Journal of the Air Transport Research Society 4 (2025) 100064

Contents lists available at ScienceDirect

Journal of the Air Transport Research Society

journal homepage: www.elsevier.com/locate/jatrs

MARRI: Towards a Multiple-Airport Region Resilience Index

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ARTICLE INFO

Keywords:
Multiple airport regions
Disruptions
Resilience

ABSTRACT

Multiple airport regions (MARs) are of increasing importance, ensuring the efficiency in access to the global air transportation system. MARs, however, are vulnerable to a multitude of disruptions, ranging from natural disasters and technological failures to economic fluctuations and security threats. Traditional resilience analyses in the literature have primarily focused on assessing the robustness of individual airports or specific components of the aviation system, such as infrastructure or operational procedures. These studies often employ complex network techniques and overlook the interdependencies and cascading effects that arise within and between airports, particularly in densely interconnected regions. In our study, we address this gap by adopting a more holistic and systemic perspective. A novel, fine-grained resilience index, the Multiple-Airport Region Resilience Index (MARRI) is proposed based on two aspects: Loss In Connectivity (LIC) and Travel Time Increase (TTI) under airport outage for the population. MARRI provides the detailed insights and recommendations necessary to build more resilient air transportation systems, capable of withstanding and recovering from disruptions.

1. Introduction

Multiple Airport Regions (MARs) are often found in major metropolitan areas; see Fig. 1 for an overview of the largest MARs in the world, according to the number of airports. They offer alternative landing sites in emergencies, such as runway closures or severe weather. With airports in close proximity, they can accommodate diverted flights more efficiently than single-airport systems, where alternate airports may be hundreds of kilometers/hours of driving away (Fuellhart, 2007; Harvey, 1987; Sun et al., 2017; Windle & Dresner, 1995; Yang et al., 2016). Better understanding the resilience of MARs is an open research challenge (Sun et al., 2024b). Efforts to enhance resilience could extend from tactical short-term solutions to strategic long-term planning, building more effective and robust MAR networks (Li & Hansen, 2021). The Greater Bay Area (GBA) in China is a prominent focus in resilience research due to its rapid growth and associated challenges. Capacity expansions for GBA airports, including terminals and runways, frequently make news headlines, yet their on-time performance lags. Chinese airports, including Hong Kong, often rank poorly in punctuality benchmarks, partly due to restricted airspace. Attempts to improve the GBA's resilience through coordination face significant hurdles, such as intense competition among airports and administrative boundaries. These issues often lead to inefficiencies, such as diverted flights being poorly managed or crew members stranded due to immigration or customs regulations. Addressing these barriers and fostering collaboration among GBA airports is crucial for enhancing their resilience, particularly as demand grows and disruptions become more frequent.

In this study, we explore the mechanisms underlying resilience within MARs, aiming to better understand the nature of resilience and the role of airport failures and their downstream effects. Most existing work on this subject has performed comprehensive evaluations of airport disruptions using one of the following two types of approaches: (1) complex networks and (2) simulation/optimization-based endeavours, leading to simplistic topological models or non-scalable methods/significant data requirements. Based on our well-tuned simulation algorithms and data management, we estimate the resilience of major MARs worldwide. The major contribution of our study is the proposition of the so-called Multiple Airport Region Resilience Index (MARRI), a simulation-based approach that measures the disruptive impact of airport closure on the population inside the MAR, measured through two aspects: Loss In Connectivity (LIC) and Travel Time Increase (TTI). Loss in connectivity refers to the reduction in the fraction of airports that are directly or indirectly reachable due to an outage

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https://doi.org/10.1016/j.jatrs.2025.100064
Received 23 January 2025; Received in revised form 7 February 2025; Accepted 7 February 2025
Available online 16 February 2025

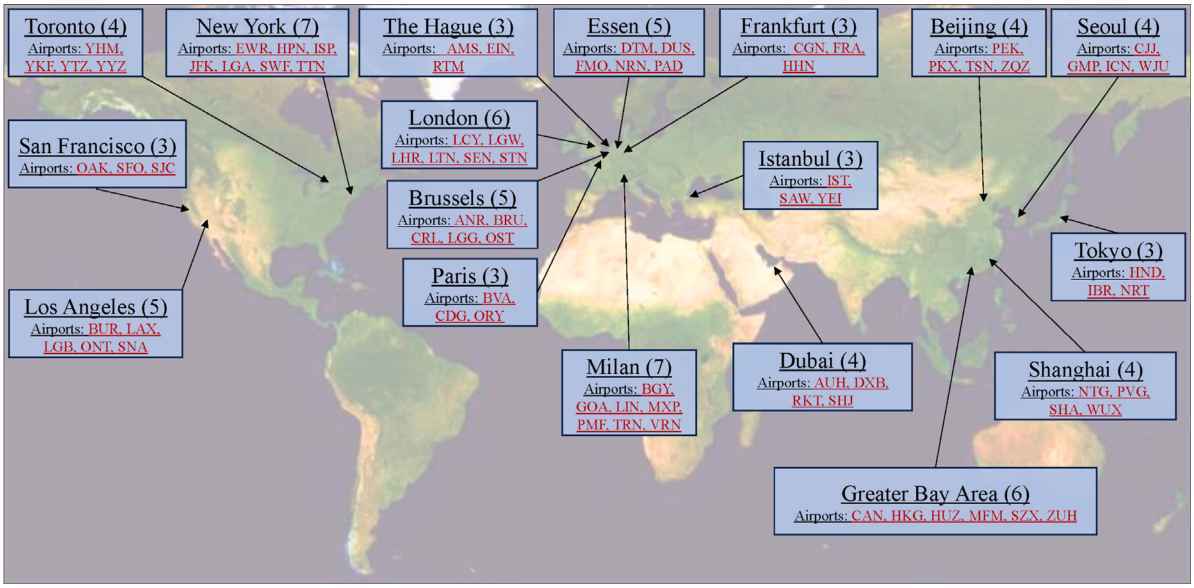

Fig. 1. Overview on multiple airport regions worldwide consisting of more than two airports. Airports are represented by the IATA-codes. The number in brackets indicates the total number of airports in the MAR.

at an individual airport, disrupting the MAR's overall reachability. Travel time increase measures the additional passenger-weighted time incurred when travelers must reroute to (still-accessible) destinations, reflecting the inefficiency introduced by longer, indirect travel routes. These two metrics, LIC and TTI, are essential, complementary measures of resilience for MARs when individual airports face disruptions. MARRI is evaluated based on global air transportation data, covering all single/multiple leg passenger itineraries between January 1st, 2023, and December 31st, 2023. Altogether, MARRI provides a comprehensive picture of a MAR's resilience. A MAR with low connectivity loss and minimal travel time increase demonstrates a robust ability to handle disruptions and maintain smooth operations despite unexpected challenges. Accordingly, our metrics help to make informed decisions on infrastructure development, contingency planning, and network optimization, ensuring that airport systems can withstand and quickly recover from individual airport outages without significantly affecting overall performance.

