3 A review of connectivity utility models and their applications

Yahua Zhang and Anming Zhang

Introduction

A safe and well-connected transport network is vital for our economy (Zhu et al., 2019a). The intertwined relationship between air transport and economic development has been examined and evidenced in numerous studies, such as Brueckner (2003), Bannò, and Redondi (2014), Zhang and Findlay (2014), Van De Vijver et al. (2014), and Matsumoto et al. (2016) (see, e.g., Zhang, 2012, for a literature survey). For example, Blonigen and Cristea (2015) show that a 50 per cent increase in an average city's air traffic growth could result in an additional 7.4 per cent increase in real GDP in the United States. Baker et al. (2015) reveal a significant bi-directional relationship between regional economic growth and regional air transport services in Australia. Liu et al. (2013) find that cities with a higher level of air connectivity are appealing to globalised business service firms, which in turn can stimulate the development of aviation connections. Campante and Yanagizawa-Drott (2017) show that air links increase business links and that the movement of people induces the movement of capital.

Researchers have used different definitions for air connectivity. Traditional approaches to measuring air connectivity include the number of destinations, flight frequencies, seat capacity, seat-kilometres, cargo-hold capacities, passenger and cargo traffic volumes, and market shares (OECD/ITF, 2018). These simple measures are easy for the general public to understand and can offer insights into the development of the air transport network. However, the OECD/ITF (2018) warns that these simple metrics are not particularly useful for policy or business analysis as they sometimes provide misleading information. One example, as illustrated in OECD/ITF (2018), is that if we use transfer share as a measure of hub connectivity, we may observe that over time, this metric is decreasing at some airports when the total number of passengers handled there is increasing, although the (absolute) number of transfer passengers is actually increasing at these airports. Relying on a single-metric may result in a wrong conclusion.

A review of more sophisticated air connectivity measures can be found in Burghouwt and Redondi (2013), Calatayud et al. (2016), Zeigler et al. (2017), and OECD/ITF (2018). One type of the air connectivity measure is based on flight schedule data (Zeigler et al., 2017). The NetScan model developed by Veldhuis (1997), Burghouwt and Veldhuis (2006), and Burghouwt et al. (2009) is an example. It is a network quality model that considers air flight-level data that allow the calculation of both direct and indirect connections as well as hub connections. The quickest path length model developed in Malighetti et al. (2008) is another network quality model based on the flight schedule data. A time-dependent minimum path approach is used to calculate the minimum travel time between each pair of airports in the network, with a consideration of flight times and waiting times. A recent study by Cattaneo et al. (2017) uses this approach to analyse the number of quickest connections and the share of indirect quickest paths that remained un-managed for a period from 2006 to 2016. However, this approach was criticised for not accounting for route frequencies, making it inadequate for assessing connectivity implications of policy changes (OCED/ITF, 2018). It is worth noting that the NetScan model and many other connectivity models only measure a single transport mode's connectivity (e.g., Alderighi et al., 2007; Malighetti et al., 2008; Paleari et al., 2010; Hossain and Alam, 2017), and have not been extended to measure possible multi-modal connections.

Another stream of measures is based on actual passenger traffic data. This kind of approach explores the topological properties of the air transport network with various measure indices for network structure (the configuration of a network), centrality (the relative importance of a node within a network), and degree correlation (a node's degree related to the average degree of its neighbours) as discussed in Wang et al. (2011). The Global Airport Connectivity Index proposed in Cheung et al. (2020) is an example that combines degree, closeness, and eigenvector topological indicators and two volumetric indicators.[1] However, Otiso et al. (2011) note that standard airline data only show individual legs of a given trip rather than the trip as a whole. Therefore, if a passenger makes a transfer at a hub, the route is collected twice in the database: from the origin point to the hub and from the hub to the destination. This may lead to an inaccurate calculation of the hub connectivity. For this reason, we prefer the flight schedule-based connectivity measure, and our connectivity measure presented in this chapter is supply-based with a consideration of multiple quality factors, such as the capacity and velocity of a connection. These quality indicators are closely associated with air passengers' travel utility. Therefore, this measure was named the Connectivity Utility Model (ConnUM), which has been developed in Zhang et al. (2017), Zhu et al. (2018), and Zhu et al. (2019a, 2019b). This model creates a network metric to measure the direct and indirect, single- and multi-modal connections of a city, region, or country, and shows how they are accessible to the outside world.

