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Network Assessment of Tier – II Indian cities' airports in terms of type, accessibility, and connectivity

Sunny Bansal[a]*, Joy Sen[b]

[a]*RCG School of Infrastructure Design and Management, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal - 721302, India*
[b]*Department of Architecture and Regional Planning, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal - 721302, India*

Abstract

Airports and its region have a two-way economic interaction between them. Thus, the airport's performance assessment is crucial for its region also. Airport's performance is not only limited to its physical infrastructure but to its air transport network as well. But, the measurement of the quality and capacity of the air transport network is multifaceted and complex. This paper assesses the network of an airport in terms of its type, accessibility, and connectivity. The study focusses on 12 Tier-II Indian cities having medium-hub international airport because of their huge growth potential. Also, their network assessment is under-addressed. An exclusive set of complementary analyses for these cities is important as a comparison with the bigger metropolises having large-hub international airports will be biased. This paper attempts to assess the network of the Tier-II cities with special emphasis on their relationship with the Tier-I cities as the connectivity of Indian airports is majorly complementary than competitive. Various tools and indices used for assessment are concentration indices, partial indicators for accessibility (daily accessibility, potential indicator, location indicator, and network efficiency), and connectivity and accessibility indices based on graph theory models (shortest path length and quickest time length). Modifications and synthesis of these indices are also attempted. Indices are majorly based on flight frequency (direct and via), destinations, travel time, distance, and demographic and economic parameters. The study brings all the indices together to assess the network and identify future potential (hubs or feeder) among the Tier-II cities airports.

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Keywords: air network assessment; air network type; air connectivity; air accessibility

1. Introduction

The aviation sector in India is growing at a remarkable rate for the last few years making it the world's fifth largest civil aviation market. It is one of the fastest growing markets in the world with the annual growth rate of air traffic

* Corresponding author. Tel.: +91-9674704832.
E-mail address: ar.sunnybansal@gmail.com; ar.sunnybansal@iitkgp.ac.in

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passengers being 17.6% for the financial year 2015-16, 18.3% for 2016-17, and 16.5% for 2017-18 (Airport Database, 2018). With the focus to upgrade the existing infrastructure and enhance the regional connectivity, the civil aviation sector in India is set to grow tremendously in the coming years. One of the main reasons for this growth is that India is also one of the fastest urbanizing and growing economy in the world (Bansal, et al., 2017). Airports and its surrounding region have a two-way economic interaction between them. The economic aptitude of a region carries great potential to impact its air traffic demand and performance. Similarly, an airport can significantly boost a region's economy at various levels and help in the branding of the region.

In this era of globalization, an airport is a strategic enabler and facilitator for a region's economic growth and connectivity. Thus, to assess the performance and efficiency of an airport is a crucial aspect for its region too. However, the performance of an airport is not only limited to its physical infrastructure and manpower but also depends on its network. Therefore, to understand the quality and capacity of an airport's network is vital for the economic setup of the region as well (Bagler, 2008). The measurement of the quality and capacity of the network of an airport is multifaceted and complex (Rocha, 2017). An airport's network can be broadly understood by assessing its accessibility, type, and connectivity.

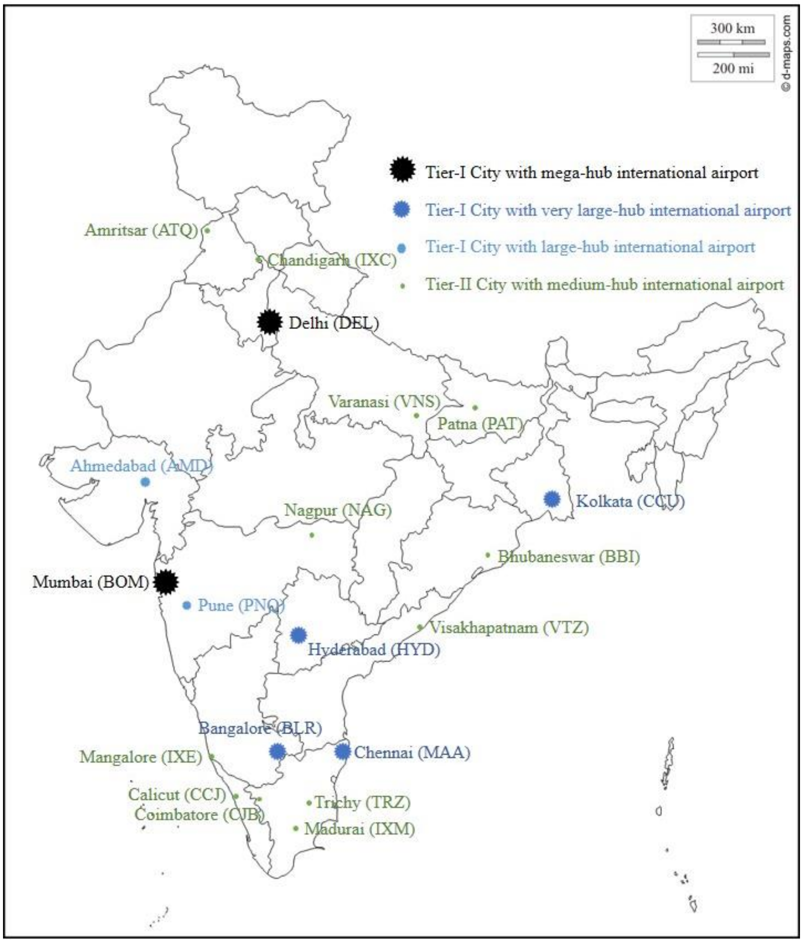

Fig. 1: Tier-I and Tier-II Indian cities for analysis

The assessment of the airport's network is under-addressed in case of Indian airports, especially for the smaller airports. Major studies for Indian airports focus on mega or large-hub international airports (more than 5% and 1% of the annual national traffic, respectively) located in the bigger metropolises or Tier-I cities (population more than 5 million) (Jose & Ram, 2018; Bagler, 2008). But this study focusses on the medium-hub international airports (1 –

0.25%) located in the Tier-II cities (0.5 – 5 million population). The airports of these Tier-II cities of India acts as a feeder to the bigger airports and are on par with the government's objective of boosting regional air connectivity. Also, these Tier-II cities of India are the current economic hotspots. They are emerging as new business locations and investment destinations due to the availability of land, opportunities, and government support. Also, the air traffic in India is quite unequally distributed as the eight Tier-I cities cater to more than 70% of the country's total annual traffic, with Delhi and Mumbai together catering to the 40% of the national traffic. This huge disparity also motivates to study the Tier-II cities' airports in slight segregation from the airports handling huge traffic to avoid any kind of shadowing.

This study becomes even more relevant in the case of India as the connectivity of airports in India is majorly complementary than competitive. Keeping this in mind, the performance of the airport network of Tier-II cities and its connectivity with the bigger cities is important to understand and assess. Thus, the present research attempts to assess the network of the Tier-II Indian cities having medium-hub international airports in terms of their accessibility, type, and connectivity with special emphasis to their relationship with the Tier-I Indian cities. There are 12 Tier-II cities in India with medium-hub international airports, viz., Amritsar, Bhubaneswar, Calicut, Chandigarh, Coimbatore, Madurai, Mangalore, Nagpur, Patna, Trichy, Varanasi, and Visakhapatnam. The location of these Tier-I and Tier-II cities in India is shown in Fig. 1. This paper is organized into five sections. Section 1 briefly introduces the research along with its motivation and relevance. Section 2 elaborates the indices and techniques selected from literature for the network assessment. Section 3 presents the detailed methodological framework and data collection process. After the analysis is carried out, Section 4 discusses the results and their interpretations in detail. Finally, the conclusion from the research and a way forward for future research is narrated in Section 5.

2. Network Assessment

As discussed earlier, the assessment of the air transport network is complex and multidimensional. There are a number of ways to define, understand, and measure this network. This study employs three ways to assess it in terms of accessibility, type (poly-centric or mono-centric), and connectivity by using various approaches from extensive literature study. In the coming sections, each of the methods is discussed in details along with the reasons to select it.

2.1. Type of Network: Poly-centric or Mono-centric

Network type is crucial to understand to know the performance of air transport as it is the central determinant of an airport's functioning. It becomes more significant in the case of the Indian aviation sector as it is still going through transformation and effects of privatization. Indian aviation is gradually moving from being welfare-oriented to becoming operationally efficient. Thus, the Indian air transport network is a mix and match of both – strict regulations and demand-orientation. It is actively serving the growing demand and creating new demand. Thus, to understand the overall picture of major hubs, dominant hubs, saturated centers, sub-centers, future hubs, and feeder airports, it is vital to examine the effects of network type. In this study, the notion of 'inter-regional polycentrism', usually applied in spatial planning and development, is used to determine the airport's network type (Melo, et al., 2006).