The remainder of this study is structured as follows. Section 2 reviews the extant literature on airport resilience, with a particular focus on MARs. Section 3 introduces the methodology and data used throughout our study. Section 4 reports on the experimental results. Section 5 concludes our study, discusses inherent limitations, and provides a set of recommendations for future research.

2. Literature review

Air transport networks, as highly interconnected systems, are vulnerable to disruptions like severe weather, technical failures, terrorist attacks, and pandemics, leading to flight delays, cancellations, and regional shutdowns. Accordingly, the resilience of air transport networks has become a vital research area (Sun & Wandelt, 2021). Resilience includes rapid recovery (Janić, 2019), impact minimization (Thompson & Tran, 2019), optimized resource allocation (Baspinar et al., 2021), and emergency response adjustments (Janić, 2015), such as rerouting flights. Enhancing resilience is essential for improving the network's anti-risk capabilities. Defined as the ability to maintain function amid disruptions (Wang et al., 2019), resilience encompasses rapid response, impact mitigation, and operational recovery. Common evaluation metrics include network topology, connectivity, and recovery speed (Pan et al., 2021; Wang et al., 2020). Resilient networks maintain connectivity even when nodes or edges fail (Zhou & Chen, 2020). Improved resilience allows networks to mitigate operational losses, ensure safety, and reduce cascading disruptions (Dunn & Wilkinson, 2016; Xu & Zhang, 2022).

With globalization and metropolitan area growth, MARs have emerged, exhibiting unique advantages over single-airport systems. Compared to single-airport systems, MARs enhance air transport resilience by dispersing risks across multiple facilities. For example, in the Beijing-Tianjin-Hebei region, New York Metropolitan Area, and the Guangdong-Hong Kong-Macao Greater Bay Area, MARs address growing aviation demand, capacity constraints, and emergencies effectively (Chen et al., 2024; Liao et al., 2019; Teixeira & Derudder, 2021). Unlike single-airport systems where disruptions can cascade through the network, MARs redistribute operational pressure when individual airports face constraints (Li & Hansen, 2021). Key strategies for enhancing MAR resilience include flight redirection, time coordination, and resource optimization. Flight redirection transfers flights to nearby airports during capacity issues (Hu et al., 2007), while time coordination synchronizes schedules across airports to minimize delays and disruptions (Liu et al., 2017). These strategies improve resilience against adverse weather, capacity limitations, and route disruptions. MARs enhance resilience through coordinated operations, mitigating challenges like flight disruptions, adverse weather, and capacity constraints (Sun et al., 2024b). Unlike standalone airports, MARs leverage shared resources and collaborative strategies to handle disruptions more effectively. As global aviation hubs grow increasingly complex, studying MARs' resilience has gained prominence (Li et al., 2023; Qian & Zhang, 2022; Sun et al., 2024a). Cross-airport collaboration within MARs strengthens anti-risk capabilities, ensuring smoother operations and bolstering the resilience of the broader air transport network. Recent studies have advanced the understanding of MAR resilience. Bai (2022) analyzed airport alliances in North China, showing a small-world network structure that facilitates efficient connectivity but highlights vulnerability to airport failures. Similarly, Chen and Sun (2024) examined disruptive events' impacts, identifying critical factors that enhance MARs' resilience. Liang et al. (2023) assessed air traffic control networks in North China using efficiency metrics to evaluate static robustness. These works underscore the importance of network structure and response strategies in maintaining stability during disruptions. Research often employs multi-layer coupling network models to study MAR resilience. These models analyze interconnections between airport layers, simulating recovery processes after disruptions.

