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Article

Application Of Stochastic Processes In Tamilnadu Airport Connectivity

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Abstract: The rapid growth of air transportation in Tamil Nadu has increased the need for robust analytical frameworks to evaluate airport connectivity under uncertainty. Airport operations are inherently stochastic due to fluctuating passenger demand, variable flight schedules, and operational disruptions, rendering deterministic connectivity measures insufficient. This study develops and applies a stochastic network-based Airport Connectivity Quality Index (ACQI) to assess and compare airport connectivity across Tamil Nadu between 2017 and 2022. The proposed methodology integrates stochastic process modeling with a hierarchical airport network representation, incorporating flight frequency, destination diversity, and airport importance weighted by normalized passenger throughput. Passenger arrivals are modeled probabilistically, and airport connectivity is quantified as an expected value measure using the ACQI framework. Empirical analysis is conducted using annual flight schedules, passenger volumes, and seat capacity data obtained from the Airports Authority of India. The results reveal a highly centralized connectivity structured ominated by Chennai International Airport, which recorded an ACQI value of168.39in2022,placingitintheexcellentconnectivitycategory.Incontrast,regionalairportssuchasCoimbatore(ACQI = 7.85), Madurai (6.12), Tiruchirappalli (5.85), and Tuticorin (5.77) exhibit limited to moderate connectivity. Despite these disparities, connectivity improved across all airport categories during the study period. Medium hub airports experienced the highest relative growth in connectivity, with ACQI values increasing by 92.01% between 2017 and 2022, followed by small hubs(89.32%)andlargehubs(88.23%).Acomparisonofconnectivitygrowthwithcapacityindicatorsshows that increases in ACQI consistently outpaced growth in both scheduled domestic flights and available seat capacity. This finding indicates the presence of capacity discipline, whereby airlines enhanced network connectivity through scheduling efficiency and route optimization rather than proportional capacity expansion. Overall, the study demonstrates that stochastic ACQI modeling provides a realistic and scalable approach for evaluating regional airport connectivity and offers policy-relevant insights for infrastructure planning, network optimization, and sustainable air transport development.

Keywords: Airport Connectivity, Stochastic Processes, Airport Connectivity Quality Index (ACQI), Air Transport Networks, Tamil Nadu.

1. Introduction

Air transportation systems play a pivotal role in contemporary economic development by enabling rapid mobility of people, goods, and services across regions and nations. Beyond serving as mere transit points, airports function as critical nodes within complex transportation networks, influencing regional accessibility, tourism growth, trade efficiency, and spatial economic integration. As air traffic volumes continue to rise globally, the effectiveness of airport connectivity has emerged as a key determinant of both operational efficiency and regional competitiveness.

In recent years, India has experienced substantial growth in its aviation sector, driven by increasing passenger demand, policy initiatives, and infrastructure expansion. Within this context, the state of Tamil Nadu represents a strategically important aviation region, hosting a mix of international hubs, medium-sized airports, and regional airfields that collectively support domestic and international mobility. Major airports such as Chennai, Coimbatore, Madurai, Tiruchirappalli, and Tuticorin play distinct yet interconnected roles in shaping the state's air transport network. However, despite this growth, significant disparities persist in terms of connectivity levels, network resilience, and accessibility among these airports. Understanding and quantifying such differences is essential for informed planning, capacity optimization, and sustainable aviation development.

Airport connectivity is inherently dynamic and uncertain. Flight schedules are subject to stochastic variations arising from weather conditions, demand fluctuations, operational disruptions, and air traffic management constraints. Traditional deterministic approaches, which assume fixed schedules and stable flows, are often inadequate for capturing the probabilistic nature of air transport systems. Consequently, there has been growing interest in the application of stochastic process models, such as Poisson processes, Markov chains, queuing theory, and stochastic decision frameworks, to analyze air traffic behavior, congestion patterns, and network performance. These methods enable a more realistic representation of airport operations by explicitly incorporating randomness and uncertainty into analytical models. Parallel to these developments, several connectivity indicators have been proposed to evaluate airport performance, typically based on metrics such as route availability, flight frequency, passenger throughput, and hub centrality. While these measures provide valuable insights, many existing indices either focus on individual airports in isolation or rely heavily on deterministic assumptions, limiting their ability to reflect temporal variability and network-level interactions. Moreover, empirical studies addressing sub-national airport systems, particularly within rapidly growing aviation markets, remain relatively limited.