Broadly, there are two types of network in which airport functions – mono-centric and poly-centric (Costa, et al., 2014). "The existence of more than one center in a city, region, or other territorial unit" is defined as polycentrism (Musterd & van Zelm, 2001). It means the presence of strong autonomous multiple poles in the study area. In contrast, mono-centric logic is the presence of one strong dominant pole while other poles are majorly serving this central pole (Davoudi, 2010). Mono-centric network is characterized by the concentration of activities at one location, while the poly-centric logic is the dispersed and distributed form where activities are linked to each other in a morphological and purposeful fashion (Kloosterman & Musterd, 2001). The same concept is applied to the network of an airport. In general perception, the mono-centric network is the basic hub-and-spoke model and the poly-centric network is the point-to-point model or a hub-and-spoke with a hierarchy of hubs. Each of these models has its own merits and demerits. This paper tries to categorize the air network of Tier-II Indian cities into poly-centric and mono-centric.

To analyze the network type, concentration indices are calculated to examine the level and hierarchy of dominance of specific destinations from each airport. This is to understand if the airport under study is dependent on a particular airport for its service. This analysis not only helps in defining the airport's network type but also portrays its current potential (in term of flight frequency) and the variety of destinations it serves. Concentration Indices (CI_j) for the airport *j* are calculated using the formula [1] mentioned below (Costa, et al., 2014):

$$CI_j = \frac{\sum_{i=1}^{k} n_i}{N_j} \, X \, 100 \qquad [1]$$

Here, n_i is the number of direct flights for destination *i* in a week and N_j is the total number of direct flights from the airport *j* in a week. *CI*s for the airport *j* are calculated by placing the destinations in decreasing order of connections (n_1 - number of connections (direct) to the most connected destination, n_2 - number of connections (direct) to the next most connected destination, and so on). Similarly, CI_1 is the percentage of connections to the most connected (popular) destination, CI_2 is the percentage of connections to the two most connected (popular) destinations from the airport *j*, and so on. Lower is the values of concentration indices for the airport, less is its dependency on the other airports. It also means that widespread destinations are directly served from this airport (Melo, et al., 2006; Costa, et al., 2014). Thus, *CI* gives the idea of the airport under study being a strong or weak pole in the air transport network.

2.2. Accessibility: Partial Indicators, Synthesis, and Modification

Accessibility, in general, can be defined as the ability to be accessed or reached in a geographical space, though it can be scenario-specific. For airports, accessibility is of two types: accessibility of the airport from the region (via land transport) and accessibility to the airport from other airports (by air). For air transport network, the latter one is being discussed. Accessibility is not limited to the hard infrastructure as a highly-developed airport may not totally ensure that it is fully accessible (or serviceable) and the commuters will use it. Many components like the choice of destinations being served, quality and frequency of connections, network performance, etc. are quite vital (Spiekermann & Wegener, 2006). To assess the airport's accessibility is a multi-perspective task. There are complex and non-parametric ways to assess accessibility (Miller, 1999). However, the present study focusses on conventional indices (modified for airports) to measure accessibility centered on economic geography concepts.

Economic geography based indices are built on two parameters – potential and distance (Hesse, et al., 2013). Potential like GDP or population of a region are incentives to make travel a derived demand so that commuters can reach their desired regions to consume. For distance, a decay function is incorporated to devaluate the potential parameter which means that the accessibility will decrease with the destination being farther away. This may be reflected in terms of the generalized travel cost function (travel time, distance, or costs) (Gutierrez, 2001). This study attempts to understand and measure the accessibility of airports with inputs like flight schedules, flight frequency, and travel time. Four partial indicators are selected from literature and used to assess the accessibility as these are built on varied perspectives but provide a complementary understanding of the airport's accessibility (Bruinsma & Rietveld, 1998). These indicators are detailed out in the coming sections.

2.2.1. Daily Accessibility (DA)

Daily Accessibility indicator depicts the economic mass (population or GDP) that can be accessed within a threshold limit of travel time. It represents how much mass is accessible from the region in question within a standard working day. The commonly used threshold for airports is three or four hours. In this paper, a threshold of three hours (180 minutes) is used to keep a slack for check-in and check-out at the airports and the travel time to access the airport from land. The potential is measured in terms of the population of destination city/region. Higher is the value for *DA*, higher is the accessibility as a great number of residents can be reached from the region in question (Gutierrez, 2001).

$$DA_i = \sum_{j=1}^{n} Pop_j * \delta_{ij} \ where \ \delta_{ij} = \begin{Bmatrix} 1, & \text{if } t_{ij} < 180 \\ & 0 \ otherwise \end{Bmatrix} \qquad [2]$$

In equation [2], DA_i is the Daily Accessibility of the region *i* in question. Pop_j is the population of the other regions *j* with whom the economic potential of the region *i* is associated. t_{ij} is the actual minimum travel time between the two regions by air and δ_{ij} is the binary variable for the threshold.

2.2.2. Potential Indicator (PI)

Potential Indicator measures the accessible potential in economic terms for the city/region in question. It is based on the fact that nearer regions are economically more important than the farther ones. It can be simply defined as the accumulation of economic mass of the regions to be accessed with the impact of decay function on the generalized travel cost function (travel time, distance, or costs). It is essentially an application of the law of gravity as with the increase in generalized cost, the economic potential of the region decreases. High values of potential indicator signify that great economic potential can be accessed from the region in question, and thus the region is more accessible (Spiekermann & Wegener, 2006).

$$PI_i = \sum_{j=1}^{n} \frac{GDP_j}{t_{ij}^{\beta}} \qquad [3]$$

In equation [3], PI_i is the Potential Indicator of the region i in question. GDP_j is the Gross Domestic Product of the other regions j with whom the economic potential of the region i is associated. t_{ij} is the minimum travel time between the two regions by air and β is used for devaluation. In this paper, the value of β is taken as unity.

2.2.3. Location Indicator (LI)

Location Indicator estimates the average travel cost function (travel time, distance, or costs) from the region in question to all the other destinations. In this indicator, the travel cost function is weighted by the economic mass (GDP or population) of the destination region, and thus, is called weighted average travel time. Higher is the value of location indicator, lower is the accessibility of the region in question (Martín & Reggiani, 2007).

$$LI_i = \frac{\sum_{j=1}^{n} t_{ij} * GDP_j}{\sum_{j=1}^{n} GDP_j} \qquad [4]$$

In equation [4], LI_i is the Location Indicator of the region i in question. GDP_j is the Gross Domestic Product of the other regions j with whom the economic potential of the region i is associated and t_{ij} is the minimum travel time between the two regions by air.

2.2.4. Network Efficiency Indicator (NE)

Network Efficiency indicator is a modification of the Location Indicator, where the actual minimum travel time is compared with optimal hypothetical travel time. This optimal hypothetical travel time is determined by calculating the straight line distance (d_{ij}) between the region in question and its destination and then dividing it by the possible air transport speed (600 kmph). This ratio between the actual minimum travel time (t_{ij}) and the optimal hypothetical travel time (t'_{ij}) is used in the formula for location indicator. Equation [5] for network efficiency indicator (NE_i) is represented below (Rotoli, et al., 2015).

$$NE_i = \frac{\sum_{j=1}^{n} \frac{t_{ij}}{t'_{ij}} * GDP_j}{\sum_{j=1}^{n} GDP_j} \qquad [5]$$

2.2.5. Synthesis of Partial Indicators

The indicators described earlier are quite useful to assess the accessibility of air transport from the perspective of the network. The main advantage of using the partial indicators is that each of these indicators portrays a different outlook for the accessibility of an airport (region). However, this heterogeneity among the indicators may not be desired always. A common accessibility index with the combination of the appropriate information from these partial indicators is, thus, required to obtain a unique ranking of accessibility for the different airport. To address this issue, a number of researchers use synthesis techniques like Principal Component Analysis (PCA) and Data Envelopment Analysis (DEA) on the partial accessibility indicators (Rotoli, et al., 2015). PCA is a statistical technique used for multivariate data's dimension reduction in a meaningful way by transforming correlated variables into linear combination sets (known as principal components). In this paper, PCA has been used for the synthesis as DEA method may lead to some theoretical errors (Hesse, et al., 2013). The index obtained after using the PCA technique is used as 'Synthetic Accessibility Index' to rank the airports as per their accessibility (Martín & Reggiani, 2007).

