures, is of great significance both for the convenience it can provide for travelers and for the strong relationship it has with the profitability of transportation service providers and the socioeconomic condition of those regions covered by the network. Therefore, airport and national airline companies can be an important part of the image a country wants to project [1-4]. In order to obtain more information about the current social and economic condition, many aspects of the network topologies are studied, such as centrality, community structure and traffic flows [5-6].

Additionally, the airline network is an infrastructure vulnerable to outside perturbations and system inefficiencies have large economic cost. For example, the September 11 attack has brought great loss to nearly all the airlines in the US, in particular, US Airways lost a combined 7.7 billion USD in 2001 and about 6 billion more in 2002 [7], and its negative effect continues to be felt today. The number of air passengers in China has been reduced by nearly 50% within a year before due to severe acute respiratory syndrome (SARS) [8]. There have been wide debates about how to minimize such impacts and improve profitability of airlines. One promising approach is to study the robustness of airline infrastructures.

A variety of studies have investigated airline networks and their robustness. Regarding network modeling, Gastner and Newman [9] studied the optimization of costs and benefits of transportation network; Barthelemy and Flammini [10] proposed a general model of weighted networks via optimization principle and they found out that an approach of varying the parameters of the cost function represented a meaningful alternative to the study of the structure of complex weighted networks. In terms of network robustness, Scott et al. [11] presented a comprehensive, system-wide approach to identifying critical links and evaluating network performance, considering network flows, link capacity and network topology; Beygelzimer et al [12] developed a decentralized approach to improve the robustness of the network.

Different from traditional general research about airline networks, we undertook a case study about airline networks in China. Like any other area, the domestic airline industry of China faces both opportunities and challenges. The passenger flows in China's air industry in 2005 reached approximately 126.7 million, an increase of 12.7% compared to 2004; however, the overall industry profit has decreased by 50%, down to 5.8 billion RMB [13]. In addition, because of the centrally-planned economic system, the structure of Chinese airlines may cause problems as the Chinese economy is increasingly becoming an integral part of the global economy.

In this paper, inspired by this background and other studies on airline networks [14], we analyze the network structure by mapping the topology of the flight networks of the 20 largest domestic airlines. We find that there are notable differences in the topologies. Some airlines have a clearly visible hub-and-spoke model, while others have a more fully connected network. We propose a general fitness function and optimize the network fitness by using a simulated annealing algorithm. Additionally, we propose a formulation to measure the robustness of the network, and compare the robustness of different networks.

In Section 2 we map the current networks of major Chinese airlines and analyze the structures of networks. In section 3 we present the mathematical modeling of network fitness and robustness. In section 4 all computational results are presented. The final section contains the conclusion and suggestions for future work.

2. Topology analysis

2.1 General comments about topologies

This analysis includes 20 airlines plus the entire Chinese airline network, comprised of the individual companies. For all cited networks common network measures are computed, such as number of nodes and edges, edge to node ratio, degree correlations, network diameter and path lengths. The goal of this analysis is to compare all airline topologies from a graph theoretical perspective and make conclusions about company strategy and age versus size (number of airports), operations (number of flights) and logistics (topology).

Table 1: Table of major airline statistics, such as number of nodes and edges, degree correlations, hubs, network diameter and robustness.

Code	**Name**	**m**	**n**	**m/n**	**corr.**	**diam**	**mean L**	**clust coeff**	**hubs**	**topology**	**robustness**
2Z	Changan Airlines	54	71	1.314815	-0.5211	8	3.2236	0.484	XIY	star-like	0.0835
3Q	Yunnan Airlines	38	46	1.210526	-0.6486	4	2.0284	0.6883	KMG	insuff. data	0.0071
3U	Sichuan Airlines	33	44	1.333333	-0.4048	5	2.6894	0.4505	CTU,CKG	scale-free	0.0784
8C	Shanxi Airlines	14	14	1	-0.5698	4	2.2857	0.2389	TYN	star-like	0.1263
CA	Air China	59	241	4.084746	-0.3622	4	2.0994	0.6054	PEK	scale-free	0.3849
CJ	China Northern Airlines	42	90	2.142857	-0.3885	4	2.2184	0.3896	SHE	star to scale-free	0.2482
CZ	China Southern Airlines	63	352	5.587302	-0.3067	4	2.063	0.59	CAN, WUH, SZX	scale-free	0.3309
F6	China National Aviation	13	12	0.923077	-0.6388	5	2.9744	0	HGH, SHE, WNZ	tree	0.3164
FM	Shanghai Airlines	38	43	1.131579	-0.847	5	2.7368	0.3653	PVG, SHA	star	0.0501
HU	Hainan Airlines	57	218	3.824561	-0.3042	5	2.2093	0.5149	PEK, TYN, NGB, XIY, HAK	scale-free	0.6892
KA	Dragonair	17	16	0.941176	-0.9526	2	1.8824	0	HKG	star	0.0000