There has been a large family of connectivity measures that capture one or more of the following four components: travellers, transport system, land use, and temporal change (Geurs and Van Wee, 2004; Taylor, 2008; Matisziw and Grubesic, 2010). In recent years, researchers have continued to develop new connectivity measures based on these components for different purposes. For example, a similar connectivity measure to our ConnUM is the Global Connectivity Index (GCI) developed by Allroggen et al. (2015). It is also a quality-weighted connectivity measure with an emphasis on the connection frequency of directness. A novel aspect of the GCI is the consideration of the destination quality, i.e., the level of potential economic interaction to which a destination airport provides access. Compared with GCI and other similar measures, our ConnUM considers more quality elements including the capacity and speed of the travel vehicles, which implies that this measure can be used to aggregate the connectivity of different transport modes. This is important in a number of other countries, and especially China, where high-speed rail (HSR) has been well developed and become a good substitute for air transport (e.g., Zhang and Zhang, 2016; Zhang et al., 2019). The following sections will present a review and demonstration of this connectivity measure.

A review of the Connectivity Utility Model

The construction of the direct air connectivity measure

The first step of constructing the ConnUM is to develop direct connectivity for an airport. This has been described in Zhang et al. (2017), in which the connectivity of 69 Chinese airports was calculated. The quality factors considered include the availability of seats (capacity) and travel time (velocity). More specifically, in Eq. (3.1) below, k represents a unique connection between origin airport c and destination airport j. Every flight linking airport i and airport j is regarded as a unique connection, even for the connection with the same flight number on a different date, as a different type of aircraft might be used. This implies that the frequency for every connection is always one (Zhu et al., 2019a). The connectivity ($\text{Connectivity}_{ijk}$) of flight k from airport i to airport j is calculated by multiplying the velocity discount factor and capacity discount factor in Eq. (3.1):

$$\text{Connectivity}_{ijk} = D_{Cap_{ijk}} \times D_{Vel_{ijk}} \tag{3.1}$$

where $D_{Cap_{ijk}}$ represents the capacity discount for connection k between airports i and j. $D_{Vel_{ijk}}$ represents the velocity discount.

To calculate the capacity discount, we need to decide on a benchmark capacity Seat_0. Seat_0 is a general term for the benchmark for the capacity of a transport vehicle. This variable can vary in different studies for different purposes. In Zhu et al. (2018), the capacity of a Boeing 747 with 434 seats was chosen as the benchmark. This can be changed to any other aircraft type however, and the connectivity (a unitless index) results will only change in scale, with relative ranking remaining unchanged, as long as the same capacity benchmark is applied for all flights. If we denote the capacity of flight k from airport i to airport j as $Seat_{ijk}$, the capacity discount $D_{Cap_{ijk}}$ can be expressed as:

$$D_{Cap_{ijk}} = \sqrt{\frac{Seat_{ijk}}{\text{Seat}_0}} \tag{3.2}$$

Most of the existing schedule-based connectivity measures, including the NetScan, adopt a linear form for the quality factors, which may fail to account for the nature of diminishing returns of the benefit of the quality factors. For example, passengers usually prefer larger aircraft, but the marginal benefit of having a larger aircraft with more seats diminishes. After a certain point, the extra benefit of adding another flight is larger than having a larger aircraft. Therefore, the ConnUM employs a concave function (square root).

The velocity discount factor is calculated based on the following system of equations:

$$Duration_{Adjusted_{ijk}} = T_{landing_{ijk}} - T_{takeoff_{ijk}} + t_{airport_{ijk}} \tag{3.3}$$

$$\text{Velocity}_{ijk} = \frac{Distance_{ij}}{Duration_{Adjusted_{ijk}}} \tag{3.4}$$

$$\text{D}_{Vel_{ijk}} = \sqrt{\frac{\text{Velocity}_{ijk}}{\text{Velocity}_0}} \tag{3.5}$$

where $Duration_{Adjusted_{ijk}}$ is the adjusted time length (duration) of flight k from airport i to airport j. The scheduled flying time between two airports is the difference between the scheduled arrival and departure times. It is worth noting that the actual flying time might be shorter than the published estimated flying time as these days, airlines tend to pad the schedules to increase their punctuality statistics. This is especially so for flights to and from big cities, which can lead to inaccurate results for the connectivity indices. This is a shortcoming for using the scheduled data. $t_{airport_{ijk}}$ is included to account for the extra time needed at departure and arrival airports for check-in, security check, and baggage collection. Normally 100 minutes for domestic flights and 180 minutes for international flights are required. Similar to the capacity benchmark, a velocity benchmark, Velocity_0, can be selected. The speed of a flight varies depending on the type of aircraft used. Statista (2018) suggests that a major commercial jet aircraft cruises at about 420–500 knots or 778–926 km/h. Therefore, Zhang et al. (2017) assume that the average speed is 900 km/h.

The connectivity due to the unidirectional flights from airport i to airport j is the aggregation of the connectivity of all k flights from airport i to airport j.

The connectivity of airport i is calculated by aggregating the connectivity due to the flights between airport i and airport j of both directions. The illustration of the airport direct connectivity calculation has been detailed in Zhang et al. (2017). This chapter uses this direct connectivity measure to quantify the air connectivity between China and the rest of the world at the country level.