2.2.6. Adjusted Travel Time

An alteration to the selected partial indicators is conducted by replacing the minimum travel time with modified travel time. This adjusted travel time ($ŧ_{ij}$) from airport *i* to airport *j* is a summation [6] of the actual travel time (AT_{ij}) (by incorporating direct and indirect flights), slack time (ST_i) (transfer and check-in/-out), and penalty/delay time due to flight schedules (DT_{ij}) (Hesse, et al., 2013).

$$ŧ_{ij} = AT_{ij} + ST_i + DT_{ij} \quad [6]$$

In the above equation [6], the first component is to estimate actual travel time (AT_{ij}) which can only be determined by knowing the total frequency of flights between the two airports. The frequency (F_{ij}) of flights between airport *i* to airport *j* is a combination of the direct flights (DF_{ij}) and the via-flights (VF_{ij}) between them as per equation [7].

$$F_{ij} = DF_{ij} + VF_{ij} \quad [7]$$

After knowing the frequency of flights and travel time for each connection, actual travel time can be calculated. For the direct flights, minimum travel time (t_{ij}) between the two regions by air is used. For the via-flights, average travel time for all the via-flights between the two airports is calculated as via-flight travel time (vt_{ij}). Actual travel time (AT_{ij}) is then calculated using formula [8].

$$AT_{ij} = \frac{t_{ij} * DF_{ij} + vt_{ij} * VF_{ij}}{F_{ij}} \quad [8]$$

Penalty time or delay time (DT_{ij}) due to flight schedules is important to consider as it depicts the difference between passengers' desired time to fly and the actual time of departure. It is the mean value of the minimum (zero) and the maximum possible waiting time. Delay time decreases with the increase in flight frequency. It can be determined for airport *i* and airport *j* by using the formula [9] as the desired time of departure for the passengers is assumed to be distributed evenly over a circular time period (Rietveld & Bruinsma, 1998).

$$DT_{ij} = \frac{M_i}{4 * F_{ij}} \quad [9]$$

Here, F_{ij} is the frequency of flights between the two airports and M_i is the maximum possible time period (or the operational hours of the airport *i* in question). The slack time (ST_i) (transfer and check-in/-out) is omitted in this study because of similar regulations for security across all Indian airports and also, the airports of Tier-II Indian cities handle similar daily traffic.

2.3. Graph Theory Models: Shortest Path Length and Quickest Path Length

Graph theory concepts are applied to study a variety of networks in different fields like computer science, biology, linguistics, social sciences, transportation, etc. Similarly, the airport network can also be assessed with the applications of graph theory in many ways (Burghouwt & Redondi, 2013). Airport network can simply be depicted as a mathematical graph to determine its connectivity and accessibility. As per the graphical depiction, each airport represents the nodes and all the direct flight connection are the links or edges (Malighetti, et al., 2008). Two models of the graph theory are used in the present study to determine connectivity and accessibility – shortest path length model and quickest path length model. These 'global' models are used in this research because they assess the network based on all possible connections and yield the shortest or quickest (Burghouwt & Redondi, 2013). Both the models and the corresponding indices developed are discussed in details in the next segment.

2.3.1. Shortest Path Length Model

As per the graph theory, shortest path length means to minimize the sum of the weights of the edges required to reach from one node to another. The adaptation of shortest path length (SPL) model for air transport is the minimum number of flight connections needed to travel from the airport in question to the desired destinations. For instance, from region *i* to region *j* if there is a direct connection then its SPL value is 1, and if the connection is via one stop, then its SPL value is 2, and so on. Various researchers have defined the connectivity and accessibility index for an airport by using the shortest path model (Bagler, 2008; Malighetti, et al., 2008).

$$CI(S)_i = \sum_{j=1}^{n} \frac{\mathrm{SPL}_{ij}}{n-1} \quad and \quad AI(S)_i = \sum_{j=1}^{n} \frac{1}{SPL_{ij}} \tag{10}$$

In equations [10], $CI(S)_i$ is the connectivity index and $AI(S)_i$ is the accessibility index as per the shortest path length model. SPL_{ij} is the shortest path length value between the airport *i* and *j* as per the direct or via connections and *n* is the total number of airports in the network being considered.

2.3.2. Quickest Path Length Model

As per graph theory, quickest path length means to minimize the travel time of the edges required to reach from one node to another. The quickest path length (QPL) model version of air transport is the consideration of the minimum travel time required to travel from the airport in question to the destinations with minimum interchanges. QPL value for direct flight connection between region *i* to region *j* is the flight time in minutes between the two airports. And if there isn't a direct connection then it involves the layover time too (Jose & Ram, 2018; Burghouwt & Redondi, 2013).

$$CI(Q)_i = 1 + \frac{\sum_{j=1}^{n} \frac{QPL_{ij}}{n-1}}{Avg. \sum_{j=1}^{n} \frac{QPL_{ij}}{n-1}} \quad and \quad AI(Q)_i = \sum_{j=1}^{n} \frac{60}{QPL_{ij}} \tag{11}$$

In equations [11], $CI(Q)_i$ is the connectivity index and $AI(Q)_i$ is the accessibility index as per the quickest path length model. QPL_{ij} is the quickest path length value in minutes between the airport *i* and *j* as per the direct or via connections and *n* is the total number of airports in the network being considered.

3. Methodology

Assessment of the performance of the airport network of Tier-II cities and its relationship with the Tier-I cities of India is the main objective of this study. This paper attempts to assess the network of the Tier-II cities of India having medium-hub international airports by applying the aforementioned techniques. This section presents the methodological framework and data collection process for the network assessment.

3.1. Methodological Framework

The step-by-step methodology for the research has been illustrated in Fig. 2. It began with an initial study about the functioning and performance assessment of the airports. It was found that the assessment and augmentation of the air transport network are certainly vital for the airport's efficient operation and also contributes to the region's growth. Further, a detailed literature study was conducted to identify the tools and techniques available for network assessment. A thorough study was also undertaken to understand the Indian air transport network conditions and its gap areas, plus quality and type of available data. From the literature, significant parameters for air transport network were selected, viz. – flight frequency (direct and via connections), destinations, and travel time (including layover times for via connections). Other related demographic and economic data were also identified for the analysis.

Using the flight frequency (direct connections) and destinations data, network type analysis was performed and concentration indices were calculated as per section 2.1. Then, by taking into account the flight frequency (direct and via connections) and destinations, accessibility and connectivity indices were determined by the application of shortest path model for air transport network as described in section 2.3.1. Afterward, by adding the travel time component to the earlier data, accessibility and connectivity indices were determined on the concept of quickest path model for air transport network as stated in section 2.3.2. To calculate the partial indicators of accessibility, demographic and economic data was also incorporated along with flight frequency, destinations, and travel time. As mentioned in Section 2.2, four partial indicators were estimated for accessibility – daily accessibility, potential indicator, location indicator, and network efficiency indicator. According to section 2.2.5, to arrive at a common ground, a synthesis method of Principal Component Analysis (PCA) was applied to the earlier obtained indices and partial indicators. Also, modified (or adjusted) travel time was incorporated in the calculations for the partial indicators of accessibility as per section 2.2.6. With all the indices, indicators, and synthesis, the cities were ranked and interpreted. In the end, final results are presented and discussed along with the future scope of the study.