To address these challenges, this study adopts the Airport Connectivity Quality Index (ACQI) as a comprehensive framework for assessing airport connectivity within a stochastic modeling paradigm. The ACQI integrates multiple dimensions of connectivity, including destination diversity, hierarchical importance of connected airports, flight frequency, and passenger-based weighting, into a unified quantitative score. By embedding this index within a probabilistic network perspective, the proposed approach captures both structural and operational characteristics of airport connectivity. This research applies the ACQI-based stochastic frame work to evaluate the evolution of airport connectivity across Tamil Nadu from 2017 to 2022. Using empirical data on scheduled flights, passenger volumes, and available seat capacity, the study systematically compares connectivity levels among large hubs, medium hubs, small hubs, and non-hub airports. In addition, the relationship between connectivity growth and capacity discipline, measured through changes in flight frequency and seat availability, is examined to understand how airlines optimize network efficiency under operational constraints.

The main contributions of this study are threefold. First, it provides a stochastic network-based methodology for quantifying airport connectivity at the regional level. Second, it offers an empirical assessment of connectivity disparities and growth patterns among Tamil Nadu's airports over a multi-year period. Third, it delivers policy-relevant insights into how capacity management and network optimization influence connectivity outcomes, there by supporting evidence-based decision-making for airport authorities and transportation planners. By demonstrating the applicability of stochastic process modeling combined with the ACQI frame work, this study contributes to the broader literature on air transport network analysis and offers a scalable methodology that can be extended to other regions and multimodal transportation systems.

Airport connectivity has increasingly been recognized as a network-level phenomenon rather than a simple count of routes or flights. Early connectivity modeling studies demonstrated how changes in network structure can significantly alter accessibility, particularly for small and regional airports, even when total traffic volumes remain stable [1]. Subsequent network-oriented analyses further highlighted the role of hub dominance and market concentration in shaping connectivity outcomes across national air transport systems [2], [3]. Quantitative evaluations of air transport accessibility have shown that connectivity disparities often emerge between major hubs and peripheral airports, especially in rapidly growing aviation markets[4]. Dynamic network analyses have also revealed that airport connectivity is not static but evolves over time in response to policy changes, airline strategies, and external disruptions [5]. These findings collectively motivate the need for region-specific connectivity assessment frameworks.

Airport operations are inherently uncertain due to fluctuating demand, weather variability, and air traffic control constraints. Stochastic safety and flow management studies have demonstrated that probabilistic modeling is essential for capturing the true behavior of air traffic systems, particularly under congested conditions[6]. Fast-time stochastic simulation approaches further confirm that delays and congestion cannot be reliably analyzed using deterministic assumptions alone [7]. Scenario-based and event-driven stochastic simulations have been shown to effectively represent random disruptions in air traffic systems and to improve operational decision-making under uncertainty [8]. Decision support frame works grounded in stochasticest imation techniques provide additional evidence that uncertainty-aware modeling enhances system-level planning and resilience [9]. Recent studies have extended stochastic modeling to airport operational state prediction, demonstrating how transition matrices can be used to anticipate congestion and recovery phases in complex airport environments [10]. These approaches directly support the application of stochastic processes in airport connectivity analysis. The interaction between airport connectivity and congestion has been widely examined using queuing theory and probabilistic flow models. Queuing-based studies illustrate how congestion emerges as a function of stochastic arrival and service processes rather than fixed schedules [11]. Chance-constrained optimization models further demonstrate how airport operations can be optimized under uncertainty while maintaining acceptable risk levels [12]