The construction of indirect air connectivity measure

Zhu et al. (2019a) have detailed this approach. To construct the indirect connection measure, the connectivity of flight k from airport i to airport j is modified as:

$$\text{Connectivity}_{ijk} = D_{Cap_{ijk}} \times D_{Vel_{ijk}} \times D_{Trans_{ijk}} \tag{3.6}$$

where $D_{Trans_{ijk}}$ is the transfer discount. Eq. (3.3) needs to include the time spent at the transfer airport and thus becomes:

$$Duration_{Adjusted_{ijk}} = T_{arrive_{ijk}} - T_{depart_{ijk}} + \mathrm{p}_T \times t_{transfer_{ijk}} + t_{airport_{ijk}} \tag{3.7}$$

where extra time needed at the transfer airport is denoted as $t_{airport_{ijk}}$. As with de Wit et al. (2009), the extra penalty for transfer time p_T is set at 50 per cent.

For simplicity, this study and previous studies concerning the ConnUM only consider the case of one transfer. This is actually a reasonable assumption. Take the market of Beijing-Sydney as an example. In 2005, 54.89 per cent of the passengers flew on direct flights from Beijing to Sydney (only Air China provided direct services between 2005 and 2016) and 45 per cent undertook one transfer; the share of those who made two or more transfers was only 0.1 per cent. In 2016, these three figures were 47.81 per cent, 52.14 per cent, and 0.04 per cent, respectively. In the Shanghai-Sydney market (China Eastern, Air China, and Qantas provided direct services), these three percentages were 84.41 per cent, 15.56 per cent, and 0.02 per cent in 2005, and 73.84 per cent, 26.13 per cent and 0.03 per cent in 2016.

The quality of indirect connections is largely dependent on the quality of transfer. Transfer time and transfer service constitute two significant aspects of the quality of transfer (Choi et al., 2019). Different lengths of transfer time provide significantly different transfer experiences for passengers. An ideal way to determine the transfer time quality function is through a large-scale passenger experience survey. For illustration purpose, we assume that the relationship between the transfer time and the transfer time quality is captured by a function illustrated in Figure 3.1. The horizontal axis denotes the time difference between the transfer time and the minimum connection time (MCT) required by an airport. When the transfer time is equal to the MCT, passengers have a good chance of catching the connecting flight, but the risk of missing

Figure 3.1 Transfer time quality.

the connecting flight still exists if there is a slight delay for the incoming flight. Therefore, the quality is set as 0.2. In fact, most passengers would prefer a transfer time longer than the MCT, so it is reasonable to assume that a transfer time that is 30 minutes longer is most desirable, so its value is one. However, if the transfer time is too long (more than three hours), the long wait will result in lower transfer quality, and thus a value of 0.7 is assigned.

Although different airlines have a different MCT at every airport, the same MCT for all airports and all airlines is assumed for simplicity. The MCT standards are listed in Table 3.1.

The service quality for transfers is mainly decided by the relationship between the airlines operating the two flight segments. Zhu et al. (2019) set different service values to each situation as shown in Table 3.2. In general, when both flights are operated by the same airline or by airlines in the same alliance, the transfer service quality is generally better than the situation where the two segments are operated by two separate airlines without any cooperation agreement. In the case where one flight is operated by an LCC, the service quality would be relatively less desirable. It should be acknowledged that the assignment of the values is arbitrary and the connectivity values will depend on the values assigned to the time and service qualities. Future studies can consider using survey data to elicit more accurate values for these parameters. In addition, code-sharing outside the alliance is not accounted for in this study, which should be addressed in future studies.

The transfer discount can be expressed as:

$$D_{Trans_{ijk}} = q_{ijk}^{T} \times q_{ijk}^{S} \tag{3.8}$$

Table 3.1 MCT (minimum connecting time) for all possible transfers

First flight segment	*Second flight segment*	*Whether at the same terminal*[4]	*MCT (minutes)*
Domestic flight	International flight	Yes	120
Domestic flight	International flight	No	160
International flight	Domestic flight	Yes	120
International flight	Domestic flight	No	160

Table 3.2 Transfer service quality

Transfer types	*Service value*
Transfer with the same airline	1
Transfer between two airlines in the same airline alliance	0.9
Transfer between two full-service airlines from different alliances	0.3
Transfer with the same low-cost carrier	0.3
Other	0.1

where q_{ijk}^{T} is the time quality for the transfer of indirect connection k from airport i to airport j, and q_{ijk}^{S} represents the service quality of transfer for indirect connection k from airport i to airport j.