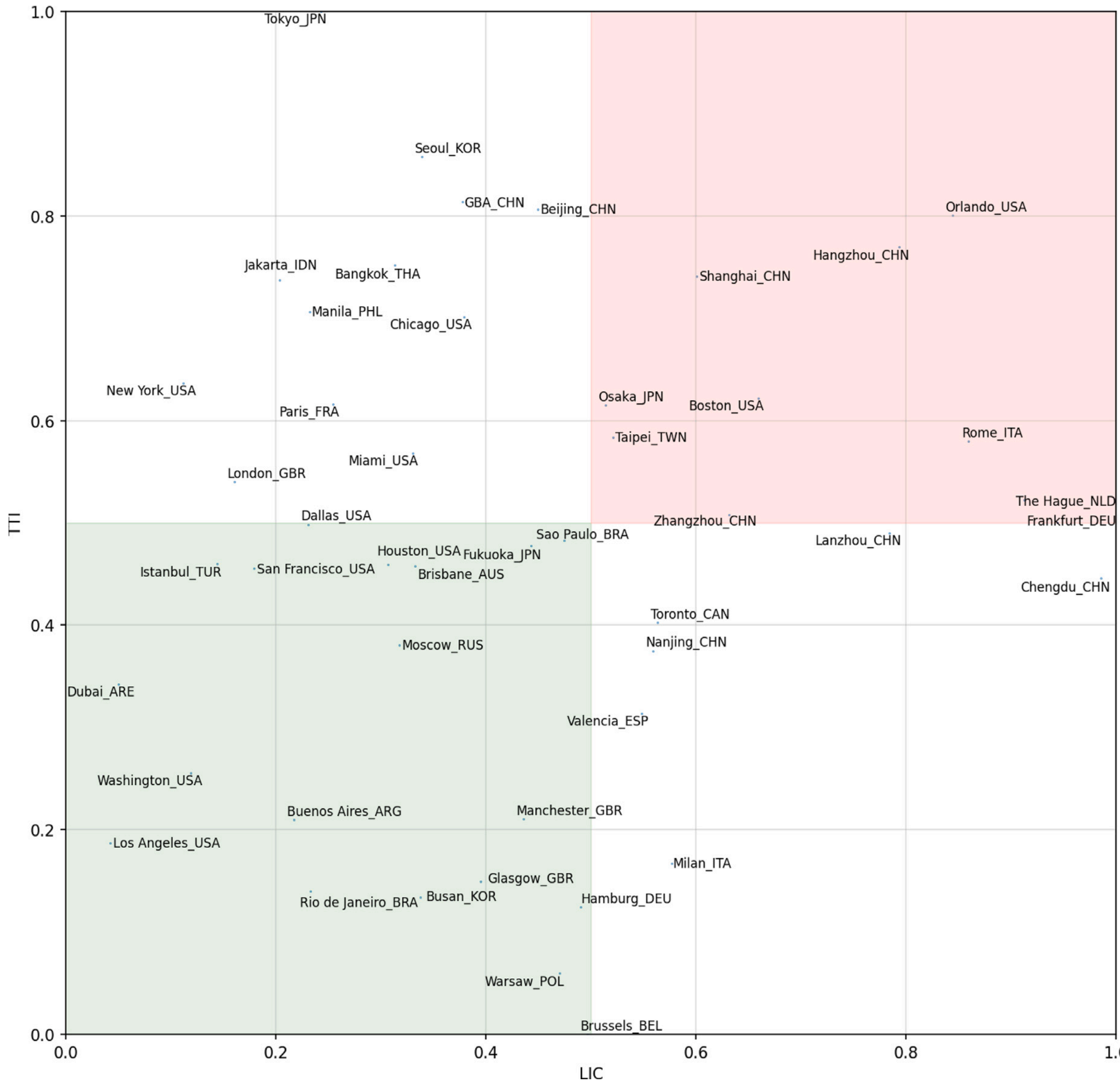

Fig. 2. Scatter plot of loss in connectivity (LIC) versus travel time increase (TTI).

For example, Fan et al. (2024) proposed a Node Congestion Cascading Failure model with higher-order rewiring strategies to enhance robustness in European multilayer networks. Zhang et al. (2019) highlighted strong internal connections within Belt and Road aviation networks, emphasizing the role of bridging layers in recovery. Such models enable evaluation of recovery strategies under diverse scenarios, such as airport closures and flight cancellations. Collaboration and resource sharing are central to MAR resilience. Information sharing on flight status, capacity, and airspace resources facilitates swift emergency responses (Wu et al., 2023). Flight schedule optimization and coordinated resource allocation enhance operational efficiency (Hou, 2021). Studies of London's MAR emphasize competitive and cooperative dynamics, demonstrating that resilience depends on inter-airport coordination and destination allocation (Sun et al., 2020). During extreme weather events, such as typhoons, MARs effectively mitigate delays through collaboration and resource sharing (Chen et al., 2020; Hao et al., 2015). These findings highlight the critical role of MAR cooperation in ensuring resilient air transport networks.

Overall, research on the resilience of MARs has gained significant attention due to their unique characteristics and advantages over traditional single-airport systems. However, existing studies at global scale predominantly use simplified concepts based on complex networks or consider direct connections/destination overlaps to assess the resilience. Other work which analyzes MARs in greater detail, is usually spatially constrained, since the required data is not available at global scale.

3. Methodology

The key question of our resilience measure is: How does an airport provide connectivity inside a MAR by providing access to domestic and international destinations. Following the work in Wandelt et al. (2024), we first define a few mathematical preliminaries which lead to the definition of our Multiple Airport Region Resilience Index (MARRI) indicator. Let I be a set of itineraries, such that each itinerary $i \in I$ is a tuple (o_i, d_i, p_i, r_i) where:

- o_i represents the origin of the itinerary i,
- d_i represents the destination of the itinerary i,
- p_i represents the number of passengers taking the itinerary i,
- r_i represents the route of itinerary i, consisting of a sequence of n nodes $r_i = [x_i^1, \dots, x_i^n]$. The first element x_i^1, corresponds to o_i and the last element x_i^n corresponds to d_i.

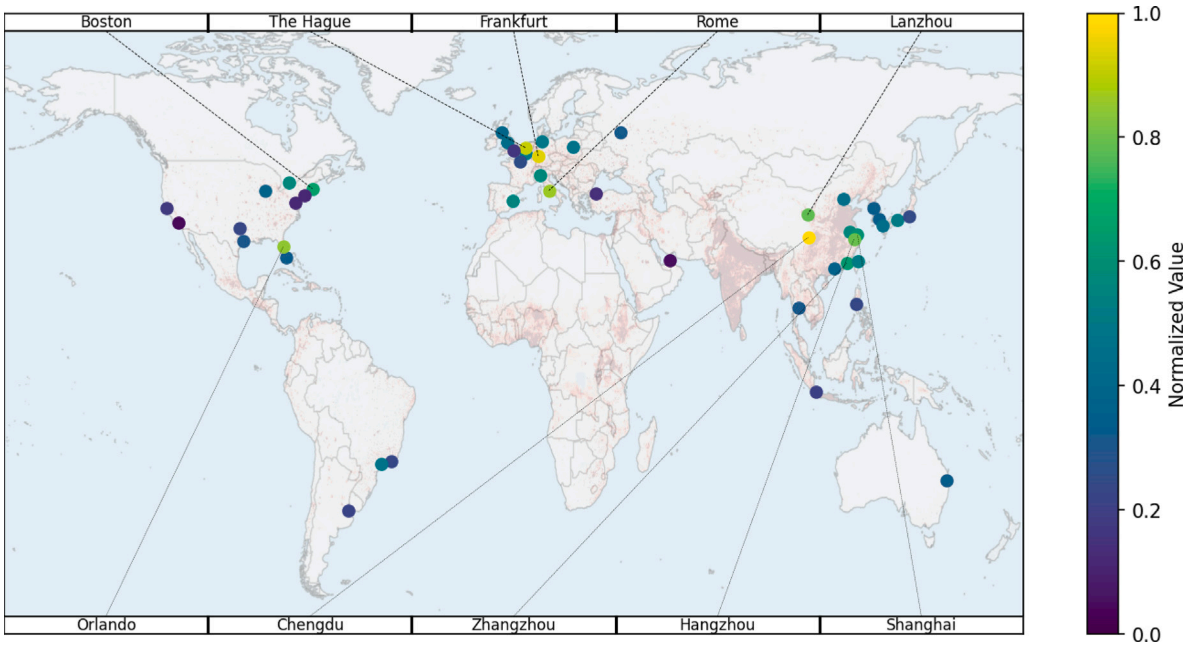

Fig. 3. Map visualizing the loss in connectivity of MARs under airport outage.