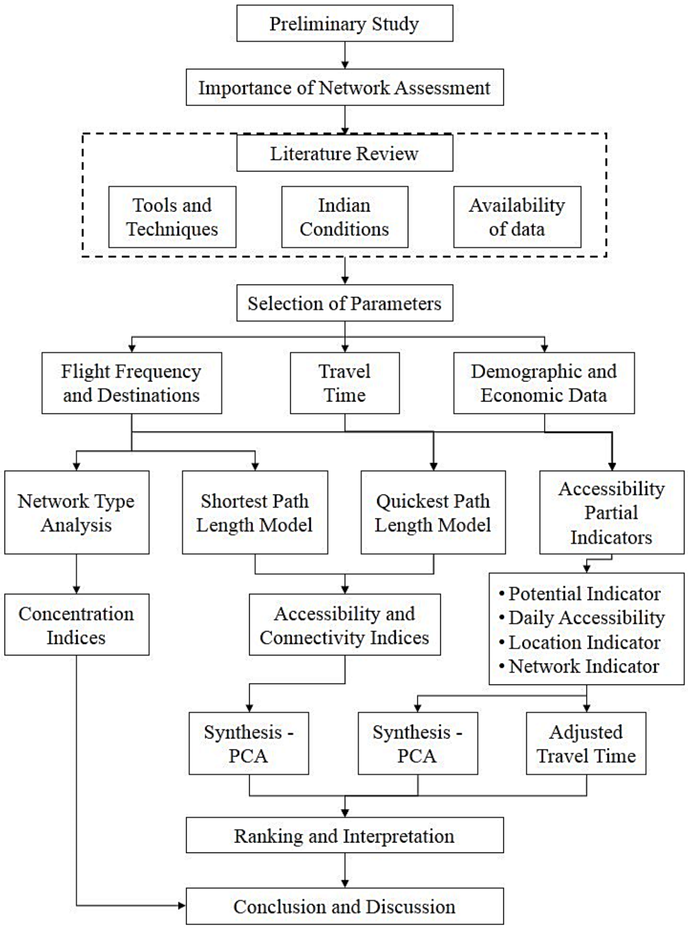

Fig. 2: Methodological Framework

3.2. Data Collection

To assess the air transport network, a variety of real-time and secondary data are required. As already mentioned, this study specifically assesses the network of the 12 tier-II Indian cities having medium-hub international airports, viz. Amritsar, Bhubaneswar, Calicut, Chandigarh, Coimbatore, Madurai, Mangalore, Nagpur, Patna, Trichy, Varanasi, and Visakhapatnam. The classification of Indian cities into different tiers is done by the central government to allocate the House Rent Allowance to the public servants. In general, the classification also fits into the population categories – Tier-I (more than 5 million), Tier-II (0.5 – 5 million), and Tier-III (0.1 – 0.5 million). As per the last census in 2011, there are eight Tier-I cities, namely, Mumbai, Delhi, Kolkata, Chennai, Bangalore, Hyderabad, Ahmedabad, and Pune. Each of these eight cities is having only one mega, very large or large hub international airport. Emphasis is put on the relationship and dependence between the 12 Tier-II cities and eight Tier-I cities presented in Table 1.

Table 1: Population-passenger information for the Tier-I and Tier-II cities and airports

S. No.	City (IATA Code)	Population - City (2011 Census)	Population - Metropolitan Region (2011 Census)	Annual Passengers (2016-17)	Percent of Nation's Annual Passengers
	Tier – I Cities				
1	Delhi (DEL)	11,034,555	16,314,838	57,703,096	21.78 %
2	Mumbai (BOM)	12,442,373	18,414,288	45,154,345	17.04 %
3	Bangalore/ Bengaluru (BLR)	8,443,675	8,499,399	22,881,392	8.64 %
4	Chennai (MAA)	4,646,732	8,696,010	18,362,215	6.93 %
5	Kolkata (CCU)	4,496,694	14,112,536	15,819,539	5.97 %
6	Hyderabad (HYD)	6,993,262	7,749,334	15,102,672	5.70 %
7	Ahmedabad (AMD)	5,577,940	6,352,254	7,405,282	2.79 %
8	Pune (PNQ)	3,124,458	5,049,968	6,768,852	2.55 %
	Total			189,197,393	71.40 %
	Tier – II Cities (with medium-hub international airports)				
1	Calicut/ Kozhikode (CCJ)	432,097	2,028,399	2,651,088	1.00 %
2	Visakhapatnam (VTZ)	2,035,922	2,035,922	2,358,029	0.89 %
3	Bhubaneswar (BBI)	837,737	881,988	2,332,433	0.88 %
4	Patna (PAT)	1,683,200	2,049,156	2,112,150	0.80 %
5	Coimbatore (CJB)	1,601,438	2,136,916	2,104,904	0.79 %
6	Varanasi (VNS)	1,201,815	1,432,280	1,916,454	0.72 %
7	Nagpur (NAG)	2,405,665	2,497,870	1,891,475	0.71 %
8	Chandigarh (IXC)	960,787	1,055,450	1,825,881	0.69 %
9	Mangalore (IXE)	499,486	623,841	1,734,810	0.65 %
10	Amritsar (ATQ)	1,132,761	1,183,300	1,566,407	0.59 %
11	Trichy/ Tiruchirappalli (TRZ)	916,674	1,022,518	1,359,447	0.51 %
12	Madurai (IXM)	1,561,129	1,561,129	978,919	0.37 %
	Total			22,831,997	8.62 %

Real-time information for daily departures, flight frequency, and travel time from these 12 airports was collected for a week (25th – 31st July 2018) from web portals. Flights were noted into two categories – direct and via-connections. For via-connections, only single stop flights were considered with a maximum layover time of four hours to have more realistic and preferred connections. For further analysis, economic data (GDP of the Tier-I cities) and demographic data (population of the Tier-I cities) was also noted. Other parameters like straight line distance between the cities, operating hours of the airport, etc. were also collected from web portals. The major sources for the data are the annual reports, annual traffic news, and individual airport reports from the Airport Authority of India (Airport Authority of India, 2018; Airports Authority of India, 2016). The population data for the Tier-I cities is taken from the Government of India's Census 2011 and other real-time information is taken from web portals like Open Flights, Airport Database, Flight Stats, and World Atlas (Airport Database, 2018; FlightStats, 2018; Open Flights, 2018; World Atlas, 2018). All the calculations and analysis have been done in Microsoft Excel 2016, SPSS 20, and Gephi 0.9.2.

4. Results and Discussion

After the design of the research methodology and data collection, various analyses were performed to calculate the different indices and indicators mentioned in Section 2. The following part of the paper presents the results from all the analyses and their interpretation.

4.1. Concentration Indices

With the information on flight frequency and destinations (only direct connections) in a week, concentration indices (*CI*) were calculated as per equation [1]. The results for the same are represented in Fig. 3 and Table 2. The name of the cities in *italics* represents the international cities and the underlined represents Tier-I Indian cities in Table 2. The results clearly show that out of the 12 Tier-II cities' airports considered, Calicut airport has the lowest dependence on other airports. Its primary destination is Muscat airport (Oman) and it represents only 14% of its connections in a week. Calicut airport also has the most number of concentration indices till 17, which means that the airport serves 17 destinations every week. The airport with the second most number of concentration indices is Chandigarh airport with 13 destinations in a week, followed by Amritsar airport and Visakhapatnam airport with 12 destinations in a week for each. Nagpur airport has the second lowest value for its first concentration index as 25% for Mumbai airport.

On the other hand, Patna airport shows the highest dependence of 48% for the Delhi airport. Similar trends are shown by the Madurai airport and Amritsar airport with 45% concentration for Chennai airport and 44% for Delhi airport, respectively. The airport that serves the least number of destinations is Bhubaneswar airport with only eight destinations being served every week. This is followed by Madurai airport and Trichy airport as each of these airports serves nine destinations every week.

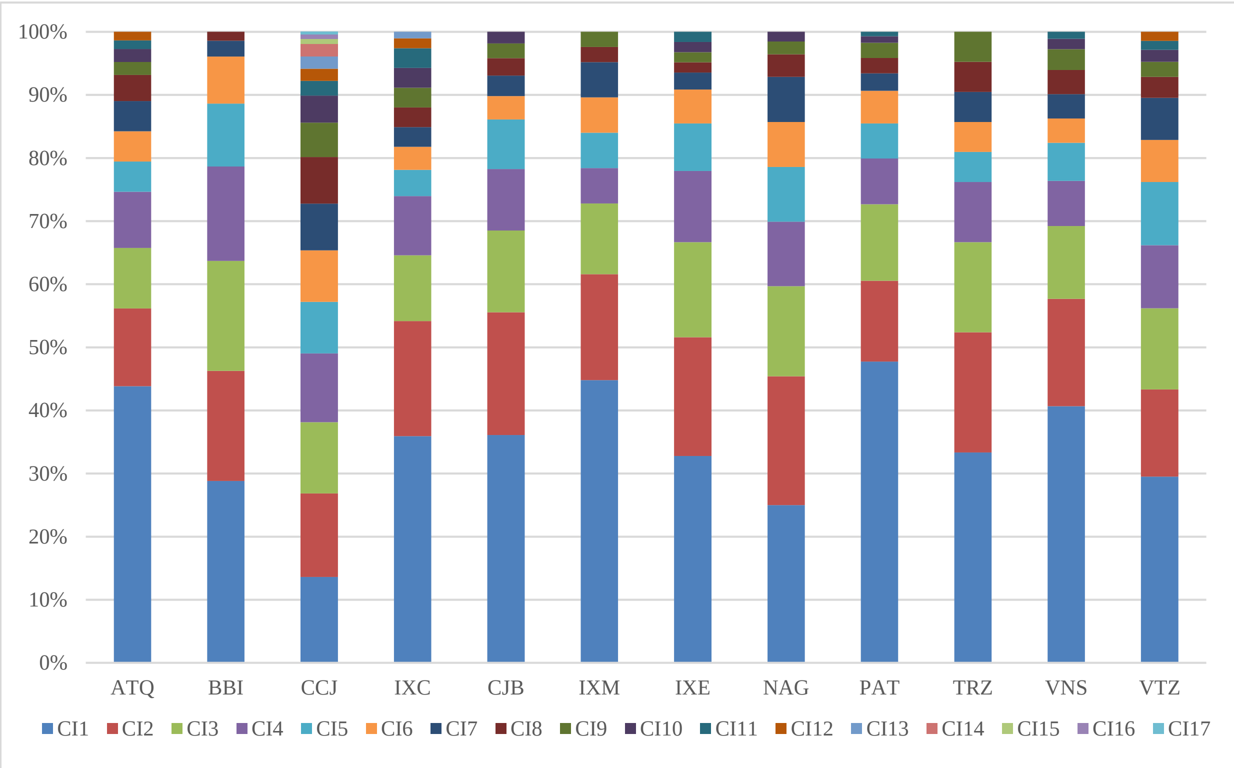

Fig. 3: Concentration Indices for all destinations

Table 2: Concentration Indices (with top 10 destinations)