It should be noted that for indirect connections from airport i to airport j transferring at airport h, some direct connections from airport i to airport h and from airport h to airport j will be calculated more than once. For example, in the case shown in Figure 3.2, connections k2, k3, and k4 take off from airport h 40, 60, and 90 minutes after the landing of connection k1, respectively. k1+k2, k1+k3, and k1+k4 are all feasible indirect connections between airport i to airport j. Therefore, there are three indirect connections between airport i to airport j, but there is only one connection between airport i and airport h.

When multiple indirect connections (e.g., k1+k2, k1+k3, and k1+k4) share one flight segment (e.g., connection k1), the capacity of these indirect connections is constrained by the capacity of the shared connection. The example shown in Figure 3.2 shows that first segment of an indirect connection is shared. In fact, the second segment can also be shared. Therefore, we add an upper limit for indirect connectivity, which can be expressed as:

$$\sum_{\forall k \text{ with } s_{k'}^{1}} D_{Cap_{i(h)jk}} \leq D_{Cap_{ih(j)s_{k'}^{1}}}, \tag{3.9}$$

$$\sum_{\forall k \text{ with } s_{k'}^{2}} D_{Cap_{i(h)jk}} \leq D_{Cap_{ih(j)s_{k'}^{2}}} \tag{3.10}$$

where $s_{k'}^{1}$ denotes the first segment of indirect connection *k'*; $s_{k'}^{2}$ denotes the second segment of indirect connection *k'*; $D_{Cap_{i(h)jk}}$ denotes the capacity

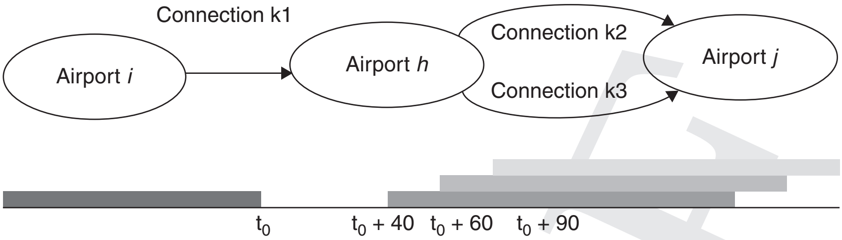

Figure 3.2 Example for repeated calculation.

discount of indirect connection k from airport i to airport j transferring at airport h; $D_{Cap_{ih(j)s^1_{k'}}}$ denotes the capacity discount of the first segment of indirect connection k', which is from airport i to airport h and is connected by a second connection from airport h to airport j; $D_{Cap_{(i)hjs^2_{k'}}}$ denotes the capacity discount of the second segment of indirect connection k', which is from airport h to airport j and connects to the first connection from airport i to airport j. The left-hand side of Eq. (3.8) sums up the capacity discount of all indirect connections taking the route $i \to h \to j$ sharing a common segment, i.e., the first segment of indirect connection k'. The right-hand side of Eq. (3.8) gives the capacity discount of the first segment of indirect connection k' ($i \to h$). Likewise, Eq. (3.9) shows that the capacity of indirect connections is constrained by the capacity of the second segment of the indirect connection. If Eqs. (3.8) or (3.9) are not satisfied, the capacity of the commonly shared segment is assigned to the indirect connection with the highest velocity discount and transfer discount.

The directional connectivity from airport i to airport j is the connectivity of route $i \to j$, which is the aggregate connectivity for all connections (direct and indirect) on the route:

$$\text{connectivity}_{ij} = \sum_k \text{connectivity}_{ijk} \tag{3.11}$$

The connectivity of airport i is the aggregate of the connectivity for all routes starting or ending at airport i, which can be expressed as:

$$\text{connectivity}_i = \sum_j \text{connectivity}_{ij} + \sum_j \text{connectivity}_{ji} \tag{3.12}$$

For a hub airport, its hub connectivity or centrality is the total of connectivity of all indirect connections with a transfer at that airport. The connectivity of a city, a region, or a country is the aggregate connectivity of all airports that contribute to the city, region, or country's transport services.

The link connectivity between airport i to airport j of an airline is the sum of the connectivity of all the flights of this airline between airport i and airport j in both directions. In the same fashion, we can obtain the link connectivity of all airlines between two countries.

The construction of a multi-modal connectivity measure

Most cities rely on multiple transport modes. In countries with a large land area such as China, rail plays an important role in the country's transport system. Zhu et al. (2018) attempt to incorporate both rail and air in their connectivity measure. However, their study only develops a direct connectivity measure without considering indirect and hub connectivity. A more comprehensive multi-modal connectivity measure is developed in Zhu et al. (2019b). They considered six types of connections in the extended multi-modal ConnUM covering direct connections such as from airport to airport, and from railway to railway, and indirect connections such as making a transfer at an airport, railway station, or both.