We distinguish two types of itineraries in this study. The first type of itinerary is called *air-side itinerary*, denoted by I^{air}, where each x_i^j consists of an airport. The set of air-side itineraries is obtained from Sabre Market Intelligence,[1] leading to a collection of passenger OD (origin–destination itineraries), including intermediate stops. While only about 20% of these itineraries consist of a single direct flight from origin to destination, these direct itineraries cover about 85% of all passenger trips worldwide. All air-side itineraries I^{air} are used as a foundation for the passenger flow in the undisrupted global air transportation system. An air-side itinerary i becomes disrupted if the destination airport $d_i \in r_i$ is disrupted, since we are concerned with the access of passengers to the air-side network of a MAR. Under a disruption, a feasible alternate itinerary need to be identified and its impact estimated, leading to a resilience MAR indicator.

Defining MAR resilience indicator without consideration of ground transportation would be oversimplified. Therefore, we extend the definition of air-side itineraries to *air-ground itineraries* in order to capture passenger choice in real-world transportation. Intuitively, the major difference to air itineraries is that r_i can now also contain nodes on the ground, mainly covering the catchment area of airports inside the MAR. Following related studies on multiple airport regions (Sun et al., 2017), we take a threshold of 1.5 h driving time as a cut-off to compute the relevant catchment area around an airport. Specifically, we use the Gridded Population of the World[2] at 2.5 min as resolution for input. Each grid cell in this dataset is annotated with the latitude/longitude and population density of the cell.[3] We use Openstreetmap to extract the worldwide ground transportation infrastructure; see Wandelt et al. (2023) for details of the network extraction procedure.

We obtain for each airport in a MAR a population-weighted catchment area grid with realistic driving times and driving routes from the airport. We denote the nodes belonging to the population-weighted catchment area of an airport ap with $catch(ap)$. In the next step, we extend the air-side itineraries I^{air} to air-ground itineraries $I^{air,ground}$. There are two major differences between I^{air} and $I^{air,ground}$. First, the r_i sequence does not only contain airports as elements but also ground transportation nodes. Second, the passengers in $I^{air,ground}$ are weighted according to the relative population density of the grid cell and distance from the airport, compared to all grid cells in the population-weighted catchment area of the airport, since we cannot determine the actual start of a passenger itinerary on the ground transportation network. This study introduces a probabilistic framework to estimate air-ground itineraries by integrating air-side trajectories with ground transportation networks. Below we provide a summary; for details see Wandelt et al. (2024). Using airport catchment areas, the framework dissects flows between airports into detailed passenger itineraries based on population density and driving distance, adhering to gravity model principles. Ground travel times are derived from OpenStreetMap data, while air-side times include scheduled flight durations with added overheads for boarding and waiting. The approach preserves the total passenger count across all itineraries, ensuring consistency with real-world data. Airport closures are modeled by removing affected airports from the network and recalculating itineraries. The framework emphasizes travel time increases caused by disruptions, highlighting the negative impacts on accessibility. Although scalable to large datasets, the method simplifies certain complexities, such as time-of-day variations and partial closures, which could be explored in future research. This framework provides a holistic view of air and ground travel, offering insights into passenger rerouting, resilience planning, and policy evaluation.

To simulate the outage of an airport in a MAR, we perform the following steps for each air-ground itinerary which starts with ap as the origin airport and denote these itineraries as U. This gives us a baseline for estimated population-weighted travel times from the airport catchment area of ap to all destinations in an undisrupted scenario. Next, we temporarily remove all air edges involving ap from the current air-ground network, essentially forbidding any flights via the airport ap. Then, for each air-ground trajectory in $jk \in U$, we (re)compute the shortest path from o_{jk} to d_{jk} in the disrupted network, i.e., avoiding the usage of ap, passing other airports in the MAR, obtaining the recovered itineraries R. Finally, we compute the travel times for all air-ground itineraries without using ap, we denote the obtained travel time difference (recovered travel time minus undisrupted travel time) of recovered itinerary jk with $ttd(jk)$. The idea underlying the computation of *MARRI* is to estimate two aspects:

[1] https://www.sabre.com/products/suites/data-and-analytics/sabre-intelligence-exchange-ix/

[2] https://sedac.ciesin.columbia.edu/data/collection/gpw-v4

[3] Technically speaking, the dataset is stored in GeoTIFF format, which allows to extract population densities from specific latitude/longitude pairs.