Recent advances incorporating stochastic deep learning techniques have shown promise in predicting clustered delay patterns across interconnected airports, reinforcing the importance of probabilistic approaches for large-scale network analysis [13]. These findings underline the relevance of stochastic frameworks when evaluating connectivity under capacity constraints. Connectivity improvements are not always driven by proportional increases in flight frequency or seat capacity. Optimization studies on multi-hub airline networks reveal that strategic scheduling and bank structures can enhance connectivity through improved coordination rather than capacity expansion [14]. Similarly, analyses of airport substitution and traffic redistribution demonstrate how airlines reallocate connectivity across networks in response to competitive and operational pressures [15].

These insights provide a strong conceptual foundation for examining connectivity growth alongside capacity discipline, particularly in regional airport systems. The development of composite connectivity indices requires careful weighting of multiple indicators. Entropy-based and multi-criteria evaluation methods have been shown to offer objective and robust mechanisms for determining indicator importance in airport infrastructure and route network assessments [16], [17]. Such approaches align closely with the weighting strategy adopted in the Airport Connectivity Quality Index framework.

Connectivity indices have also been widely used to assess airport competitiveness and regional integration, reinforcing their suitability for empirical connectivity evaluation [18].

In the Indian context, accessibility and connectivity challenges are particularly pronounced for regional and non-hub airports. Empirical studies focusing on India highlight how inadequate surface connectivity and un even infrastructure development constrain airport usage and network integration [19]. These findings emphasize the importance of region-specific connectivity assessments.

Service quality and operational performance analyses of Indian airports further reveal that network connectivity plays a critical role in passenger experience and airport effectiveness [20]. Together, these studies justify the application of stochastic connectivity analysis within the Tamil Nadu airport system. External disruptions such as the COVID-19 pandemic have demonstrated the vulnerability of small and regional airports to sudden connectivity losses. Empirical evidence shows that connectivity reductions during such shocks are not uniform across airport categories and are strongly influenced by network position and airline strategies [21]. These observations further support the need for stochastic and dynamic approaches in connectivity modeling.

Transportation systems have been increasingly characterized as complex adaptive systems, where nonlinearinteractionsanduncertaintydriveemergentbehavior.Complexity-awaremodelingapproachesreinforce the argument that airport connectivity should be analyzed using probabilistic and network-based frameworks rather than static metrics [22]. Hybrid stochastic forecasting models also demonstrate improved short-term prediction performance under uncertain conditions, further validating the methodological foundation of this study [23].

2. Methodology

This study adopts as to chastic network-based frame work to evaluate airport connectivity in Tamil Nadu. Airport operations and passenger movements are inherently uncertain due to demand fluctuations, weather conditions, and operational disruptions. To realistically capture this uncertainty, stochastic process models are employed and integrated with the Airport Connectivity Quality Index (ACQI).The methodology consists of four main components:

Stochastic representation of airport systems,

Network modeling,

ACQI formulation, and

Normalization and interpretation.

2.1 Stochastic Representation of Airport Systems

Stochastic processes provide a mathematical framework for modeling systems that evolve over time under uncertainty. In many real-world systems, outcomes are influenced by random factors, making deterministic modeling insufficient. A stochastic process is formally defined as a collection of random variables indexed by time or space and is represented as

$$\{X(t), t \in T\} \tag{1}$$

where X(t) denotes the state of the system at time t. Such processes are widely applied in transportation systems, where demand fluctuations, operational constraints, and user behavior introduce inherent randomness. Air transportation networks exhibit strong stochastic characteristics due to uncertain passenger arrivals, variable demand across routes, weather conditions, flight delays, and dynamic scheduling decisions. Passenger arrival at an airport can be modeled as a random process, often approximated using a Poisson distribution, where the probability of n arrivals in a time interval t is given by

$$P(N(t)=n)=\frac{(\lambda t)^{n}e^{-\lambda t}}{n!} \quad (2)$$

with λ representing the average arrival rate. This randomness directly affects airport congestion, connection availability, and overall network performance, thereby justifying the use of stochastic processes in airport connectivity analysis.