The basic ideas of the extended multi-modal ConnUM are the same as that of the simple ConnUM. A novel innovation in the multi-modal connectivity measure is the use of various radiation functions that not only help to aggregate the overall connectivity of different transport modes' terminals (e.g., rail terminal and airport terminal) in a city, but also capture their contribution to neighbouring cities' connectivity. For example, Shanghai's two airports not only contribute to its own air connectivity, but also increase its neighbouring cities' air connectivity. Suzhou is a city 50 km west of Shanghai. People living in Suzhou can easily access Shanghai Hongqiao airport in 20 minutes by HSR. Even though there is no airport within the administrative area of Suzhou, its air connectivity is high thanks to the presence of HSR. This is also the case for Wuxi that is 140 km west of Shanghai and has its own airport, although many Wuxi citizens choose to travel to Shanghai via HSR and use Shanghai's airports for flying. The existence of Shanghai airports and the HSR link greatly improve its neighbouring cities' overall connectivity. Therefore, the connectivity contribution from $terminal_i$ to $city_a$ can be assumed to be a function of $terminal_i$'s connectivity and the relative location of $terminal_{\mathrm{i}}$ against $city_a$. The connectivity of $city_a$ can be expressed as:

$$connectivity_a = \sum_{\mathrm{i}} f(terminal_i, location_{ia}) \tag{3.13}$$

To capture the impact of a terminal on a city's connectivity, various forms of functions could be adopted for formula (5). The impact of a terminal is smaller when the distance between the terminal and the city becomes greater. Zhu et al. (2019b) name this consideration radiation discount, which can be illustrated in Figure 3.3. Eq. (3.13) is an example of the radiation function. However various forms can be used as long as they show a non-linear inverse relation between the distance and the radiation discount. This is quite similar to the decay function in the destination quality model presented in Allroggen et al. (2015).

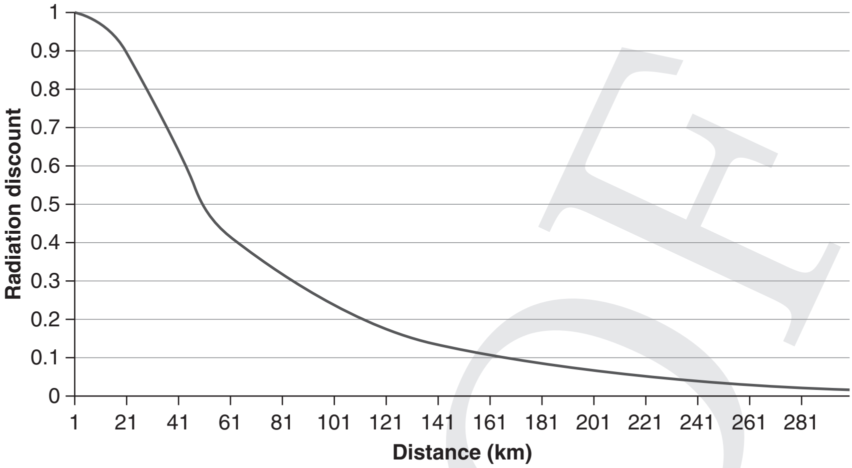

Figure 3.3 An example of radiation discount distance.

$$\begin{array}{l} e^{-\frac{d_{ia}}{70}}, d_{ia} > 50 \\ \dfrac{\cos(\dfrac{d_{ia}}{31.84}) + 1}{2}, 0 \le d_{ia} \le 50 \end{array} \qquad (3.14)$$

Applications of the Connectivity Utility Model

China's direct air connectivity with other countries/economies

The simple direct connectivity measure is used to examine how China is connected with the outside world with only direct connections considered. We examine a period from 2005 to 2016. For each year, two weeks' flight information was collected: 10–16 April and 10–16 November. All the direct flight information was extracted from IATA AirportIS database. The flight data include flight number,[2] number of seats, origin airport, destination airport, take-off time, and landing time. The time zone is then matched to every airport, and airline block time is calculated in minutes.

Table 3.3 ranks the 20 best connected economies/economies with China in 2016. Much information can be observed from the table. First, most of China's top 20 trading partners such as the United States, Hong Kong, Japan, Korea, Vietnam, Germany, India, Singapore, Taiwan, Russia, Malaysia, Australia, and Thailand are in Table 3.3, reflecting a close link between international trade and

Table 3.3 The best connected countries/economies with China (direct connectivity)