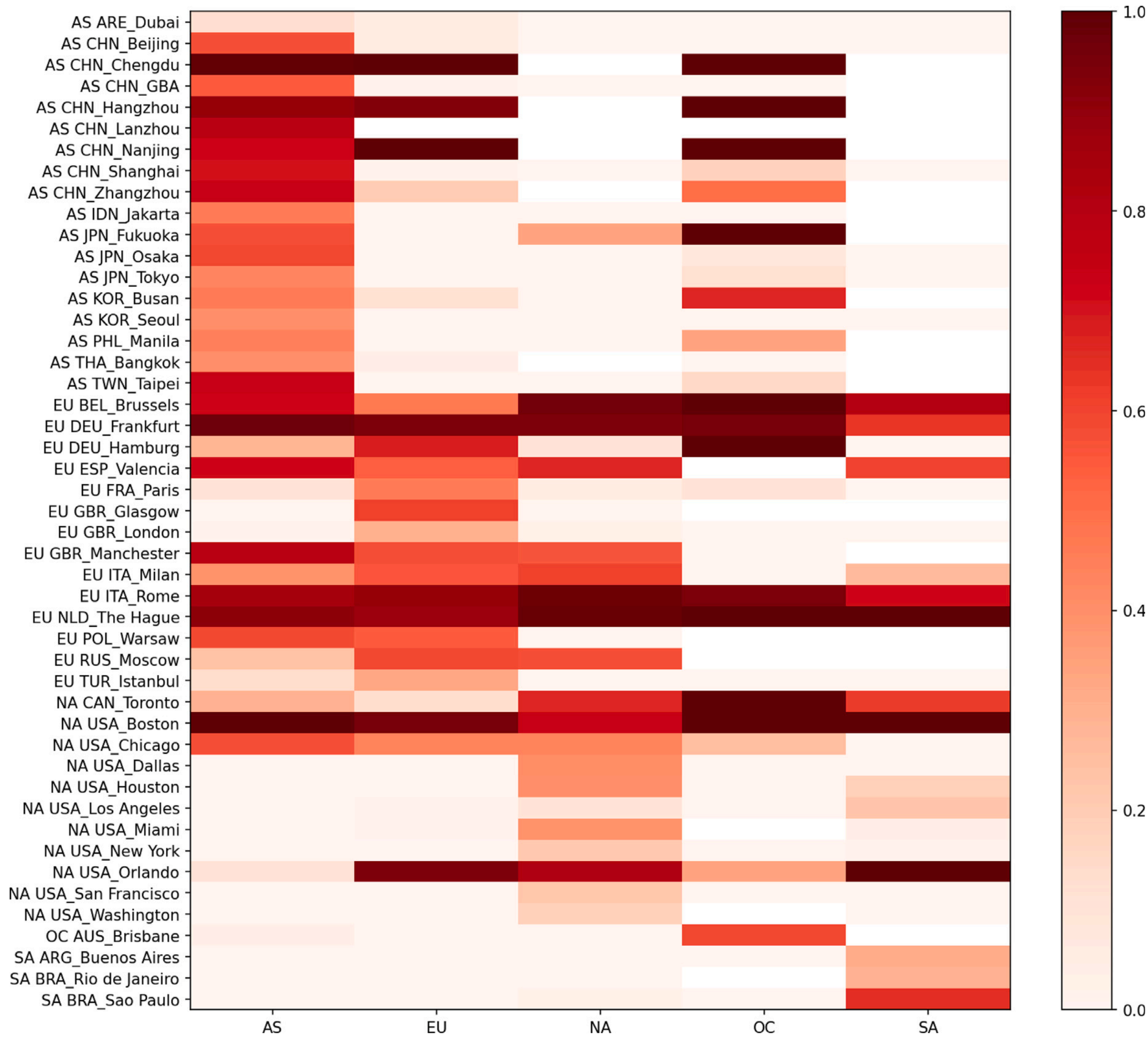

Fig. 4. Regional aggregation of loss in connectivity.

1. **Loss In Connectivity (LIC)**: The reduction in the fraction of airports that are directly or indirectly accessible due to an outage at an individual MAR airport, disrupting the MAR's overall accessibility. The LIC is computed by taking the fraction of air-ground itineraries in U which have no route in the disrupted network. The resulting value is between 0.0 (all destinations can still be reached) and 1.0 (the MAR is completely disconnected).
2. **Travel Time Increase (TTI)**: The additional passenger-weighted time incurred when travelers must reroute to still-accessible destinations, reflecting the inefficiency introduced by longer, indirect travel routes. The TTI is computed based on all still-reachable air-ground itineraries in U, by summing up the incurred passenger-time increases $p_{jk} * ttd(jk)$.

Finally, we define the Multiple Airport Region Resilience Index (MARRI) of a MAR as follows, where MAP^{ap} denotes the set of airports in the MAR:

$$LIC(MAR) = \frac{\sum_{\{ap \in MAP^{ap}\}} LIC(ap)}{len(MAP^{ap})}$$

$$TTI(MAR) = 1 - \frac{1}{log(\frac{\sum_{\{ap \in MAP^{ap}\}} TTI(ap)}{len(MAP^{ap})})}$$

$$MARRI(MAR) = \frac{1}{LIC(MAR) + TTI(MAR)}$$

Intuitively, MARs with a large MARRI will have a combination of small LIC and TTI, meaning that they are very resilient against disruptions at single airports. For MAR with high MARRI, on the other hand, many destinations either become unreachable or the remaining destinations incur large travel time increases.

4. Experiments

Table 1 (in Appendix) provides an overview of MARs worldwide investigated in our study, covering key metropolitan areas with their corresponding airports. Each entry includes an ID, the MAR name, the country, and a list of airports – with their IATA codes – associated with the region. The MARs span diverse geographical areas, showcasing both established and emerging global aviation hubs. For example, the Greater Bay Area (GBA) in China includes a dense cluster of major airports such as Hong Kong (HKG) and Shenzhen (SZX). Similarly, London in the United Kingdom encompasses six airports, including Heathrow (LHR) and Gatwick (LGW), emphasizing its status as a leading global aviation center. Notably, some regions, like New York (USA) and Beijing (CHN), demonstrate high airport density, with seven and four airports respectively, reflecting their critical roles in facilitating domestic and international connectivity. The table also highlights regional hubs with fewer but strategically important airports, such as Rome (Italy) and Jakarta (Indonesia). Additionally, the inclusion of smaller

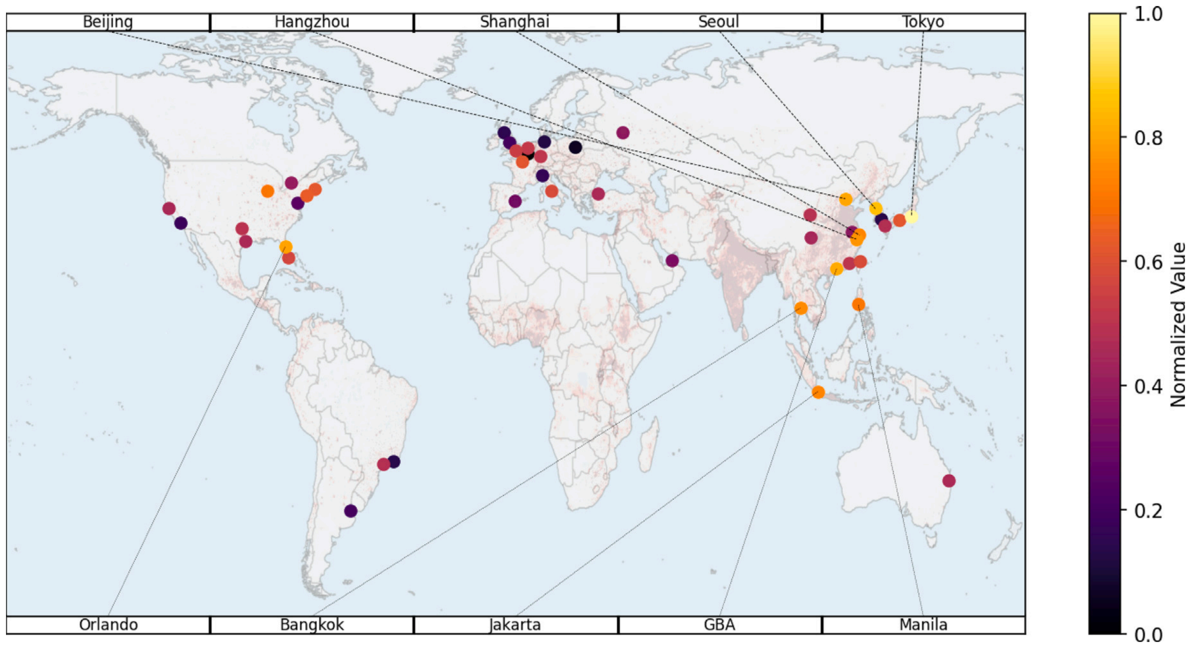

Fig. 5. Map visualizing the travel time increase of MARs under airport outage.

airport regions like Zhangzhou (China) with two airports indicates the study's broad scope in evaluating regions of varying sizes and connectivity levels.