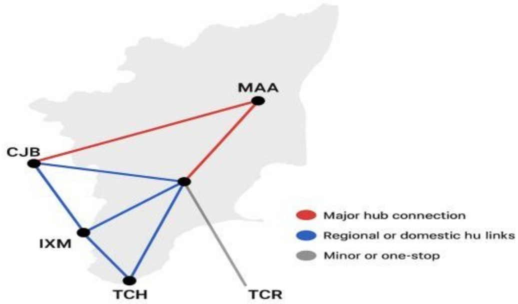

Figure 1: Airport connectivity diagram

2.2 Airport Network Modeling Using Markov Processes

An airport system can be represented as a stochastic network or graph as shown in Figure 1, where airports are modeled as nodes and flight connections as edges. The existence and strength of each connection are not constant but depend on probabilistic factors such as flight frequency, passenger load factors, and operational reliability. Let $G=(V,E)$denotetheairportnetwork,whereVisthesetofairportsandEisthesetofconnections. Each edge e_{ij} between airport i and airport j is associated with a probability P_{ij}, representing the likelihood of successful travel or connectivity between the two airports. Thus, airport connectivity becomes a probabilistic measure rather than a fixed quantity.

Most airline networks operate under a hub-and-spoke structure, in which a limited number of major airports serve as hubs, while smaller airports act as spokes. Passenger movement within this structure is stochastic, as travelers may choose different routes depending on availability, cost, and time. The transition of passengers from one airport to another can be modeled using a Markov process, where the probability of moving to the next airport depends only on the current location. If x_n denotes the airport visited at the n-th step, then

$$p(x_{n+1}=j|x_{\eta}=i)=p_{ij} \quad (3)$$

where $p_{ij}$is the transition probability from airport i to airport j. Major hubs exhibit higher transition probabilities due to greater flight frequency and connectivity.

2.3 Airport Weight Determination

Airports differ significantly in their role within the network, and this variation must be captured quantitatively. To account for differences in operational importance, airports are assigned weights that reflect their contribution to connectivity. These weights are influenced by passenger throughput, number of destinations served, and hub classification. Passenger throughput is itself a random variable, as traffic varies daily and seasonally. Let p_i denote the annual passenger throughput of airport i. To ensure comparability across airports, a normalized weight is defined as

$$W_i=\frac{p_i}{m(p)} \quad (4)$$

where $m(p)$ represents the maximum passenger throughput among all airports in the network. This normalization ensures that weights lie between 0 and 1 and reflect the relative importance of each airport in probabilistic terms.

2.4 Airport Connectivity Quality Index (ACQI)

Airport connectivity is not solely determined by the presence of direct connections but also by the quality and reach of onward connections. To capture this aspect, the Airport Connectivity Quality Index (ACQI) is introduced as a composite stochastic measure. The ACQI represents the expected connectivity of an airport by accounting for the number of connections, the category of destination airports, and their corresponding weights. Mathematically, the ACQI for airport a is expressed as

$$ACQI_a = \sum_k N_k L_k w_k \tag{5}$$

where N_k denotes the number of flights to airports of category k, L_k represents the number of reachable locations in that category, and w_k is the assigned weight. This formulation reflects the expected value of connectivity under stochastic conditions, integrating both quantity and quality of connections.

2.5 Airport Connectivity Quality Index (ACQI)

The ACQI can be interpreted as an expected connectivity score, measuring how effectively an airport is integrated into the air transportation network. Higher ACQI values indicate greater accessibility, higher probability of successful on ward travel, and stronger network resilience. Conversely, lower ACQI values suggest dependence on limited routes and higher uncertainty in travel options. Based on the computed ACQI values, airports can be categorized into different connectivity levels, ranging from limited to excellent connectivity. This classification provides a meaningful basis for evaluating regional accessibility and identifying airports that require infrastructural or policy intervention.