Ranking	*Country*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*
1	Korea	964	1,173	1,475	1,935	1,861	738	1,665	1,735	1,913	2,165	2,629	3,056	3,108
2	Japan	1,531	1,673	1,706	2,029	2,085	956	1,924	1,806	1,950	1,771	1,990	2,666	3,026
3	Thailand	346	421	454	484	436	193	514	644	805	1,142	1,513	2,202	2,767
4	Hong Kong	1,697	1,988	2,192	2,119	2,095	944	1,959	2,117	2,147	2,370	2,450	2,369	2,370
5	Taiwan	0	0	0	0	33	376	826	1,070	1,407	1,462	1,775	1,847	1,759
6	Singapore	451	515	514	578	625	281	622	736	868	891	880	889	994
7	Malaysia	238	222	243	265	369	183	399	425	440	539	553	549	727
8	US	304	411	472	535	574	276	382	427	451	489	533	617	665
9	Macau	248	349	346	352	329	113	217	279	322	420	477	511	465
10	Vietnam	98	112	140	151	174	90	222	247	225	263	229	304	459
11	Russia	128	145	143	183	178	78	203	294	302	308	316	336	390
12	UAE	42	70	69	100	157	79	207	222	253	240	267	294	334
13	Philippines	67	96	102	115	118	67	136	178	185	256	234	232	275
14	Indonesia	44	46	102	94	70	32	85	86	99	123	176	188	274
15	Germany	173	198	264	262	275	129	229	261	256	237	259	268	268
16	Australia	77	121	130	130	131	62	129	182	232	220	205	217	240
17	Cambodia	25	46	45	51	68	33	78	87	101	147	196	228	234
18	France	132	151	152	153	175	87	174	178	187	198	203	224	231
19	Canada	68	83	97	99	101	42	91	113	101	118	127	133	155
20	India	21	40	43	54	96	37	102	120	128	169	134	132	147

air connectivity. Hong Kong, Macau, Taiwan, Thailand, Japan, Vietnam, Korea, Singapore, and the United States are the top ten destinations for Chinese tourists that are also included in Table 3.3, suggesting a close association between the provision of air services and tourism.

Second, air connections with China experienced remarkable increases for all the economies listed in Table 3.3. However, the negative impact of the 2008–2009 global financial crisis on the direct connectivity was real and substantial, indicating the strong association between air transport and macroeconomic conditions.

Third, Hong Kong was the most connected place with China in 2004, but in 2016, it was in the fourth place as Hong Kong experienced the slowest growth from 2004 to 2016 among the economies listed in Table 3.3. Hong Kong was a gateway to China for many decades. Its hub status in terms of attracting mainland Chinese passengers seems to have weakened in the last decade. For example, according to Zhu et al. (2019a), Hong Kong was the number one transfer hub between China and Australia measured by hub connectivity in 2008. However, in 2016, it was in fourth place. Guangzhou has a far greater hub connectivity in the China-Australia market today.

Fourth, Korea was in third place in 2004, but surpassed Japan in 2013 and Hong Kong in 2014, becoming the best connected country with China in 2015 and 2016. Korea has been actively negotiating open skies agreement with China to strengthen Seoul's hub status. Korean airlines have operated air services to many medium-sized Chinese cities and transport many Chinese passengers to many international destinations via Seoul by offering very competitive prices.

Air connectivity between countries has significant policy implications. For example, there has been much discussion about the establishment of an integrated aviation market in Northeast Asia in recent years. Negotiations on a free trade agreement (FTA) in this region has progressed well. However, air transport as a key infrastructure in facilitating the flows of goods and people is not part of the proposed FTA. The strong air connectivity between China and Japan and Korea suggests that it is worth exploring the possibility of forming a single aviation market in this region. Table 3.3 also shows that Southeast Asia, North America, and the EU are key destination markets for Chinese passengers. Each of them have had quite liberal aviation arrangement. These markets are also important to Japan and Korea, implying that if the three countries can form a single aviation market and act as one in negotiating air services agreements with other countries or blocs, the centre of gravity of the air transport will shift from the western hemisphere to this region. In addition, by using the ConnUM, we can also generate route-level connectivity and reveal each individual airline's network to inform airline management and decision makers about the likely winners and losers when a regional open skies agreement applies. This can be a future research topic.

China's overall connectivity (the sum of direct and indirect connectivity)

To illustrate the methodology of calculating indirect connectivity, we use the flight schedule data from the IATA AirportIS database for a period between 4 and 26 October 2016 to calculate the air connectivity scores. Table 3.4 reports the results of the overall connectivity including both direct and indirect connections. For indirect connection, only one transfer is assumed. In addition, we restrict the total distance of the indirect connection to less than twice of the direct distance between the origin and destination airports. The time at the transfer airport is limited to between 30 minutes and 24 hours.

Interestingly, as can be seen in Table 3.4, the US becomes the best connected country with China, followed by Thailand, Japan, and Korea. The connectivity of the United States with China is more than double that of the second and third country. Germany, Australia, Canada and Russia are among the top ten, indicating their close economic ties with China. Australia and Canada are the main migration destinations for Chinese citizens, which may suggest a close relationship between immigration and air transport.