MF	Xiamen Airlines	49	121	2.469388	-0.4747	4	2.0442	0.7036	XMN, FOC	star to scale-free	0.4700
MU	China Eastern Airlines	52	232	4.461538	-0.4395	4	2.043	0.5105	PEK, PVG, WUH, SHA, KMG	scale-free	0.3231
SC	Shandong Airlines	55	127	2.309091	-0.4271	5	2.2209	0.6602	TNA, TAO	star to scale-free	0.2838
SZ	China Southwest Airlines	33	63	1.909091	-0.2122	5	2.5947	0.4363	LXA, YNT, SHA, XIY, KMG, CTU	scale-free	1.0000
WH	China Northwest Airlines	34	50	1.470588	-0.4685	5	2.2834	0.4579	XIY	star-like	0.0568
WU	Wuhan Airlines	41	50	1.219512	-0.5108	6	2.5866	0.3042	WUH, YIH	scale-free	0.0641
XO	Xinjiang Airlines	47	61	1.297872	-0.3909	5	2.8261	0.2029	URC, XIY	scale-free	0.4246
XW	China Xinhua Airlines	14	18	1.285714	-0.4545	5	2.3846	0.4815	PEK, KMG, TSN	scale-free	0.7098
ZH	Shenzhen Airlines	45	58	1.288889	-0.6822	4	2.0697	0.2964	CAN, SZX, NNG, PEK	star-like	0.3143
China	All Chinese Airlines	112	1038	9.267857	-0.352	4	2.0914	0.72	Xi'An - XIY	uniform code star	0.2670

Table 1 lists all studied airlines with their codes, sizes and most important measures. There are about 5 additional companies which are excluded from the analysis due to their small size, serving less than 10 airports. International routes of large companies are also excluded. No single company services all national airports. The largest airline is China Southern Airlines, followed closely by Air China. The average number of served airports is 40 with on average 96.4 serving routes. The average edge to node ratio of about 2 is typical for technological networks and is explained by capacity and other constraints [15]. Small airlines have mostly tree and star-like topologies and very small number of edges, showing a minimalist strategy for a small-scale or young company. Larger companies have many more interconnecting routes, trading redundancy in operations for flexibility in service. For example, China Southern serves 63 airports, and 352 routes between them, giving an edge to node ratio of about 5.6 compared to the average 2.

Most airlines with tree or star topologies have maximum two hubs, usually capitals of the province in which the airline is based. Large carriers usually have a core of high-degree airports with single branching flights to small, more remote cities.

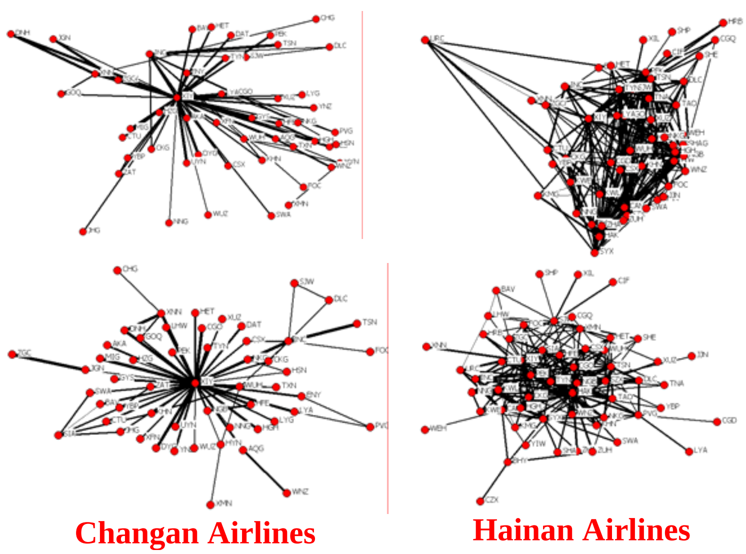


Figure 1. Changan Airlines (left) compared to Hainan Airlines (right). The top plots show the actual geography of airports and flights. The bottom plots show the two topologies optimized for energy using the Kamada-Kawaii algorithm.

In Figure 1, the bottom plots help to understand the abstract topology of the networks, which is not always evident from the geography. Changan Airlines is an example of middle-sized carrier which started out as a star network with Xi'An as hub and then started to add interconnecting flights as necessary by demand. Hainan Airlines is an example of a more developed airline network with a dense core of well-connected airports and branches to more remote cities. It is conceivable that these are examples of different stages of growth of an airline company. This is not a general claim, because there are examples of other smaller Chinese carriers with non-star topologies.

Interesting are double-star topologies, such as the case of Shanghai with its two airports, equally well-connected. Shanghai is the single hub, from a demand point of view, but the airline logistics, cost and operations are split between two airports. Interestingly, some popular tourist destinations like Xiamen and Kunming are connected to both cities. Shandong Airlines also has a double-star topology, serving not the same city, but cities in the same province, Jinan and Qingdao, of which Jinan is the capital, and Qingdao is the more popular tourist destination. The Shanghai and Shandong Airlines topologies are shown in Figure 2.