2.6 Sample ACQ I Calculation

To illustrate the computation of the Airport Connectivity Quality Index (ACQI), consider an airport with connections to multipledestinationcategories.Assumethattheairportoperatesanaverageoftwodailyflightsto 20 large hub airports, one daily flight to 30 medium hub airports, and one daily flight to 50 small hub airports. The corresponding hierarchical weights for large, medium, and small hub categories are taken as 3.0, 2.5, and 2.0, respectively. Using the proposed ACQI formulation, the connectivity index is computed as

$$ACQI = \sum_{k=1}^{K} (F_{ak} \times D_k \times W_k^{\text{struct}})$$

Substituting the above values,

$$ACQI = (2\times20\times3.0)+(1\times30\times2.5)+(1\times50\times2.0)$$
$$ACQI = 120+75+100=295$$

This value represents the structural connectivity strength of the airport based on destination diversity, service frequency, and network hierarchy. When combined with the normalized passenger throughput weight of the airport, the final operational ACQI score is obtained as described in Results Section

In summary, stochastic processes offer a realistic and mathematically sound framework for modeling airport connectivity. By incorporating randomness in passenger movement, flight availability, and network structure, the proposed ACQI captures the probabilistic nature of real-world air transportation systems. The application of this framework to Tamil Nadu airport connectivity enables a systematic assessment of network performance and supports informed decision-making for transportation planning and regional development.

2.7 Normalization of ACQI

Since the parameters involved in airport connectivity analysis operate on different numerical scales, normalization is essential to ensure balanced contribution of each factor. Without normalization, large hubs with high passenger volumes may dominate the connectivity index and obscure the relative importance of smaller airports. Therefore, the connectivity measures are scaled to maintain numerical stability and interpretability. Let $ACQI_a$ denote the raw connectivity score of airport a. The normalized connectivity index is defined as

$$ACQI_a^* = \frac{ACQI_a - min(ACQI)}{max(ACQI) - min(ACQI)} \tag{6}$$

where $max(ACQI) and\ min(ACQI)$ represent the maximum and minimum ACQI values across the network. This transformation maps connectivity values to a standardized range, enabling fair comparison among airports.

2.8 Assumptions and Model Constraints

The proposed methodology is developed under a set of assumptions to ensure tractability and clarity. Passenger arrivals, flight frequencies, and connectivity patterns are assumed to represent average operational conditions over the study period. Short-term fluctuations such as seasonal peaks, extreme weather disruptions, and airline-specific scheduling changes are not explicitly modelled. However, these uncertainties are implicitly captured through the stochastic interpretation of passenger through put and connection probabilities. Furthermore, all connections are assumed to be independent, and inter-airline coordination effects are not separately accounted for. These assumptions allow the ACQI framework to focus on structural connectivity characteristics while maintaining analytical simplicity.

2.9 Model Validation and Interpretative Framework

To validate the proposed connectivity model, computed ACQI values are interpreted using predefined connectivity ranges. These ranges provide a qualitative assessment of air port connectivity performance and serve as a benchmark for comparative analysis. Airports classified under higher ACQI ranges are expected to exhibit greater accessibility and network resilience, while those with lower scores indicate limited integration within the air transportation system. This interpretative framework ensures that the numerical results obtained from the model can be meaningfully related to real-world connectivity conditions.