Fig. 2 evaluates the resilience of MARs to airport outages, using TTI on the x-axis and LIC on the y-axis. The figure enables to categorize the resilience of MAR based on their position. Cities like Orlando and Hangzhou are in the top-right quadrant, showing both high LIC and TTI, indicating significant network vulnerability. In contrast, regions such as Los Angeles, Dubai, and Washington in the bottom-left quadrant exhibit low LIC and TTI, suggesting strong network resilience. Other cities, such as Frankfurt, Rome, and Chengdu, in the top-left quadrant show high LIC but manage to keep TTI relatively low, indicating a capacity to mitigate travel time impacts despite accessibility losses. Conversely, regions such as Jakarta, New York, and San Francisco, in the bottom-right quadrant, maintain lower LIC but at the cost of higher TTI. The implications of this analysis reveal important insights into MAR resilience. Cities in the top-right quadrant, with both high LIC and TTI, require significant improvements to enhance network robustness. These regions may benefit from strategies like adding redundancy in routes or diversifying airport roles to reduce dependency on specific hubs. In contrast, regions in the bottom-left quadrant represent models of resilience, maintaining both connectivity and efficiency during disruptions. For cities like Frankfurt or Chengdu, where LIC is high but TTI remains low, strategies that focus on improving indirect connectivity or backup transport options could further enhance their resilience. Meanwhile, cities like Jakarta and New York, which have relatively low LIC but higher TTI, could benefit from measures that streamline rerouting processes to reduce travel time penalties. Overall, the chart underscores the need for tailored strategies to improve resilience, balancing both connectivity preservation and travel time efficiency across diverse airport regions.

Fig. 3 illustrates the loss in connectivity under airport disruption for MARs in our study. Each dot on the map corresponds to an MAR, with the color indicating the loss of connectivity. The values range from 0.0 (indicating no loss) to 1.0 (indicating maximal connectivity loss), as represented by the color bar on the right. The geographic variation in connectivity loss reveals significant differences in resilience among MARs. Asian MARs such as Lanzhou, Chengdu, and Hangzhou show higher values, indicating that disruptions in these regions lead to substantial connectivity reductions. This is likely due to their reliance on a smaller number of critical airports or routes, which creates bottlenecks when disruptions occur. Conversely, some European MARs generally exhibit lower normalized losses, reflecting their robust integration into the broader European air transportation network, where multiple alternative routes and hubs exist to absorb the impacts of localized disruptions. North American MARs display moderate connectivity losses, highlighting some resilience due to their integration with other hubs but also some vulnerability stemming from regional dependency on key airports. In the Asia-Pacific region, MARs exhibit more significant losses, particularly in emerging regions like Zhangzhou, where network redundancy is limited compared to larger hubs like Shanghai. The figure highlights the uneven impacts of airport disruptions on global connectivity, emphasizing the importance of redundant and integrated airport networks for mitigating the effects of disruptions.

Fig. 4 visualizes the loss of connectivity under airport disruptions on a continental aggregation. The y-axis lists the MARs, sorted by their geographic regions, while the x-axis shows the five continental destinations: Asia (AS), Europe (EU), North America (NA), Oceania (OC), and South America (SA). The color intensity represents the extent of connectivity loss, ranging from white (minimal loss) to dark red (severe loss). The figure highlights significant variations in connectivity resilience across MARs and their respective continental destinations. For Asian MARs, such as Chengdu, Hangzhou, and Lanzhou, disruptions result in severe connectivity losses, especially for routes within Asia, indicating a high reliance on regional connections with limited redundancy. Major hubs like Shanghai and Beijing display more moderate losses due to their robust network integration. Similar trends are visible in European MARs. Cities like Frankfurt, Paris, and London exhibit moderate connectivity losses across all continents, demonstrating their capacity to absorb disruptions due to their strong intercontinental linkages. However, smaller MARs such as Hamburg and The Hague experience higher losses, particularly within Europe. In North America, major hubs like New York, Chicago, and Los Angeles show moderate disruption impacts, thanks to their extensive domestic and international connections. In contrast, Orlando and Dallas exhibit greater losses, indicating vulnerabilities in their regional network structures. Oceania (e.g., Brisbane) and South American MARs (e.g., Buenos Aires and São Paulo) generally show limited connectivity losses, partly due to their smaller-scale networks and fewer intercontinental linkages. This figure reveals that disruptions tend to have the most significant impact on