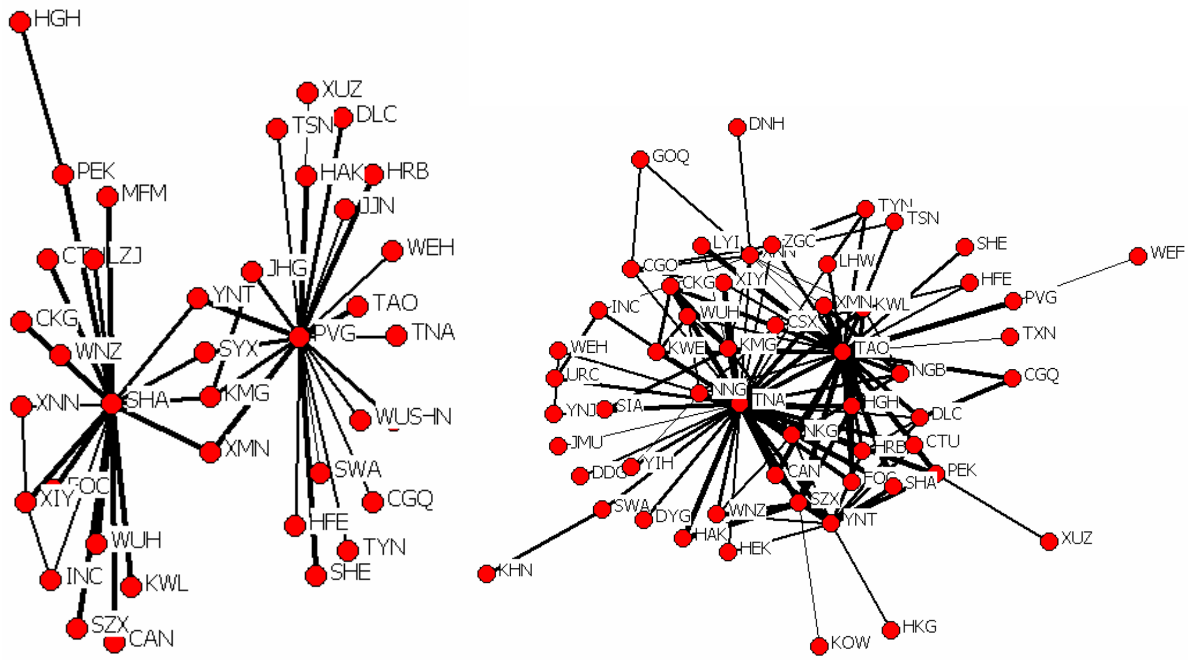


Figure 2: Double-star topologies of Shanghai Airlines with hubs the two Shanghai airports and Shandong Airlines with hubs Jinan and Qingdao, which are also geographically close.

2.2 Network measures

All network *degree correlations* are negative, similar to many technological networks, though there is no evidence that this is a general law [9,16]. It is hard to claim that these networks are not wired preferentially, because the geography plots show very well-organized, terrain specific structure. It is possible that correlations are negative due to the still more uniform connectivity — probably an artifact of government regulation or of the relatively young age of the Chinese industry.

An interesting measure is the network diameter, which regardless of the airline size, varies around 5. This means that for any Chinese airline, the largest number of hops from remote airports is at most five. Given an average size of 40 nodes, small average path lengths of about 2.4, and the relatively large clustering coefficients, it can be claimed that all Chinese airlines are small worlds, maybe with the exception of China National Aviation which has a pure tree structure, with a diameter of 5 for only 13 airports.

2.3 Distributions

The distributions types of degree and nodal betweenness vectors are fitted to exponential curves, linears, quadratics, normal, Poisson and power law curves. The most common distributions are exponential, power law and power laws with kinks in the curve. However, there are four large airlines with normal-like betweenness distributions: China Southern Airlines, China Eastern, Shandong Airlines and China Southwest (Figure 3). Normal distributions for large airlines mean greater connectivity, redundancy in flight patterns, making them closer to random and completely connected networks. This is a very different model from the prevalent hub-and-spoke model in the United States. Usually, there is a uniform distribution plateau reflecting a uniform density cluster of airports, followed by a power law drop off for connections to remote cities (see Figure 4 – China Southern). When there are good power-law approximations, there is a great variety in exponents, and no general trends, though most |k|~0.1-3 ($P \sim x^k$) and for exponential distributions the most frequent coefficient of the exponential is -0.1, and is always between -1 and 0. Summary of all distribution results is presented in Table 2.

Table 2: Degree and betweenness distributions of Chinese airlines.

Code	**Name**	**deg dist**	**betw dist**	**topology**
2Z	Changan Airlines	pow, k~-0.5	pow, k=-16	star-like
3Q	Yunnan Airlines	pow, k~-0.888	insuff. data	insuff. data
3U	Sichuan Airlines	exp, b=-0.68, pow, k~-0.99	exp,b=-0.09, pow, k~3.3	scale-free
8C	Shanxi Airlines	insuff. data	insuff. data	star-like
CA	Air China	exp, b=-0.1	exp, b=-0.02, pow, k~-2.7	scale-free
CJ	China Northern Airlines	exp, b=-0.3, pow, k~-0.7	cdf pow, k~-2.78	star to scale-free
CZ	China Southern Airlines	pow law with a kink	normal-like	scale-free
F6	China National Aviation	insuff. data	insuff. data	tree
FM	Shanghai Airlines	exp, b=-0.687	insuff. data	star
HU	Hainan Airlines	exp, b~-0.1	pow law with a kink	scale-free
KA	Dragonair	insuff. data	insuff. data	star
MF	Xiamen Airlines	pow, k~-1.64	quad cdf	star to scale-free
MU	China Eastern Airlines	exp, b~-0.1	normal-like	scale-free
SC	Shandong Airlines	exp, b~-0.345	normal-like	star to scale-free
SZ	China Southwest Airlines	exp, b~-0.347, pow, k~-1.7	normal-like	scale-free
WH	China Northwest Airlines	pow, k~-1.04	pow, k~-9	star-like
WU	Wuhan Airlines	pow, k~-0.54	pow, k~-8.4	scale-free
XO	Xinjiang Airlines	pow, k~-1, exp, b=-0.6	pow, k~-15.8	scale-free
XW	China Xinhua Airlines	exp, b~-0.5	insuff. data	scale-free
ZH	Shenzhen Airlines	pow, k~-2.4	insuff. data	star-like
China	All Chinese Airlines	pow law with a kink	skewed normal	uniform code star