It is important to clarify that two distinct but complementary weighting schemes are employed in the proposed ACQI framework. The hierarchical weights (e.g., 3.0, 2.5, 2.0, 1.5, and 1.0) represent the structural importance of airports within the air transport network and are based on standard hub classification criteria. These weights capture the relative role of airports as large hubs, medium hubs, small hubs, or regional airports and remain constant across the study period. In contrast, the passenger throughput–based weights are operational weights, normalized between 0 and 1, and reflect the actual traffic intensity handled by each airport in a given year. These operational weights vary over time and account for demand-driven changes in airport usage. In the ACQI computation, hierarchical weights are applied at the destination category level to represent network structure, while normalized passenger weights are used at the airport level to capture operational scale. The integration of both weighting schemes enables the ACQI to jointly represent network hierarchy and stochastic traffic behavior, ensuring conceptual consistency between the methodology and results.

3 Results and Discussion

This section presents the results obtained using the revised stochastic Airport Connectivity Quality Index (ACQI) framework and provides an analytical discussion aligned with the methodology described in Section 3. The analysis focuses on airport hierarchy, connectivity disparities, temporal evolution of connectivity, and the relationship between connectivity growth and capacity discipline across airports in Tamil Nadu from 2017 to 2022.

3.1 Airport Weight Calibration and Hierarchical Structure

The weights reflect the relative operational significance of airports within the air transportation network, as determined by their role in handling passenger traffic and supporting network connectivity. Airports classified as large hubs or international gateways are assigned the highest weight values, indicating their dominant position in facilitating passenger movement and offering extensive routing possibilities. These airports typically serve as primary transfer points and contribute substantially to network integration.

Medium and small hub airports receive intermediate weight values, reflecting their role in supporting regional and secondary connectivity. Although these airports handle lower passenger volumes than major hubs, they remain essential for linking smaller cities to the broader network. The assigned weights indicate a reduced but still meaningful contribution to overall connectivity, emphasizing their importance in maintaining regional accessibility.

Non-hub and regional airports are assigned lower weight values due to their limited traffic and restricted routing options. These airports primarily serve point-to-point or feeder functions and have fewer onward connections. Consequently, their influence on network-wide connectivity is comparatively smaller. Essential Air Service and remote airports receive the lowest weights, reflecting minimal passenger throughput and limited integration into the national or international air transport system.

The weight distribution shown in Table 1 highlights the hierarchical structure of airport connectivity. Higher weights correspond to airports with greater influence on network performance, while lower weights represent airports that primarily serve localized connectivity needs. These results establish a structured basis for evaluating airport connectivity and interpreting subsequent connectivity index values.

Table 1: Airport Classification (Standard Approach)

Airport Type (h)	Description	Suggested Weight ()
Large Hub / International	Handles >1% of total passenger enplanements	3.0
Medium Hub	Handles 0.25–1%	2.5
Small Hub	Handles 0.05–0.25%	2.0
Non-Hub / Regional	<0.05% of total traffic	1.5
EAS / Remote Airport	Essential Air Service or low-traffic	1.0

3.2 Passenger Throughput–Based Weight Results

The airport weight values obtained using passenger through put data, reflecting the relative scale of passenger movement a cross major airports in Tamil Nadu. The variable Pi represents the annual passenger volume handled by airport iii, measured in millions. To enable comparison across airports of different sizes, the resulting weight Wi expresses the relative magnitude of passenger traffic with respect to the busiest airport in the network.

Chennai International Airport(MAA), with an annual passenger volume of PMAA=22million,attainsa weight value of WMAA=1.00, indicating its position as the dominant hub and primary gate way in the regional air transport network. This value represents the maximum observed passenger through put and serves as the reference level for interpreting other airport weights.

Coimbatore Airport (CJB) records a passenger volume of PCJB=3.0 million and a corresponding weight of WCJB=0.14, reflecting its role as a secondary hub with moderate connectivity. Madurai (IXM) and Tiruchirappalli (TRZ) handle passenger volumes of PIXM=2.1millionand PTRZ=1.9 million, resulting in weights of 0.10 and 0.09 respectively. These values indicate comparable levels of regional importance and suggest similar contributions to network connectivity.