	Amritsar (ATQ)	Bhubaneswar (BBI)	Calicut (CCJ)	Chandigarh (IXC)	Coimbatore (CJB)	Madurai (IXM)
c1	44%	29%	14%	36%	36%	45%
	Delhi (DEL)	Delhi (DEL)	*Muscat (MCT)*	Delhi (DEL)	Chennai (MAA)	Chennai (MAA)
c2	56%	46%	27%	54%	56%	62%
	+Mumbai (BOM)	+Kolkata (CCU)	*+Dubai (DXB)*	+Mumbai (BOM)	+Mumbai (BOM)	+Hyderabad (HYD)
c3	66%	64%	38%	65%	69%	73%
	+Dubai (DXB)	+Bangalore (BLR)	*+Sharjah (SHJ)*	+Bangalore (BLR)	+Bangalore (BLR)	*+Colombo (CMB)*
c4	75%	79%	49%	74%	78%	78%
	+Bangalore (BLR)	+Hyderabad (HYD)	*+Doha (DIA)*	+Srinagar (SXR)	+Hyderabad (HYD)	+Mumbai (BOM)
c5	79%	89%	57%	78%	86%	84%
	+Srinagar (SXR)	+Mumbai (BOM)	+Mumbai (BOM)	+Pune (PNQ)	+Delhi (DEL)	+Bangalore (BLR)
c6	84%	96%	65%	82%	90%	90%
	+Doha (DIA)	+Chennai (MAA)	*+Abu Dhabi (AUH)*	+Hyderabad (HYD)	*+Singapore (SIN)*	*+Dubai (DXB)*
c7	89%	99%	73%	85%	93%	95%
	+Kuala Lumpur (KUL)	+Visakhapatnam (VTZ)	+Bangalore (BLR)	+Kolkata (CCU)	+Pune (PNQ)	*+Singapore (SIN)*
c8	93%	100%	80%	88%	96%	98%
	+Ashgabat (ASB)	*+Kuala Lumpur (KUL)*	+Chennai (MAA)	+Ahmedabad (AMD)	+Kochi (COK)	+Delhi (DEL)
c9	95%		86%	91%	98%	100%
	+Tashkent (TAS)		*+Bahrain (BAH)*	+Kullu (KUU)	*+Sharjah (SHJ)*	+Kochi (COK)
c10	97%		90%	94%	100%	
	+Birmingham (BHM)		*+Dammam (DMM)*	+Jaipur (JAI)	*+Colombo (CMB)*	

	Mangalore (IXE)	Nagpur (NAG)	Patna (PAT)	Trichy (TRZ)	Varanasi (VNS)	Visakhapatnam (VTZ)
c1	33%	25%	48%	33%	41%	30%
	Bangalore (BLR)	Mumbai (BOM)	Delhi (DEL)	Chennai (MAA)	Delhi (DEL)	Hyderabad (HYD)
c2	52%	45%	61%	52%	58%	43%
	+Mumbai (BOM)	+Delhi (DEL)	+Bangalore (BLR)	*+Kuala Lumpur (KUL)*	+Mumbai (BOM)	+Bangalore (BLR)
c3	67%	60%	73%	67%	69%	56%
	+Dubai (DXB)	+Bangalore (BLR)	+Kolkata (CCU)	*+Singapore (SIN)*	+Hyderabad (HYD)	+Delhi (DEL)
c4	78%	70%	80%	76%	76%	66%
	+Hyderabad (HYD)	+Pune (PNQ)	+Lucknow (LKO)	*+Colombo (CMB)*	+Bangalore (BLR)	+Kolkata (CCU)
c5	85%	79%	85%	81%	82%	76%
	+Chennai (MAA)	+Indore (IDR)	+Mumbai (BOM)	+Mumbai (BOM)	+Kolkata (CCU)	+Chennai (MAA)
c6	91%	86%	91%	86%	86%	83%
	+Abu Dhabi (AUH)	+Kolkata (CCU)	+Ranchi (IXR)	+Bangalore (BLR)	+Jaipur (JAI)	+Mumbai (BOM)
c7	94%	93%	93%	90%	90%	90%
	+Delhi (DEL)	+Hyderabad (HYD)	+Pune (PNQ)	+Kochi (COK)	+Chennai (MAA)	+Vijayawada (VGA)
c8	95%	96%	96%	95%	94%	93%
	+Doha (DIA)	*+Doha (DIA)*	+Hyderabad (HYD)	*+Dubai (DXB)*	*+Sharjah (SHJ)*	+Bhubaneswar (BBI)
c9	97%	98%	98%	100%	97%	95%
	+Muscat (MCT)	*+Sharjah (SHJ)*	+Varanasi (VNS)	*+Sharjah (SHJ)*	+Ahmedabad (AMD)	+Port Blair (IXZ)
c10	98%	100%	99%		99%	97%
	+Bahrain (BAH)	+Allahabad (IXD)	+Allahabad (IXD)		+Agra (AGR)	*+Kuala Lumpur (KUL)*

Also, the concentration of direct connections from these 12 airports was viewed in terms of their share to the Tier-I Indian cities and international destinations as depicted in Fig. 4. It can be seen that the Bhubaneswar airport has the highest concentration of direct connections to the Tier-I cities at a value of 96%, followed by Varanasi airport at 90%. Calicut airport has the least concentration (25%) of direct connections to the Tier-I Indian cities followed by Trichy airport at 43% and Amritsar airport at 65%. For the international direct connections, Calicut airport has the highest concentration at 73%, followed by Trichy airport at 52%. Among the least direct international connections, Patna airport has no direct international flight and Bhubaneswar airport has just 1% concentration for direct international destinations. For all the 12 cities, Dubai airport (UAE) is the most popular international destination with 22% of total direct international connections serving it, followed by Sharjah airport (UAE) at 12% concentration.

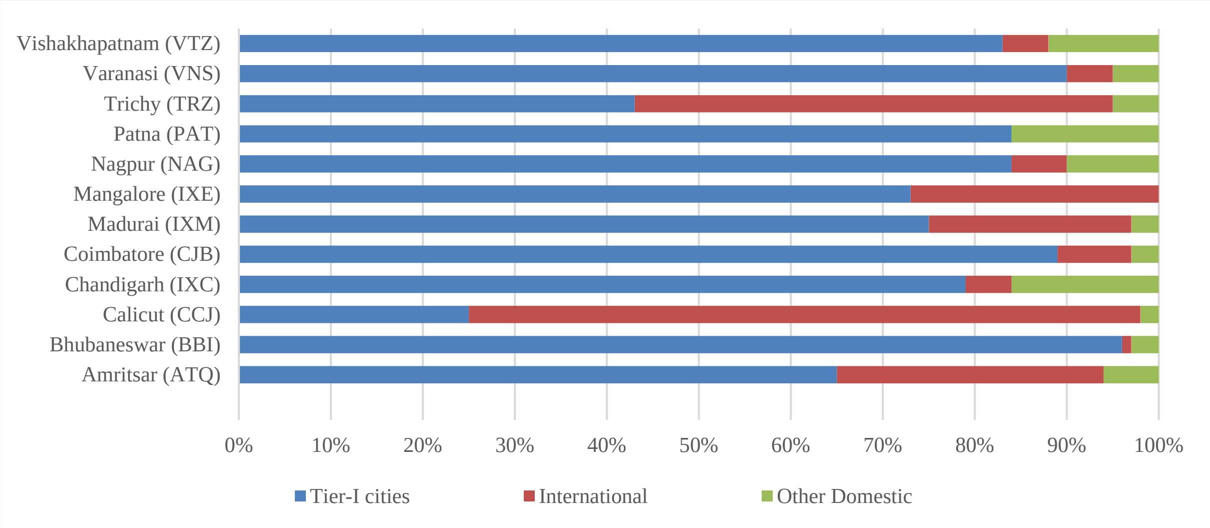

Fig. 4: Concentration Indices - Tier-I, International, and others

4.2. Network Type Analysis

Concentration indices discussed before are interpreted to determine the network type. It is observed that out of the 12 airports, nine are directly dependent on the Tier-I Indian cities as their concentration indices for the Tier-I cities is around 75% and above. This means that three-fourths and more of the total air traffic movements from these nine airports (Bhubaneswar, Chandigarh, Coimbatore, Madurai, Mangalore, Nagpur, Patna, Varanasi, and Visakhapatnam) is to Tier-I cities. It depicts their dependence on the Tier-I cities and suggests that these nine airports play a feeding role to Tier-I cities. Thus, the presence of a mono-centric network for these nine airports is evident with Tier-I city as a dominant pole. There is a definite hub and spoke logic with different hubs for each of these nine airports. Also, for Amritsar airport, the concentration index for Tier-I cities is 65% but it still follows a mono-centric logic as 44% of its connections are to Delhi airport. Among the Tier-I cities, Delhi airport is the most strong hub with 21% of total traffic from these Tier-II cities, followed by Bangalore airport and Mumbai airport with 13% and 12% connections respectively. The primary hubs for these ten airports are considered to be the airports with which they have the most direct connections. The value of first concentration index (CI_1) is given in brackets for their most served destination.