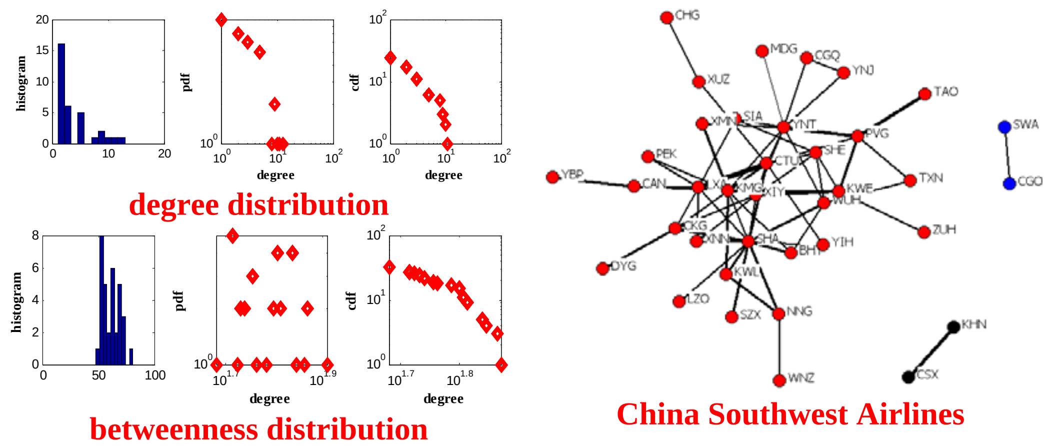


Figure 3: China Southwest degree and betweenness distributions. Notice the hub-and-spoke topology and the normal-like betweenness distribution.

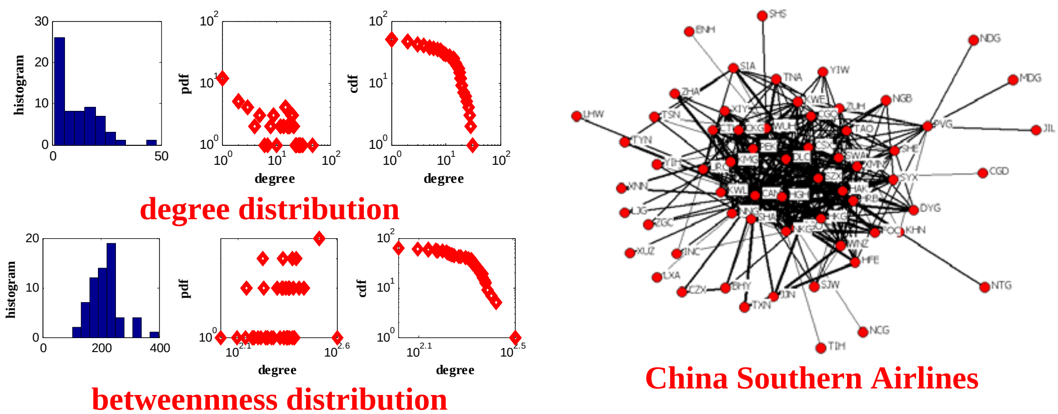


Figure 4: China Southern Airlines degree and betweenness distributions. The degree distributions has a two-part power law cdf curve, corresponding to a plateau in the histogram. This is due to a uniform density cluster with fewer branches out to smaller cities. The betweenness distribution is similar to a normal distribution.

2.4 The entire Chinese airline network

Statistically valuable is the entire Chinese network of flights, comprised of the routes of all airlines. The main statistical measures of this network are shown in the last line of Table 1. Notably, the entire Chinese network is completely connected, serving all recorded 112 airports and has a total of 1038 serving routes, with the largest edge to node ratio of about 9.3. Despite the small size, the network still has a small diameter of 4, very short average path length of 2.09 and a larger clustering coefficient than any single airline. As such, all of China is small world network. Surprisingly, the most connected city, just based on routes is Xi'An. If the number of flights, or edge weights, is considered, the most connected hub becomes Beijing. The city with highest betweenness is Shanghai, but only because of Shanghai PVG airport. Indeed Shanghai PVG is most frequently cited among hubs for separate airlines. This probably reflects the role of the business sector in Shanghai.

Figure 5: All Chinese airline routes: geographical and spring-energy optimized plot.