Tuticorin Airport (TCR), with a passenger throughput of PTCR=0.3 million, receives a substantially lower weight of0.01.This highlights its limited passenger handling capacity and comparatively minor influence on the overall l airport network. The sharp contrast between Tuticorin and the larger airports illustrates the uneven distribution of passenger traffic across the state.

Overall, the weight values in Table2 reveal a pronounced hierarchical structure in passenger throughput, where a single dominant hub is supported by a small number of regional airports with moderate influence, while smaller airports contribute primarily to localized connectivity. These results provide a quantitative basis for interpreting connectivity quality and support subsequent analysis using the Airport Connectivity Quality Index.

Table 2: Airport Based on Passenger Throughput (Data-Driven Approach)

Airport	Annual Passengers (millions)	Weight
Chennai (MAA)	22	1.00
Coimbatore (CJB)	3.0	0.14
Madurai (IXM)	2.1	0.10
Tiruchirappalli (TRZ)	1.9	0.09
Tuticorin (TCR)	0.3	0.01

3.3 ACQI Scale and Connectivity Classification

To facilitate interpretation of ACQI values, connectivity scores were grouped into qualitative categories ranging from limited to excellent connectivity. This classification enables meaningful comparison across airports and time periods.

Table 3: ACQI Score Range

ACQI Score Range	Connecting Quality
>150	Excellent Connectivity
50 -150	Good Connectivity
10 -50	Moderate Connectivity
0 -10	Limited Connectivity

3.4 Airport Connectivity Performance in 2022

ACQI scores for each 20 airports in Tamil Nadu from 2017 to 2022 by taking data from AAI (Airport Authority of India). The marketing airline, end point, equipment, source, and Available Seat Miles (ASMs) over a specified time period, seats as well as the number of scheduled flights information are included in this data. Data was collected annually from January to December for every year from 2017 to 2022 for the calculation of ACQI score. Airport in Tamil Nadu with no scheduled flights will be deleted from the data sheet.

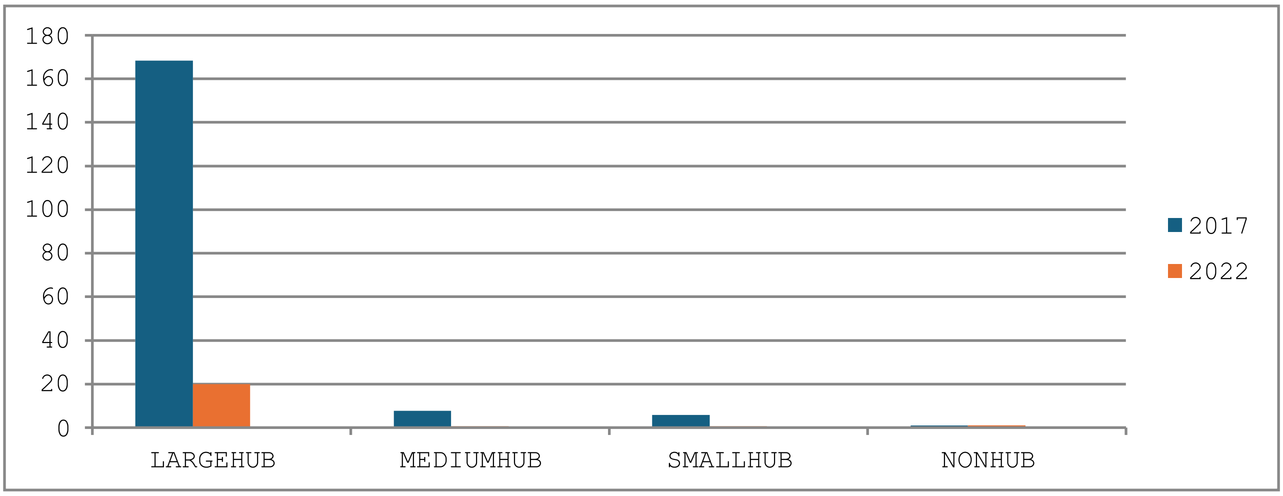

Figure 2: ACQI Values

The comparative variations in connectivity scores among types of airports are shown in the Table 4 below lists all of Tamil Nadu's connected airports as ACQI Score