- Bhubaneswar airport (29%), Chandigarh airport (36%), Patna airport (48%), and Varanasi airport (41%); Primary hub: Delhi airport
- Madurai airport (45%) and Mangalore airport (33%); Primary hub: Bangalore airport
- Nagpur airport (25%); Primary hub: Mumbai airport
- Coimbatore airport (36%); Primary hub: Chennai airport
- Visakhapatnam airport (30%); Primary hub: Hyderabad airport

In contrast, Calicut airport has the highest number of destinations (17) served in a week, out of which 12 are international destinations (Middle-Eastern nations). It definitely provides more direct international destinations as 73% of the total connections are non-domestic. Trichy airport has a concentration of 33% of its connections to Chennai airport but 52% of its total connections are also international. Both these airports are in close proximity (within one-hour flying distance) with each other and also with Tier-I cities like Bangalore and Chennai and Tier-II cities like Mangalore, Coimbatore, and Madurai. Thus, it is explicit that these two airports run in a polycentric logic with the presence of strong hubs around but still, both of these are resilient poles. The overall network with 53 nodes and 2,427 links (edges) is shown in Fig. 5. The links in green are the connections between Tier-II and Tier-I cities with thickness as a number of connections and the rest of the connections are in red (Rocha, 2017).

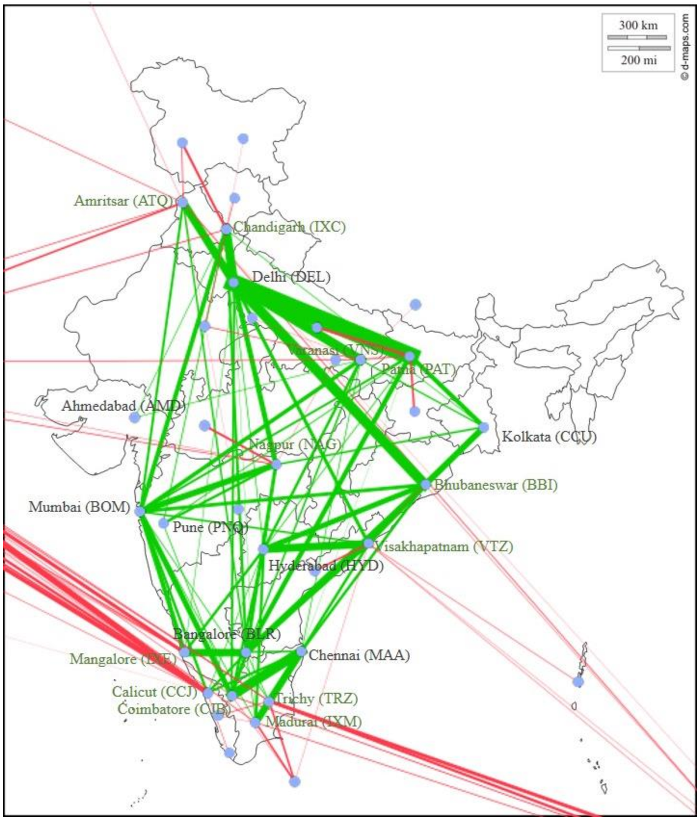

Fig. 5: Visualisation of the air transport network of the 12 tier-II cities

4.3. Accessibility and Connectivity: Graph Theory Models

As described in Section 2.3, two models based on graph theory are incorporated to estimate accessibility and connectivity. The models are the shortest path length (SPL) model and the quickest path length (QPL) model. Table 3 and Table 4 shows the connectivity indices and accessibility indices respectively based on the application of graph theory. For SPL, there are a number of cities having alike values and, thus, having the same ranks. According to SPL, the ranking for better connectivity (values closer to 1) and better accessibility (higher values) is exactly the same. Northern-central cities like Varanasi, Chandigarh, and Patna are better as per SPL. However, according to QPL, no two cities have the same value for connectivity and accessibility. The top three cities – Coimbatore, Nagpur, and Visakhapatnam are the same for both connectivity and accessibility as per QPL. Similarly, the bottom three cities – Amritsar, Calicut, and Trichy are also same for both connectivity and accessibility as per QPL. It is observed that the cities in central and southern-central are better as per QPL.

Table 3: Connectivity Indices - Graph Theory

Shortest Path Length (SPL)			Quickest Path Length (QPL)			B vs. A
Rank	City-Airport	value	Rank	City-Airport	value	Change
1	Varanasi (VNS)	1.13	1	Nagpur (NAG)	1.77	+3
1	Chandigarh (IXC)	1.13	2	Visakhapatnam (VTZ)	1.84	+2
1	Patna (PAT)	1.13	3	Coimbatore (CJB)	1.84	+1
4	Nagpur (NAG)	1.25	4	Patna (PAT)	1.91	-3
4	Coimbatore (CJB)	1.25	5	Bhubaneswar (BBI)	1.91	-1
4	Visakhapatnam (VTZ)	1.25	6	Varanasi (VNS)	1.92	-5
4	Bhubaneswar (BBI)	1.25	7	Chandigarh (IXC)	1.93	-6
8	Madurai (IXM)	1.38	8	Madurai (IXM)	2.03	-
8	Mangalore (IXE)	1.38	9	Mangalore (IXE)	2.04	-1
10	Calicut (CCJ)	1.50	10	Calicut (CCJ)	2.13	-
11	Amritsar (ATQ)	1.63	11	Trichy (TRZ)	2.31	-
11	Trichy (TRZ)	1.63	12	Amritsar (ATQ)	2.37	-1

Table 4: Accessibility Indices - Graph Theory

Shortest Path Length (SPL)			Quickest Path Length (QPL)			B vs. A
Rank	City-Airport	value	Rank	City-Airport	value	Change
1	Varanasi (VNS)	7.5	1	Coimbatore (CJB)	4.8	+3
1	Chandigarh (IXC)	7.5	2	Nagpur (NAG)	4.5	+2
1	Patna (PAT)	7.5	3	Visakhapatnam (VTZ)	4.4	+1
4	Nagpur (NAG)	7.0	4	Madurai (IXM)	4.4	+4
4	Coimbatore (CJB)	7.0	5	Bhubaneswar (BBI)	4.3	-1
4	Visakhapatnam (VTZ)	7.0	6	Chandigarh (IXC)	4.1	-5
4	Bhubaneswar (BBI)	7.0	7	Mangalore (IXE)	4.0	+1
8	Madurai (IXM)	6.5	8	Varanasi (VNS)	3.9	-7
8	Mangalore (IXE)	6.5	9	Patna (PAT)	3.8	-8
10	Calicut (CCJ)	6.0	10	Calicut (CCJ)	3.8	-
11	Amritsar (ATQ)	5.5	11	Trichy (TRZ)	3.6	-
11	Trichy (TRZ)	5.5	12	Amritsar (ATQ)	2.8	-1

4.4. Accessibility: Partial Indicators and Adjusted Travel Time

Using the data like flight frequency, destinations (only direct connections), minimum travel time, GDP, population, and straight line distance between the two airports, four partial indicators are estimated as mentioned in section 2.2. Descriptive statistics of the different parameters and variables used are presented in Table 5. The four partial indicators estimated for accessibility are daily accessibility, economic potential, location indicator, and network efficiency indicator. Also, by using the via-connections and the technique described in section 2.2.6, adjusted travel time is determined. The value of M in equation [9] is used as the weekly operating hours of each airport. Thus, two scenarios are developed and compared – Scenario-A (with minimum travel time) and Scenario-B (with adjusted travel time). It is seen that for all the cities, adjusted travel time is more than the minimum travel time. For calculating daily accessibility, economic potential, and location indicator in Scenario-B, adjusted travel time was used instead of minimum travel time. For network efficiency indicator in Scenario-B, instead of the ratio of minimum travel time to hypothetical optimal travel time, ratio of adjusted travel time to minimum travel time was used. All the indicators are ranked for both the scenarios. The city-airports with values for daily accessibility and economic potential higher than the mean are in italics and the city-airports with values for location indicator and network efficiency indicator lower than the mean are in italics. These are the airports having better accessibility than the average.