These connectivity indices represent the existing air transport infrastructure between countries, which are useful in international trade and tourism studies where transport is regarded as a key impediment for the flows of goods and people. Many proxies have been used for the availability and quality of the overall transport infrastructure. Our ConnUM, particularly the extended

Table 3.4 Connectivity of foreign countries/economies with China (top 20)

Ranking	*Country*	*Connectivity*
1	USA	130,906.82
2	Thailand	52,889.50
3	Japan	50,977.87
4	Korea	28,980.19
5	Germany	25,483.90
6	Australia	23,274.81
7	Malaysia	21,973.46
8	Canada	20,092.10
9	Indonesia	19,340.50
10	Russia	19,184.89
11	Taiwan	17,166.97
12	Italy	16,077.64
13	Singapore	15,955.22
14	UK	15,069.49
15	France	14,328.14
16	India	13,463.61
17	Vietnam	13,063.69
18	United Arab Emirates	11,298.23
19	Spain	10,073.00
20	Turkey	9,535.90

ConnUM, can provide a comprehensive measure, which is a good representation of the transport infrastructure.

Using the extended ConnUM for vulnerability analysis

This section will use the calculated connectivity values to conduct a vulnerability analysis for China's transport network.[3] Any kind of incidents taking place in a city's transport network will affect the connectivity of the city. Train breakdowns, electrical failures, road construction, air traffic control, etc., would result in a connectivity decrease. In extreme situations such as war or a natural disaster it is possible to lose an entire route, terminal, or even a city. Vulnerability, which is defined by Berdica (2002) as the degree of susceptibility of a network to certain incidents that may lead to reduced service or accessibility levels, is critical under these circumstances. When a city has a resistant transport network, which means that it will remain functional under extreme situations, it brings flexibility and ease for the government, private sector, and individuals to rebuild and restore the city. Therefore, it is important to analyse the vulnerability of a city's transport services.

There has been much research concerning how to define, evaluate, and handle the vulnerability of a region's transport systems (Berdica, 2002; Taylor, 2008; Taylor, 2012; Rodríguez-Núñez and García-Palomares , 2014). In this research, the characteristics of the incidents are not considered. The focus is on the consequence in terms of connectivity, when the incident has already happened and affected a terminal, route, or city.

We consider two kinds of vulnerability here. The first one is city impact, which is the loss of overall network connectivity when a city's transport links with other cities are suddenly disrupted as a result of an incident. When a city is impacted by such an incident, not only is its connectivity affected but also is that of other cities connecting with it. City impact represents the importance of the city in the network. Figure 3.4 presents the impact of the top 25 cities in terms of overall connectivity and direct connectivity. Shanghai, Beijing, Guangzhou, and Nanjing are the top four cities in overall city impact. When Shanghai is affected by an incident, 9.6 per cent of the overall connectivity and 15.1 per cent of the direct connectivity of the country's transport systems will be lost. Nanjing surpasses Guangzhou to be the third most important city in direct connectivity with respect to city impact. If Nanjing is isolated from other cities, 10.0 per cent of the direct rail and air connectivity of China will be lost. Hangzhou, Wuhan, Zhengzhou, Changsha, Tianjin, and Xuzhou also rank higher in terms of direct city impact than in overall city impact, meaning that these cities play an important role in forming direct connections in China's rail and air networks.

The second vulnerability considered is city resistance, which is the loss of a city's remaining connectivity when a certain number of top-ranking routes connecting it are lost. If a city is only well connected with one city, it will be disconnected from the world when the only route is destroyed. However, if a

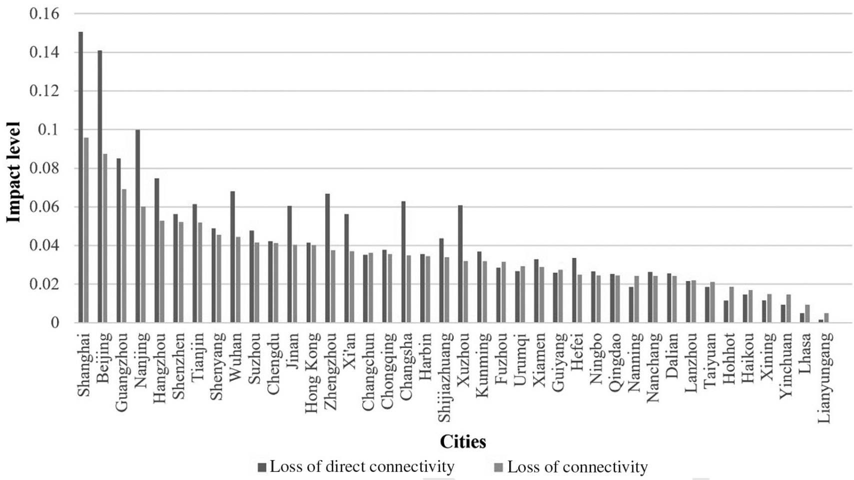

Figure 3.4 City impact of Chinese cities.

city is well connected with multiple cities, the city will still be well connected when one route is lost. Figure 3.5 presents a city's remaining connectivity when up to the top 20 routes connecting the city are lost. Only cities ranking in the top five and the bottom five are presented. It is observed that Hong Kong, Shanghai, Beijing, Hangzhou, and Ningbo are the most resistant to route losses. Hong Kong is the leader, keeping 88.94 per cent of its original connectivity without the top 20 routes, while Lhasa would keep only 59.05 per cent of its connectivity if the top 20 routes were cut.