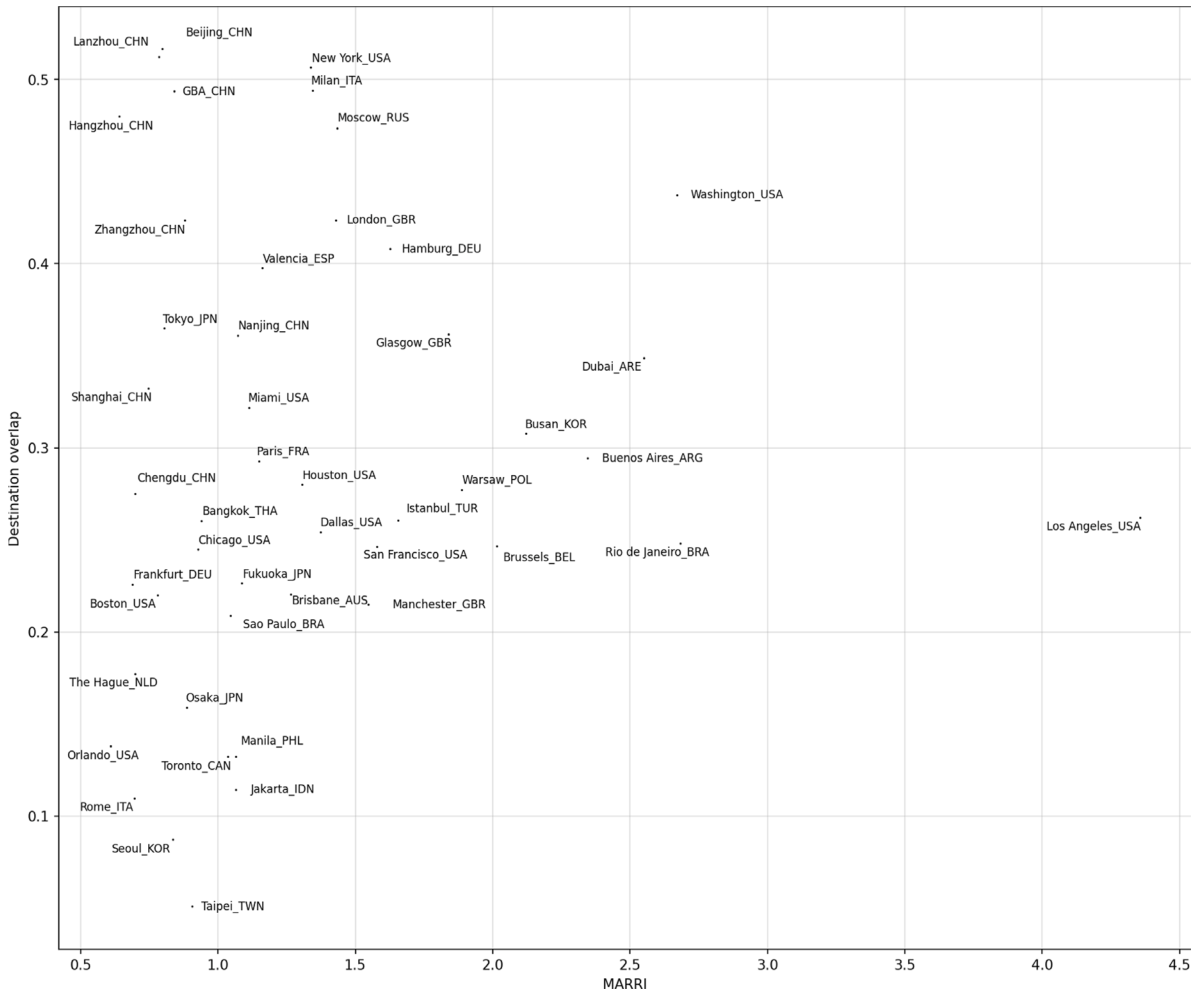

Fig. 6. Correlation between MARRI and destination overlap.

intra-regional connections, especially in less integrated MARs. Global hubs with diversified route networks, such as Frankfurt and New York, exhibit greater resilience.

Fig. 5 presents a global map illustrating normalized travel time increases under airport disruption scenarios for MARs in our study. Each colored dot on the map represents an MAR, with the color intensity indicating the normalized value of travel time increases, ranging from 0.0 (minimal impact) to 1.0 (maximum impact), as shown in the accompanying color bar. The dashed lines connect the most vulnerable MARs with their names. The geographic distribution of resilience is evident, with MARs in Asia, North America, and Europe exhibiting varying levels of vulnerability. Regions such as Tokyo and Seoul show relatively high normalized values, indicating that disruptions in these regions lead to significant increases in travel times. Conversely, some MARs in Western Europe, demonstrate lower normalized travel time increases, reflecting better resilience due to alternative routes or higher connectivity. While regions in Asia, such as Beijing and Shanghai, are critical nodes in the global air transportation network, their higher normalized values suggest a greater dependency on specific airports, making them more vulnerable to disruptions. Overall, the map provides a visual summary of how disruptions propagate differently across the global air transportation network.

Fig. 6 illustrates the correlation between MARRI and a simpler destination overlap measure, as defined in prior literature (Sun et al., 2017). A slightly positive trend can be observed, where regions with higher destination overlap tend to have higher MARRI values, indicating that greater redundancy in destination coverage may contribute to resilience. However, notable variations are present. For example, Los Angeles, USA, stands out with a significantly high MARRI score compared to its destination overlap, suggesting that factors beyond simple redundancy – such as robust alternative routes or operational coordination – enhance its resilience. Conversely, Taipei, TWN, exhibits a low destination overlap and correspondingly low MARRI, indicating limited redundancy and resilience. Regions like Washington, USA, and Dubai, ARE, are interesting cases, as their relatively high destination overlap does not proportionally translate into very high MARRI scores, highlighting potential limits to redundancy's role. Conversely, regions such as GBA and Beijing balance moderately high MARRI and destination overlap values, showcasing resilience through a mix of redundancy and other supporting factors. The figure underscores the importance of considering comprehensive indices like MARRI for evaluating MAR resilience. While destination overlap provides a quick approximation of redundancy, MARRI offers a deeper perspective by capturing the operational and temporal dimensions of airport network disruptions. This dual evaluation approach helps identify specific areas where resilience strategies can be targeted, emphasizing the multifaceted nature of airport network robustness.

5. Conclusions

In this study, we have developed a Multiple Airport Region Resilience Index (MARRI) that is composed of the loss in connectivity (LIC) and travel time increases (TTI) under airport disruptions. We believe that MARRI provides a comprehensive understanding of the vulnerabilities in global air transportation networks, with implications for

Table 1
Multiple airport regions investigated in this study.