Table 5: Descriptive Statistics of the parameters and variables for partial accessibility

	Mean	Standard deviation	Min.	Max.
Distance (d_{ij}) (km)	1103.1	497.1	224.47	2183.62
Minimum travel time (t_{ij}) (minutes)	158.7	80.3	40	350
GDP (USD millions)	107,625	55,369.1	48,000	209,000
Population	10,648,578	4,624,009	5,049,968	18,414,288
Direct flights (DF_{ij})	19	24	0	138
Via-flights (VF_{ij})	76	43	10	238
Frequency (F_{ij})	94	47	12	254
Via-flight travel time (vt_{ij})	346	37.9	248.4	447
Actual travel time (AT_{ij})	299.5	72.1	71.6	424.8
Delay Time (DT_{ij})	31	30	5.1	183.8
Adjusted travel time (t_{ij})	330.5	77.2	97	510.3

For daily accessibility indicator (Table 6), the key component is a time threshold. As already mentioned, a time threshold of three hours is used in this research. All the Tier-II cities have daily accessibility to four or more Tier-I cities in Scenario-A and central cities like Varanasi and Patna have a higher value. However, the situation is very different in Scenario-B as only six Tier-II cities have daily accessibility to one Tier-I city each and the highest value is for Patna, followed by Coimbatore, Madurai, and Trichy.

Table 6: Daily Accessibility Indicator

With minimum travel time (A)			With adjusted travel time (B)			B vs. A
Rank	City-Airport	number	Rank	City-Airport	number	Change
1	*Varanasi (VNS)*	80,138,659	1	*Patna (PAT)*	16,314,838	+1
2	*Patna (PAT)*	78,836,373	2	*Coimbatore (CJB)*	8,696,010	+5
3	*Chandigarh (IXC)*	76,492,617	2	*Madurai (IXM)*	8,696,010	+6
4	*Visakhapatnam (VTZ)*	73,786,405	2	*Trichy (TRZ)*	8,696,010	+10
4	*Bhubaneswar (BBI)*	73,786,405	5	*Mangalore (IXE)*	8,499,399	+3
6	*Nagpur (NAG)*	70,140,363	6	*Visakhapatnam (VTZ)*	7,749,334	-2
7	*Coimbatore (CJB)*	64,723,837	-	Varanasi (VNS)	-	-
8	Madurai (IXM)	43,359,031	-	Chandigarh (IXC)	-	-
8	Mangalore (IXE)	43,359,031	-	Bhubaneswar (BBI)	-	-
8	Calicut (CCJ)	43,359,031	-	Nagpur (NAG)	-	-
11	Amritsar (ATQ)	43,228,525	-	Calicut (CCJ)	-	-
12	Trichy (TRZ)	35,609,697	-	Amritsar (ATQ)	-	-

Potential indicator (Table 7) depends on two factors – proximity to bigger economies and travel time. In Scenario-A, cities like Chandigarh, Bhubaneswar, and Nagpur have high values (more than eight billions USD per minute) for potential indicator. However, in Scenario-B, the overall value of potential indicator for all the cities decreases as the adjusted travel time is much higher than the minimum travel time. In Scenario-B, cities like Patna and Coimbatore have higher values and, thus, have more potential. In comparing Scenario-A vs. B, the range of potential indicator also changes, with Scenario-A having a wider range. As these are Tier-II cities with medium-hub airports, the issue of self-potential will not have many consequences and thus, is not included in the analysis.

Table 7: Potential Indicator

With minimum travel time (A)			With adjusted travel time (B)			B vs. A
Rank	City-Airport	USD millions per minute	Rank	City-Airport	USD millions per minute	Change
1	*Chandigarh (IXC)*	8345.08	1	*Patna (PAT)*	3133.26	+6
2	*Bhubaneswar (BBI)*	8292.03	2	*Coimbatore (CJB)*	3111.93	+4
3	*Nagpur (NAG)*	8273.57	3	*Visakhapatnam (VTZ)*	2926.90	+1
4	*Visakhapatnam (VTZ)*	7940.90	4	*Madurai (IXM)*	2926.16	+5
5	*Varanasi (VNS)*	7675.46	5	*Bhubaneswar (BBI)*	2920.52	-3
6	*Coimbatore (CJB)*	7641.37	6	*Mangalore (IXE)*	2918.45	+2
7	*Patna (PAT)*	7373.23	7	Nagpur (NAG)	2773.16	-4
8	Mangalore (IXE)	7040.92	8	Chandigarh (IXC)	2765.86	-7
9	Madurai (IXM)	6939.88	9	Amritsar (ATQ)	2707.30	+2
10	Calicut (CCJ)	6389.57	10	Varanasi (VNS)	2678.11	+5
11	Amritsar (ATQ)	5988.78	11	Calicut (CCJ)	2624.99	-1
12	Trichy (TRZ)	5856.45	12	Trichy (TRZ)	2466.52	-

In Scenario-A for location indicator, the first few rankers are quite similar (Table 8). Also, the six of the seven cities performing better than the average values are the same in both scenarios – Bhubaneswar, Chandigarh, Coimbatore, Nagpur, Patna, and Visakhapatnam. This is because these cities are relatively close to either one of the biggest economies or near to two-three medium-sized economies. In scenario-A, the minimum value for the location indicator is 113.54 minutes for Nagpur. However, in Scenario-B, the minimum value itself gets multiplied by 2.5 times. This clearly depicts the influence of long via-connections and their effects.

Table 8: Location Indicator

With minimum travel time (A)			With adjusted travel time (B)			B vs. A
Rank	City-Airport	minutes	Rank	City-Airport	minutes	Change
1	*Nagpur (NAG)*	113.54	1	*Coimbatore (CJB)*	297.62	+6
2	*Visakhapatnam (VTZ)*	123.84	2	*Bhubaneswar (BBI)*	302.81	+2
3	*Varanasi (VNS)*	126.38	3	*Patna (PAT)*	307.32	+2
4	*Bhubaneswar (BBI)*	130.18	4	*Visakhapatnam (VTZ)*	312.72	-2
5	*Patna (PAT)*	132.71	5	*Nagpur (NAG)*	316.65	-4
6	*Chandigarh (IXC)*	136.67	6	*Mangalore (IXE)*	318.26	+2
7	*Coimbatore (CJB)*	144.24	7	*Chandigarh (IXC)*	324.71	-1
8	Mangalore (IXE)	162.07	8	Varanasi (VNS)	332.40	-5
9	Madurai (IXM)	167.06	9	Madurai (IXM)	342.53	-
10	Calicut (CCJ)	183.46	10	Amritsar (ATQ)	343.64	+1
11	Amritsar (ATQ)	189.90	11	Calicut (CCJ)	344.76	-1
12	Trichy (TRZ)	211.83	12	Trichy (TRZ)	376.47	-

Table 9: Network Efficiency Indicator

With minimum travel time (A)			With adjusted travel time (B)			B vs. A
Rank	City-Airport	ratio	Rank	City-Airport	ratio	Change
1	*Patna (PAT)*	1.21	1	*Amritsar (ATQ)*	2.05	+8
2	*Bhubaneswar (BBI)*	1.22	2	*Trichy (TRZ)*	2.22	+10
3	*Varanasi (VNS)*	1.24	3	*Mangalore (IXE)*	2.26	+7
4	*Visakhapatnam (VTZ)*	1.26	4	*Madurai (IXM)*	2.28	+1
5	*Madurai (IXM)*	1.26	5	*Calicut (CCJ)*	2.31	+6
6	*Chandigarh (IXC)*	1.26	6	*Coimbatore (CJB)*	2.33	+1
7	*Coimbatore (CJB)*	1.35	7	Patna (PAT)	2.54	-6
8	Nagpur (NAG)	1.49	8	Visakhapatnam (VTZ)	2.75	-4
9	Amritsar (ATQ)	1.49	9	Chandigarh (IXC)	2.79	-3
10	Mangalore (IXE)	1.52	10	Bhubaneswar (BBI)	2.86	-8
11	Calicut (CCJ)	1.60	11	Varanasi (VNS)	2.88	-8
12	Trichy (TRZ)	1.74	12	Nagpur (NAG)	2.96	-4

Network efficiency indicator (Table 9) uses the ratio of minimum travel time to hypothetical optimal travel time in Scenario-A and the ratio of adjusted travel time to minimum travel time in Scenario-B. Since adjusted time is quite higher than minimum travel time, the ratio is higher in Scenario-B and thus, the values of network efficiency are also higher in scenario-B. Also, the airports with a lower value in Scenario-A have a relatively higher value in Scenario-B. This indicator shows the most notable differences between the two scenarios because of hypothetical parameters.