2.5 Section summary

Among all Chinese airlines, there is a great variety of sizes and topologies. Broadly, topologies can be classified in three categories: stars and trees, scale-free graphs and random-like cores and protruding branches, as shown in Figure 6. Almost all Chinese airlines are small worlds, defined by small diameter or average path length and relatively large clustering coefficient. They are not necessarily all scale-free networks though, as their degree distributions only barely sometimes approximate good power-laws, and more often they have many equally important hubs or strictly exponential degree distributions.

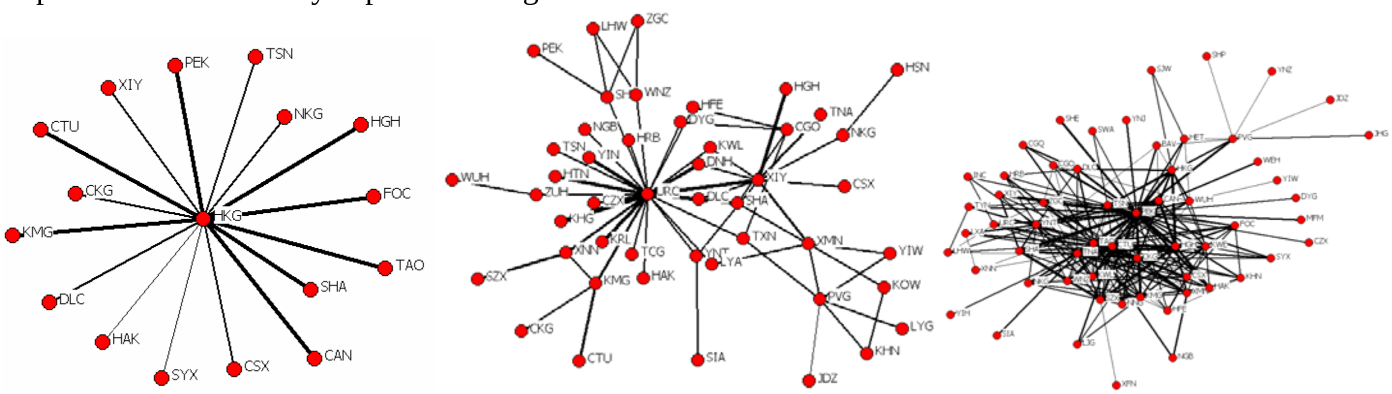


Figure 6: Dragonair, Xinjiang Airlines and Air China showing the transition from a star to scale-free topology.

Another measure listed in Table 1 is robustness which will be discussed in Section 4 with the rest of the computational results. In conclusion, Chinese airline networks show a transition from star to scale-free topologies with the network size.

3. Mathematical Modeling

Nomenclature:
d_{ij} : the distance between vertex i and j
n: the number of vertices
d : The diameter of a network which is the length (in number of edges) of the longest geodesic path between any two vertices.
w_{ij}: the weight of the link between vertex i and j
m : the number of remaining components after knocking out a hub. The component to which a vertex belongs is that set of vertices that can be reached from it by paths running along edges of the graph.
C_m: the set of nodes that belong to component m
R: the robustness value of a network

3.1 Network Rewiring

From a passenger point of view, a good network is such that the shortest path from any one vertex to any other, the geodesic path, is as small as possible. In the air-network analogy, we believe that customers pay more attention to the number of stops along the path connecting two nodes than the actual flying time, and thus we use the number edges as proxy for the distance between two airports. So the fitness of the network is good when it has small diameter, and based this, we assume that the fittest network is obtained with the minimization given in (1):

$$\min \sum_{i=1}^{n} \sum_{j=i+1}^{n} d_{i,j} \tag{1}$$

Another indicator for fitness is the traffic along each edge. To increase airline revenue, we try to maximize the network flow for each link. In our model, the capacity of each edge, which is obtained through multiplying the frequency of flights by the capacity of each flight, is a proxy for passenger demand. The weight w_{ij} represents the number of passengers on the link (i, j) and is symmetric $t_{ij} = t_{ji.}$. To travel from a generic vertex i_0 to another generic vertex i_p walking through a path $\{i_0, i_1, i_2\ldots, i_{p-1}, i_p\}$ the operations revenue is the sum of weights associated with the links that compose the path. In order to take into account both elements: the network diameter and network flow, our optimization objective is:

$$\min \sum_{i=1}^{n} \sum_{j=i+1}^{n} \frac{d_{ij}}{w_{ij}} \tag{2}$$

In the optimal network, long-range links carry heavy traffic and connect regional hubs dispatching traffic on a small scale ensuring an efficient global distribution.

3.2 Robustness

Robustness is the resilience of the system under stress or invalid input. In the airline network, stress occurs by the removal of one or several nodes due to the influence of weather, terrorism or other emergent factors. In this study, we methodically remove hubs and observe the changes in the topologies of all Chinese airlines. Our robustness measure account for three factors: the sum of the weights of the edges of the largest surviving component, the sum of weights of the original network, and the number of disconnected components after a hub removal. The fewer the disconnected components, the better the overall connectivity of the network is, hence its capacity to carry traffic under stress. The robustness function is shown in (3).

$$R = \frac{\sum_{(i,j)\in C_m} w_{ij}}{\sum_{i=1}^{n}\sum_{j=i+1}^{n} w_{ij}} \times \frac{1}{m} \tag{3}$$

4. Computational Results

4.1 Robustness

The robustness measure relies heavily on network topology, in particular on the number of hubs. Most airlines have maximum 2 hubs, with only few of the bigger carriers having many more than 2 hubs. As described in Section 3.2, the point of this robustness measure is to answer what happens to the routing if a hub suddenly disappears. This is measure in two ways: first, how many components does the network disintegrate into (the more the worse) and second, what is the percentage in traffic decrease (see Equation 3)?