ID	Name	Country	Airports
Bangkok_THA	Bangkok	THA	[BKK,DMK]
Beijing_CHN	Beijing	CHN	[PEK,PKX,TSN,ZQZ]
Boston_USA	Boston	USA	[BOS,MHT,PVD]
Brisbane_AUS	Brisbane	AUS	[BNE,MCY,OOL,WTB]
Brussels_BEL	Brussels	BEL	[ANR,BRU,CRL,LGG,OST]
Buenos Aires_ARG	Buenos Aires	ARG	[AEP,EZE]
Busan_KOR	Busan	KOR	[HIN,KPO,PUS,TAE,USN]
Chengdu_CHN	Chengdu	CHN	[CTU,MIG]
Chicago_USA	Chicago	USA	[MDW,ORD]
Dallas_USA	Dallas	USA	[DAL,DFW]
Dubai_ARE	Dubai	ARE	[AUH,DXB,RKT,SHJ]
Frankfurt_DEU	Frankfurt	DEU	[CGN,FRA,HHN]
Fukuoka_JPN	Fukuoka	JPN	[FUK,HSG,KKJ,KMJ]
GBA_CHN	GBA	CHN	[CAN,HKG,HUZ,MFM,SZX,ZUH]
Glasgow_GBR	Glasgow	GBR	[EDI,GLA]
Hamburg_DEU	Hamburg	DEU	[BRE,HAJ,HAM]
Hangzhou_CHN	Hangzhou	CHN	[HGH,NGB,YIW]
Houston_USA	Houston	USA	[HOU,IAH]
Istanbul_TUR	Istanbul	TUR	[IST,SAW,YEI]
Jakarta_IDN	Jakarta	IDN	[CGK,HLP]
Lanzhou_CHN	Lanzhou	CHN	[LHW,XNN]
London_GBR	London	GBR	[LCY,LGW,LHR,LTN,SEN,STN]
Los Angeles_USA	Los Angeles	USA	[BUR,LAX,LGB,ONT,SNA]
Manchester_GBR	Manchester	GBR	[LPL,MAN]
Manila_PHL	Manila	PHL	[CRK,MNL]
Miami_USA	Miami	USA	[FLL,MIA]
Milan_ITA	Milan	ITA	[BGY,GOA,LIN,MXP,PMF,TRN,VRN]
Moscow_RUS	Moscow	RUS	[DME,SVO,VKO,ZIA]
Nanjing_CHN	Nanjing	CHN	[CZX,NKG,YTY]
New York_USA	New York	USA	[EWR,HPN,ISP,JFK,LGA,SWF,TTN]
Orlando_USA	Orlando	USA	[MCO,SFB]
Osaka_JPN	Osaka	JPN	[ITM,KIX,SHM,TKS,UKB]
Paris_FRA	Paris	FRA	[BVA,CDG,ORY]
Rio de Janeiro_BRA	Rio de Janeiro	BRA	[GIG,SDU]
Rome_ITA	Rome	ITA	[CIA,FCO]
San Francisco_USA	San Francisco	USA	[OAK,SFO,SJC]
Sao Paulo_BRA	Sao Paulo	BRA	[CGH,GRU,VCP]
Seoul_KOR	Seoul	KOR	[CJJ,GMP,ICN,WJU]
Shanghai_CHN	Shanghai	CHN	[NTG,PVG,SHA,WUX]
Taipei_TWN	Taipei	TWN	[TPE,TSA]
The Hague_NLD	The Hague	NLD	[AMS,EIN,RTM]
Tokyo_JPN	Tokyo	JPN	[HND,IBR,NRT]
Toronto_CAN	Toronto	CAN	[YHM,YKF,YTZ,YYZ]
Valencia_ESP	Valencia	ESP	[ALC,CDT,VLC]
Warsaw_POL	Warsaw	POL	[LCJ,RDO,WAW,WMI]
Washington_USA	Washington	USA	[BWI,DCA,IAD]
Zhangzhou_CHN	Zhangzhou	CHN	[JJN,XMN]

both operational management and policy-making. Our findings highlight a consistent pattern: disruptions tend to disproportionately affect regions with a high reliance on regional and hub-and-spoke connectivity structures, emphasizing the critical need for network diversification and redundancy in mitigating system-wide impacts.

The LIC analysis reveals disparities in the resilience of MARs across continents. Asian MARs, such as Chengdu, Lanzhou, and Hangzhou, exhibit severe connectivity losses due to their reliance on regional connections. Similarly, MARs like Hamburg and The Hague in Europe and Orlando in North America face significant LIC, underscoring their vulnerability to disruptions. In contrast, global hubs such as Frankfurt, New York, and Shanghai demonstrate greater resilience, with moderate LIC levels reflecting their diversified intercontinental route networks. The heatmap of LIC across MARs and continental destinations further highlights the critical role of network redundancy in absorbing shocks. Asian MARs, in particular, suffer pronounced connectivity losses for intra-regional travel, revealing a pressing need for investment in alternative routes and regional cooperation.

In parallel, the TTI analysis underscores the compounding impact of disruptions on passenger travel time. We found substantial increases in travel time for regions reliant on highly centralized or capacity-constrained hubs. For instance, Asian MARs like Lanzhou experience the highest TTI values, while other MARs such as Boston, Frankfurt, and The Hague display moderate increases due to their ability to reroute passengers through alternative connections. This reinforces the need for robust contingency planning, especially in regions with fewer alternative routes. The spatial distribution of TTI impacts also highlights the importance of fostering decentralized and well-integrated networks, particularly in rapidly growing regions where air traffic demand continues to rise.

From a managerial perspective, these results underscore the importance of strategic investments in air transportation infrastructure to enhance resilience. Operators and stakeholders should prioritize developing secondary airports and expanding point-to-point connections to reduce reliance on single hubs. Additionally, advanced disruption management systems and predictive models should be implemented to minimize the cascading effects of disruptions on passenger itineraries. Collaborative measures, such as inter-airline agreements and regional partnerships, can further enhance network flexibility and enable swift recovery. From a policy standpoint, the findings advocate for international cooperation to ensure equitable access to air transportation services. Vulnerable regions with pronounced LIC and TTI impacts, such as Asia and parts of Europe, would benefit from coordinated policies encouraging capacity sharing and network optimization. Policymakers should also encourage innovation in airport operations, ensuring that disruptions are managed without exacerbating environmental impacts.

Overall, MARRI offers a nuanced understanding of LIC and TTI under airport disruptions, providing actionable insights for both managers and policymakers. Future work should emphasize optimizing inter-airport coordination mechanisms and improving the efficiency of flight schedules to guarantee passenger safety and convenience during crises. Further research should include the use of data-driven decision support systems to enhance airport resilience. These systems can assist decision-makers in developing more flexible emergency response strategies and optimizing flight scheduling and resource allocation through real-time data analysis and prediction.

CRediT authorship contribution statement

Xiaoqian Sun: Writing – review & editing, Writing – original draft. **Wei Cong:** Writing – review & editing, Writing – original draft. **Kun Wang:** Writing – review & editing, Writing – original draft. **Jianliang Mu:** Writing – original draft, Writing – review & editing. **Xinyue Chen:** Writing – review & editing, Writing – original draft. **Sebastian Wandelt:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors report financial support was provided by National Natural Science Foundation of China. They authors have no other known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study is supported by the Beijing Natural Science Foundation, China (IS24035) and by the National Key Research and Development Program of China (Grant No. 2022YFB26024041).

Appendix

See Table 1.

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