Table 4: Five top most connecting airport in Tamil Nadu 2022

Airport	ACQI score (2022)	Rank (2022)
Tuticorin Airport	5.77	5
Trichy International Airport	5.85	4
Madurai Airport	6.12	3
Coimbatore International Airport	7.85	2
Chennai International Airport	168.39	1

3.5 Temporal Evolution of Connectivity (2017–2022)

Connectivity trends over time were examined to identify growth patterns across different airport categories. Figure 2 presents the evolution of average ACQI values for non-hub, small hub, medium hub, and large hub airports.

Table 5: Percentage variation in the ACQI score by the type of airport, 2017-2022

Airport Type	% Variation in ACQI (2017–2022)
Non-Hub/EAS	22.56%
Small Hub	89.32%
Medium Hub	92.01%
Large Hub	88.23%

The significant grow thin connectivity occurred at average hub airports from 2010 to 2015 with increase of 92.01% ACQI in those years. However, major hub airports did well comparatively, increasing their connectivity by 88.23% over the same year. From 2017 to 2022, Tamil Nadu's connectivity improves.

3.6 Connectivity Growth and Capacity Discipline

Finally, it is essential to examine the extent to which connectivity has been affected by capacity management, including reductions in available seats and scheduled domestic flights. If connectivity is directly related to capacity, one would expect declines in connectivity to correspond closely with decreases in flights and seating at these airports. Table 6 presents a comparison of the percentage changes in ACQI alongside variations in capacity metrics, such as available domestic seats and scheduled domestic flights, between 2017 and 2022.

Table 6:Variations in capacity and connectivity by the type of airport 2017-2022

Airport type	% Variation in ACQI (2017-2022)	% Variation in seats (2017 – 2022)	% Variation in domestic flights (2017-2022)
Non-Hub	22.56%	50.82%	10.54%
Small Hub	89.32%	78.54%	52.45%
Medium Hub	92.01%	87.90%	63.67%
Large Hub	88.32%	90.78%	73.45%

Throughout the study period, the percentage change in connectivity for every kind of airport was not ably higher than the percentage change in domestic flights and seats. This implies a capacity discipline method which is the considerable part of airlines that directly improve service and passengers to access the world's air transportation network. Passengers may easily get the seats in air transportation because the percentage variation in seats exceeded that of percentage variation in domestic flights at every kind of airports.

4 Conclusion

The present study developed and applied a stochastic Airport Connectivity Quality Index (ACQI) framework to evaluate airport connectivity in Tamil Nadu. The key conclusions are summarized as follows:

A stochastic, network-based ACQI framework was successfully formulated by integrating flight frequency, destination diversity, airport hierarchy, and passenger through put, enabling a realistic representation of uncertainty in airport operations.

The connectivity structure of Tamil Nadu exhibits strong hub dominance, with Chennai International Airport achieving an ACQI value of 168.39 in 2022 and clearly outperforming all other airports in the state.

Regional airports such as Coimbatore, Madurai, Tiruchirappalli, and Tuticorin demonstrate limited to moderate connectivity, highlighting persistent spatial disparities in network accessibility.

Connectivity improved across all airport categories between 2017 and 2022, with medium hub airports recording the highest relative growth in ACQI (92.01%), followed by small hubs (89.32%) and large hubs (88.23%).

The observed growth in connectivity consistently exceeded increases in scheduled flights and seat capacity, indicating the presence of capacity discipline and the effectiveness of network optimization strategies adopted by airlines.

The proposed ACQI framework offers practical insights for policymakers and airport authorities by identifying connectivity gaps and supporting evidence-based decisions on infrastructure investment and network planning.

The methodology is scalable and can be extended to other regions or incorporated with real-time operational data to support dynamic connectivity assessment and sustainable air transport development.

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