Even without this measure, it is obvious that star-topologies are not robust at all, as confirmed in Table 3. More hubs, more interconnectivity, or higher clustering, provides more alternative routes when a hub disappears. This is why scale-free nets, uniform or random, well-clustered networks perform better. The most unique topology from all Chinese airlines turns out to be of China Southwest airlines. It is not in the realm of the largest carriers, or the smallest, but it has an almost perfect scale-free nature. With an exponential degree distribution and normal-like betweenness distribution, this network has node hierarchy, but at various node levels (unlike single-node hierarchy in power laws) which provides great flexibility. The China Southwest distributions and topology is shown in Figure 3.

Table 3: Chinese airlines sorted in descending order by robustness. Robustness is normalized with respect to the maximum for a comfortable comparative scale.

Code	Name	deg dist	betw dist	topology	Robustness
SZ	China Southwest Airlines	exp, b~-0.347, pow, k~-1.7	normal-like	scale-free	1.0000
XW	China Xinhua Airlines	exp, b~-0.5	insuff. data	scale-free	0.7098
HU	Hainan Airlines	exp, b~-0.1	pow law with a kink	scale-free	0.6892
MF	Xiamen Airlines	pow, k~-1.64	quad cdf	star to scale-free	0.4700
XO	Xinjiang Airlines	pow, k~-1, exp, b=-0.6	pow, k~-15.8	scale-free	0.4246
CA	Air China	exp, b=-0.1	exp, b=-0.02, pow, k~-2.7	scale-free	0.3849
CZ	China Southern Airlines	pow law with a kink	normal-like	scale-free	0.3309
MU	China Eastern Airlines	exp, b~-0.1	normal-like	scale-free	0.3231
F6	China National Aviation	insuff. data	insuff. data	tree	0.3164
ZH	Shenzhen Airlines	pow, k~-2.4	insuff. data	star-like	0.3143
SC	Shandong Airlines	exp, b~-0.345	normal-like	star to scale-free	0.2838
China	All Chinese Airlines	pow law with a kink	skewed normal	uniform code star	0.2670
CJ	China Northern Airlines	exp, b=-0.3, pow, k~-0.7	cdf pow, k~-2.78	star to scale-free	0.2482
8C	Shanxi Airlines	insuff. data	insuff. data	star-like	0.1263
2Z	Changan Airlines	pow, k~-0.5	pow, k=-16	star-like	0.0835
3U	Sichuan Airlines	exp, b=-0.68, pow, k~-0.99	exp,b=-0.09, pow, k~3.3	scale-free	0.0784
WU	Wuhan Airlines	pow, k~-0.54	pow, k~-8.4	scale-free	0.0641
WH	China Northwest Airlines	pow, k~-1.04	pow, k~-9	star-like	0.0568
FM	Shanghai Airlines	exp, b=-0.687	insuff. data	star	0.0501

3Q	Yunnan Airlines	pow, k~-0.888	insuff. data	insuff. data	0.0071
KA	Dragonair	insuff. data	insuff. data	star	0.0000

Figure 7 shows the topologies of the three most robust Chinese airlines. All three are extremely well-clustered and medium-sized in number of nodes.

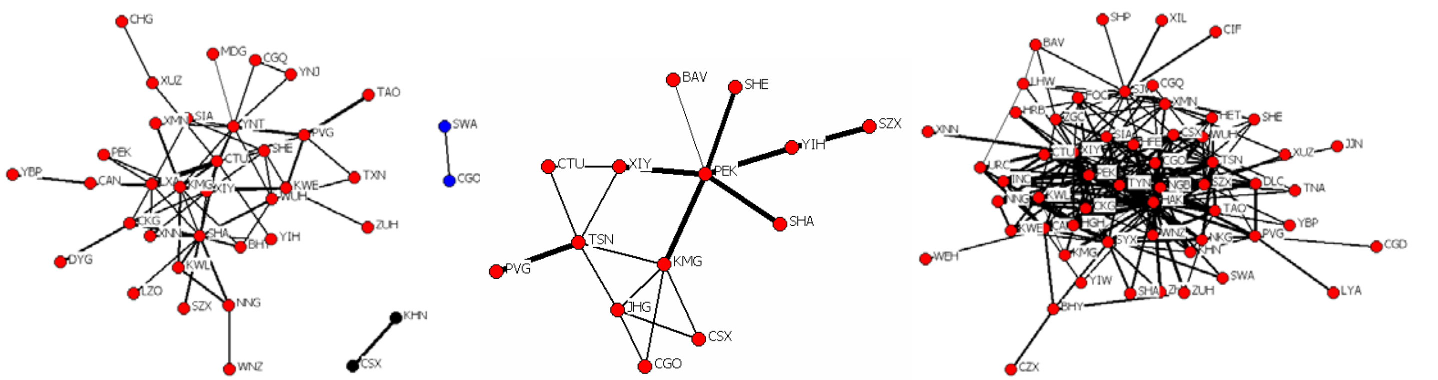


Figure 7: The three most robust Chinese Airlines: China Southwest, China Xinhia Airlines and Hainan Airlines