4.5. Accessibility: Partial Indicators Synthesis

Table 10: Spearman's rank correlation coefficient

	Scenario A				Scenario B			
	PI	DA	LI	NE	PI	DA	LI	NE
PI	1				1			
DA	0.86	1			0.31	1		
LI	-0.94	-0.91	1		-0.84	-0.18	1	
NE	-0.69	-0.77	0.74	1	0.10	-0.12	-0.48	1

As it is evident that the partial accessibility indicators portray the accessibility from different perspectives and their results vary from one another. The same can be seen in Table 10 which shows the Spearman's rank correlation coefficient for the four indicators for both the scenarios

Table 11: Test Statistics for PCA

	Scenario A Value	Inference	Scenario B Value	Inference
KMO Measure of Sampling Adequacy	0.813	acceptable	0.384	unacceptable
Bartlett’s Test of Sphericity: Chi-square	42.408		18.958	
Degrees of freedom	6		6	
Significance	0.000	acceptable	0.004	acceptable

To obtain maximum information from the four indicators, synthesis technique of PCA is applied to find a synthetic accessibility indicator. Since all the indicators have different units and varying standard deviation, first these indicators are standardized. Basic test statistics of KMO measure of sampling adequacy and Bartlett's test of sphericity are performed on the data for both the scenarios. However, PCA is only applicable for Scenario-A as KMO measure of sampling adequacy is unacceptable for scenario-B (Table 11). Thus, PCA is conducted for Scenario-A only.

Table 12: Eigenvalues of PCA for Scenario-A

Component	Total	% of variance	Cumulative %
1	3.461	86.520	86.520
2	0.357	8.930	95.450
3	0.131	3.284	98.734
4	0.051	1.266	100.000

The eigenvalues obtained after PCA are shown in Table 12 and it is observed that the first eigenvalue alone can explain around 86% of the total variance. The same result has been verified by the scree plot. Hence, only the first principal component is used to calculate the synthetic accessibility (*SA*) index. Using the coefficients of the eigenvectors, the contribution of each of the partial indicator for accessibility to the principal component is known.

$$SA_i = 0.942 * PI_i + 0.953 * DA_i - 0.968 * LI_i - 0.853 * NE_i \qquad [12]$$

In equation [12], it can be seen that daily accessibility and potential indicator have a positive sign with the coefficient and location indicator and network efficiency indicator have a negative sign. This is logically correct as accessibility increases with the increase in the first two indicators and decreases with the increase in the latter two. Using this equation, synthetic accessibility index for the Tier-II cities is estimated in Table 13. The cities with the accessibility index more than the average value are in italics. It is observed that the cites located in central India are more accessible as compared to the ones in the extreme north or extreme south of the country though major of the Tier-I cities are located in the south and central India

Table 13: Synthetic Accessibility Index

Rank	City-Airport	Synthetic Accessibility	Normalized Synthetic Accessibility
1	*Bhubaneswar (BBI)*	3.40	1.000
2	*Chandigarh (IXC)*	3.19	0.980
3	*Varanasi (VNS)*	3.14	0.975
4	*Visakhapatnam (VTZ)*	3.05	0.967
5	*Patna (PAT)*	2.64	0.926
6	*Nagpur (NAG)*	2.38	0.901
7	*Coimbatore (CJB)*	1.03	0.768
8	Madurai (IXM)	-1.25	0.546
9	Mangalore (IXE)	-2.32	0.441
10	Calicut (CCJ)	-4.16	0.261
11	Amritsar (ATQ)	-4.25	0.253
12	Trichy (TRZ)	-6.84	0.000

5. Conclusion and Way Forward

The study aimed to assess the air transport network of Tier-II Indian cities having medium-hub international airports from three perspectives – type, accessibility, and connectivity. Special emphasis was put to understand the relation between the Tier-II and Tier-I cities. Various techniques are found in literature to assess the network as shown in Section 2. Section 3 described the methodology and data needed to achieve the objective. Finally, all the indices and indicators are calculated and analyzed in Section 4. Major results and interpretations are summarized below.

- Concentration indices are used to determine the type of network. Among the twelve cities, only two cities follow polycentric logic – Calicut and Trichy. Both are located in the extreme south of the country and are strong poles as these are not dependent on a specific airport and has international destinations as well. All the other cities have a strong dependence on their primary and secondary hubs as shown in Fig. 6.
- Connectivity and accessibility indices are estimated based on graph theory model (shortest path length and quickest path length). The results indicate that Coimbatore, Nagpur, and Visakhapatnam are the most connected and accessible airports with Tier-I cities followed by Bhubaneswar, Chandigarh, Patna, and Varanasi. All these airports are located in the broad central region. The poorest performs are Amritsar, Calicut, and Trichy.
- Four partial indicators for accessibility, namely, daily accessibility, potential indicator, location indicator, network efficiency indicator are estimated for the twelve cities with minimum travel time and adjusted travel time to get a more comprehensive image of accessibility. Contrasting differences are seen between the two scenarios which indicate the need for improvement of via-connections and increasing direct connections.
- Synthesis of the four partial indicators is performed using PCA and a synthetic accessibility index is constructed. Using this index final accessibility is calculated as shown in Fig. 6. The results are found to be in coherence with the graph theory results as Bhubaneswar, Chandigarh, Varanasi, Visakhapatnam, Patna, Nagpur, and Coimbatore are more connected with the Tier-I cities and Amritsar, Calicut, and Trichy have very low values of accessibility.

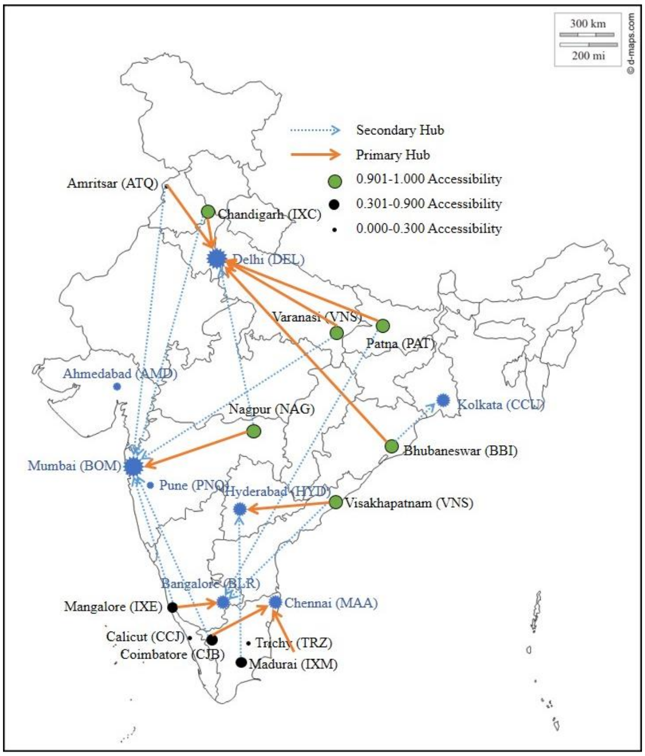

Fig. 6: Final Results for Network Assessment

The research clearly draws the dependence of the nine airports (Bhubaneswar, Chandigarh, Coimbatore, Madurai, Mangalore, Nagpur, Patna, Varanasi, and Visakhapatnam) on the Tier-I cities. These airport act as feeders to the bigger hubs. Whether to strengthen this feeder relationship or broaden the individual airport's market is still arguable. The results prove the potential of the three airports (Trichy, Calicut, and Amritsar) of becoming future hubs and less dependency on Tier-I cities. These airports serve their regions more widely and with less number of stops. The research illustrates the need for more strong hubs in the northern part of India to distribute the critical mass.

Similar research can be conducted for Chinese, Southeast Asian, or Middle Eastern airports having alike conditions to interpret the potential of future hubs and strengthen the feeder connections. Suitable comparisons with Indian airports can be made to learn from one another. The graph theory application can be further extended by weighing the nodes with airport attributes like GDP or infrastructural capacity. The estimated accessibility and connectivity indices may further be used to estimate the airport’s efficiency, which is currently finance-oriented in India. The research can also be enhanced by incorporating more airport categories into the analysis and assessing the accessibility and connectivity of the total network to overall improve the system.

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