Conclusions

This chapter has discussed the methodology of constructing a connectivity measure, the ConnUM. This measure was developed in several papers and each paper focused on a specific area with its broad usefulness not being spelled out. The purpose of this chapter is to integrate the different versions and show that this model can generate results of significant policy implications at country levels. For example, previous studies only use this model to look at the connectivity of an airport or a city. This chapter shows that the direct and indirect air connectivity between countries can be calculated, which can be used to test and predict the relationship between air transport and economic activities. They are particularly useful for trade and tourism studies that need a good proxy for transport infrastructure. In addition, the connectivity indices can be compared over years and across regions to evaluate the success of transport policy reforms, and to support open skies and FTA negotiations. It is ideal that such indices can be complied at the city, regional, and country levels and updated each year for policy makers and industry practitioners.

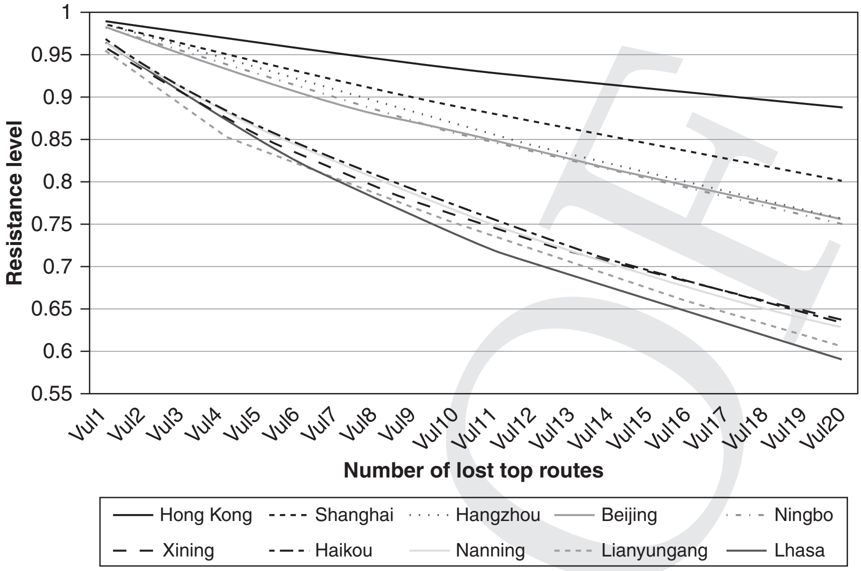

Figure 3.5 City resistance of Chinese cities.

This chapter also conducted a vulnerability analysis for China's air and rail transport network. The vulnerability analysis suggests that if Shanghai were affected by an incident, 9.6 per cent of the overall connectivity and 15.1 per cent of the direct connectivity of the country's transport systems would be lost. This again shows that the connectivity values calculated from the ConnUM have significant policy implications as they can be used to test the robustness of the exiting transport network and guide future infrastructure construction.

However, it should be acknowledged that although the word 'utility' is included in the name of ConnUM, this connectivity measure is not derived from a utility model, and is actually a physical node-to-node measure. This measure ignores the fact that different passenger groups (business and leisure passengers) place different values on travel time (Burghouwt, 2017). More importantly, airfare, a significant choice parameter for passengers, is not included. For a utility-based connectivity measure, readers may want to refer to the one developed by Mandel et al. (2017) based on the path aggregation theorem (PATH). This utility-based measure captures passengers' monetary cost and the value of travel time. The utility weights of this measure are derived from the actual path choice model estimates, and the actual path utilities between the departure and destination points are measured with logit models. It is not surprising to see that the physical network measure and the utility-based measure produce quite different rankings for the European airports (Mandel et al., 2017). Thus, when policy makers use connectivity measures to make decisions, they should be clear of the limitations of each measure and choose the most appropriate one that suits their needs.

Notes

1 Relatedly, O'Connor, K. (2003) and Wong et al. (2019) examine whether a spatial dispersal trend dominates the development of the global aviation industry by considering the aviation network at both the airport level and the airport–city level, with a city consisting of one or more airports.
2 For code-sharing flights, only the operating flights are retained.
3 Li et al., (2019) have also conducted a vulnerability analysis for China's air and rail transport network by using a different methodology.
4 Transfers at the same airport but at different terminals are considered, while transfers at different airports in the same city are not considered in this research. The latter cases are rather small in number in our sample.

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