4.2 Rewiring

Rewiring, as a tool of optimization, is practical only for networks without physical infrastructure built into the edges. Airline networks, as modeled in this study, have flexible edges, while all infrastructure is concentrated in the nodes and the network flow of airlines, passengers and cargo. Given the current and projected losses in revenue of certain Chinese airlines, optimization can suggest structural improvements given the current market situation to help reverse these losses. The mathematical model of our optimization technique is explained in Section 3.1. The objective function (Equation 2) is reproduced here.

$$\min \sum_{i=1}^{n} \sum_{j=i+1}^{n} \frac{d_{ij}}{w_{ij}} \tag{2}$$

The objective function used minimizes two factors, both of service quality importance, aiming to attract more passenger demand. The first is network diameter, which means minimizing the number of flight changes a passenger needs to make across the whole route network. This is a factor even more important than travel time, as take-off and landing are the most cumbersome part of the flight, adding to delays at airports, inconvenience of luggage, passenger, cargo transfers and overnight stops. The second measure aims to maximize total traffic (passenger) flow through the entire network to help airline revenues.

Rewiring gives different results for different airlines, which provides a new comparative measure of airline topologies. Greater changes in the network wiring mean that the original network is less optimized for minimal travel time and maximum passenger flow.

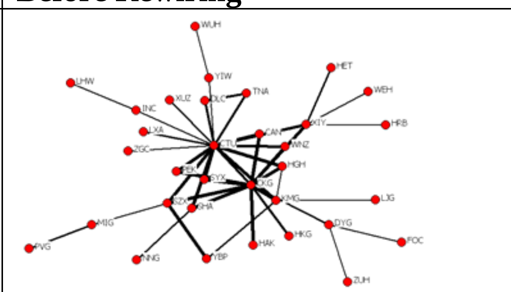
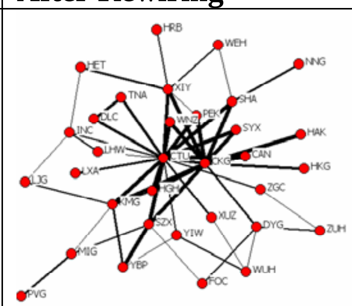
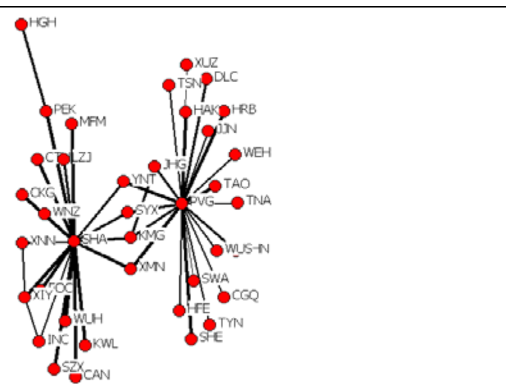
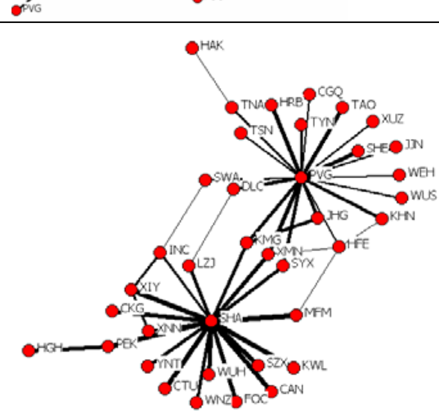
Table 4 shows an example of rewiring for Dragonair, a pure star network. The results represent a general trend observed for all airlines, of higher clustering. Minimizing network diameter, results in creating more short-cuts, which creates higher clustering between nodes. For Dragonair the clustering coefficient increases from 0 to

0.772, with 9 new triangle loops. In most rewiring examples, the network diameter and average path length do not change much. Most changes are in the number of edges, increased clustering and different degree and betweenness distributions.

Table 4: Dragonair statistics before and after rewiring.

Stats	Real	Rewired
# nodes – n		17
# edges – m		25
m/n		1.4706
{max,mean,min} deg	{16,1.882,1}	{15,2.941,1}
max degree node	HKG	HKG
{max,mean,min} betw	{17,17,17}	{19,17.706,17}
max betw node	-	PEK
degree correlation	-1	-0.461
clustering coefficient	0	0.772, 0.682
# triangle loops	0	9
Mean path length	1.882	1.919
network diameter	2	3

Figure 8 shows the changes in topologies after rewiring for various airlines. In general, the number of alternative paths increases, translating to gradual normalization of the betweenness distribution. Unfortunately, because of the bad computational time of the shortest path algorithm, fewer than the desired optimization steps were run. As a result, often airline topologies did not show much change. In our future work, we plan to increase the fidelity of the computation.

Airline	**Before Rewiring**	**After Rewiring**
Sichuan Airlines		
Shanghai Airlines		

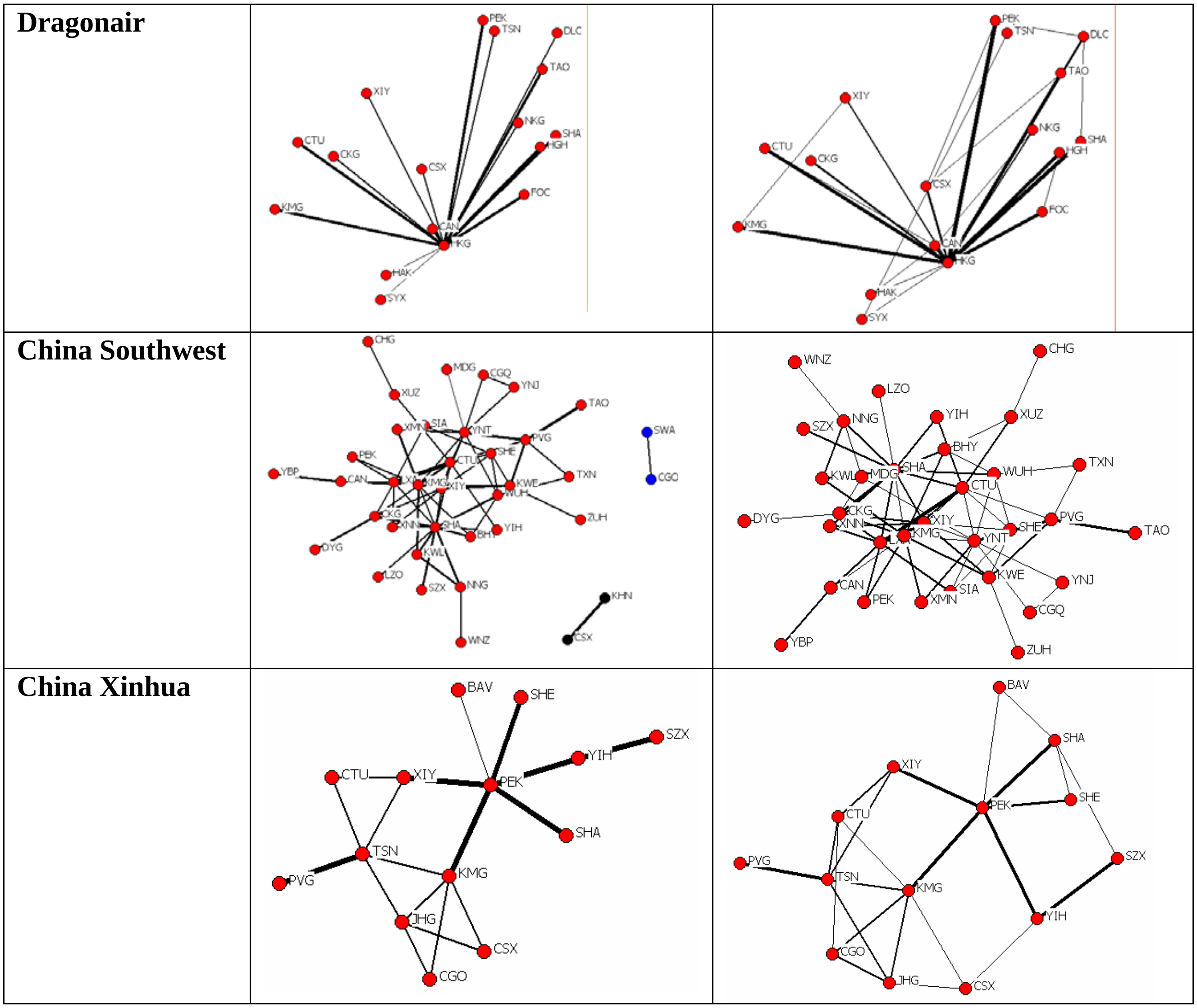


Figure 8: Topology changes after rewiring optimization for various Chinese airlines.

5. Conclusions

The success of this project depended on the plentiful data found early in the study. Twenty airline topologies are analyzed and compared with various network measures. In addition, the networks are rewired for minimum travel time and maximum traffic flow. The results are presented and discussed for major trends and special cases. In general, scale-free networks are robust, among which China Southwest Airlines stands out. Rewiring creates more clustering, as expected, and seen even at few steps of the rewiring algorithm. In our future work, we plan to increase the fidelity of the simulated annealing algorithm given more time for computation.

This study is a stepstone for further research in the area of Chinese airlines. It is true that the airline topologies are not wholly flexible, and that the rewiring we suggest may not be possible given geographic or economic constraints. We hope to investigate more metrics for comparison and analysis and include more factors in the current objective functions. There is also hope for incoming actual demand data, and modifications to the optimization algorithm to accommodate an economic model and result in suggestions for successful airline strategies.

Acknowledgements

We would like to thank the Santa Fe Institute and the Institute of Theoretical Physics, Chinese Academics of Sciences for their passion and devotion in organizing this Complex System Summer School. We also thank Dr. Raissa D'sourza and Shahrame Nosrati for their enlightening suggestions.

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