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Assessing the Robustness of European and Chinese Air and High Speed Rail Network Accessibility

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ABSTRACT

Aviation and High-speed rail (HSR) are primary modes for continental long-distance travel. While their integration can significantly enhance systemic robustness, network topologies and governance models differ drastically between Air and HSR networks across regions. We conduct a quantitative, comparative robustness analysis of the aviation-only network against the integrated aviation-HSR network for both Europe and China. Using a multi-layer network representation of scheduled services, topological metrics and a schedule-based routing algorithm, the networks are subjected to simulated random airport failures, adaptive targeted hub attacks, and operational airline shutdowns. The results reveal that under random failures, both unimodal aviation networks exhibit similar topological decay. However, under targeted attacks, China's reliance on a highly concentrated hub-and-spoke system leads to an earlier topological collapse compared to Europe's decentralized, point-to-point network. Crucially, integrating the HSR layer fundamentally shifts this dynamic. China's unified HSR mega-grid acts as a safeguard that nearly halves topological vulnerability and preserves substantial service availability during major aviation disruptions. Conversely, Europe's fragmented HSR "patchwork" provides only marginal redundancy during aviation crises. While China can strategically leverage its HSR grid to mitigate disruptions in the aviation network, Europe must prioritize cross-border rail services to create a viable multimodal safety net for long-distance travel.

1 Introduction

The aviation sector is increasingly vulnerable to unexpected disruptions. These risks include modern security threats, such as drone incidents that sabotage airport operations for hours¹, as well as severe weather conditions, like the winter blizzards of January 2026 that canceled thousands of flights at Amsterdam Schiphol Airport². Similarly, sudden labor strikes can quickly bring to a halt operations at major hubs, leaving thousands of passengers stranded³. Furthermore, when a major airport fails, travel delays spread quickly across the continent, demonstrating the danger of relying on just one mode of transport.

High-speed rail (HSR) and aviation are the two primary modes for long-distance travel on a continental scale. Over the past few decades, HSR has become a highly competitive, low-carbon alternative to air travel, especially for medium distances of up to 1000 km^{4,5}. There is evidence to suggest that the introduction of HSR causes significant drops in air passenger volumes on competing corridors, particularly within the 500 to 800 km range⁴. While most related works looked at how these two modes compete, a review of recent studies points out how they might play complementary roles⁶. Connected HSR lines can act as vital feeders to major airports, expanding their geographic catchment areas^{7,8}. This helps passengers from smaller cities reach international flights more easily and thereby improves the whole transport system^{7,9}. Importantly, this integration has the potential to make the transport network much more robust¹⁰. If a main airport or rail hub fails, the other mode may provide a backup to keep cities connected.

Comparative studies have sought to bridge these conceptual gaps by evaluating and comparing service quality across these regions. On the aviation side, Paleari et al.¹¹ used a time-dependent approach to show that while China provides fast direct travel due to its network scale, the European network offers a highly equitable and homogeneous service across its primary and secondary airports. Wang et al.¹² show that peripheral airports in the Chinese air network bypass regional centers to connect directly to national mega-hubs. Complementing this functional perspective, Cai et al.¹³ examined the air route network in China, revealing that while the structural topology is relatively homogeneous in terms of degree and centrality metrics, operational traffic flows are extremely heterogeneous and highly concentrated on a small subset of trunk corridors. In regional comparisons, aviation networks in the US and EU often display distributed, point-to-point structures, whereas the Chinese network remains highly dependent on specific transit hubs¹⁴.

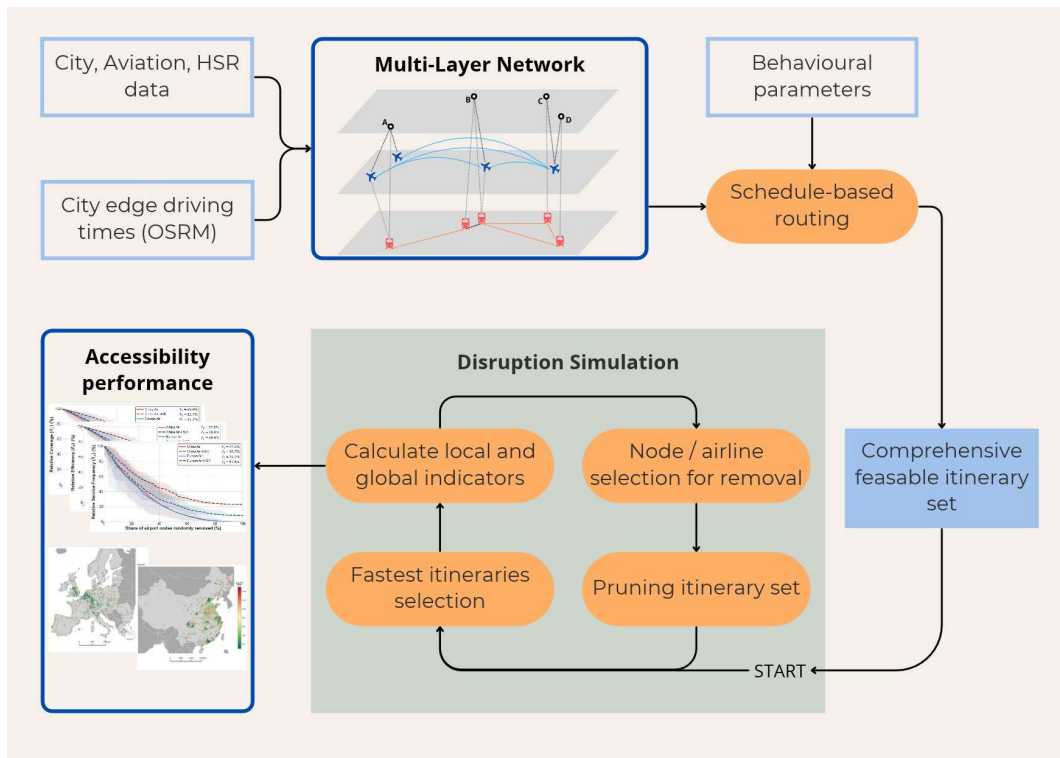


Figure 1– Methodological framework overview. Multimodal transport data and OSRM driving times form a Multi-Layer Network, which is evaluated via schedule-based routing and behavioral parameters to yield feasible itineraries. These itineraries are then iteratively pruned under node and airline disruptions to recalculate fastest paths and assess resulting accessibility performance.

A similar structural divergence is visible in rail infrastructure. The Chinese HSR grid has expanded rapidly under a centralized planning model, creating a highly connected, small-world system with a bimodal centrality distribution^{15,16}. Conversely, the fragmentation of the European HSR network creates major cross-border bottlenecks. Grolle et al.¹⁷ demonstrated the potential outcomes of a unified service planning approach. Borgogno et al.¹⁸ proposed an iterative network growth model, arguing that a centralized appraisal process is necessary to transition Europe away from domestic segments towards a cohesive continental system. Furthermore, advanced modeling techniques have assessed the vulnerability of these topologies.

The robustness of transport networks is commonly measured in terms of the performance loss in the event of disruptions by simulating a series of node or link failures. Past studies have simulated random failures and targeted attacks to study the robustness of metro^{19–21}, European²² and Chinese^{23,24} rail and the European^{22,25,26}, Chinese^{25,27,28} and global²⁹ aviation networks. Some of these works have moved beyond static topological representations to consider operations by integrating information about service lines and their frequencies, service delays or passenger demand, or by means of measuring disruption impacts in terms of accessibility rather than merely connectivity. Notwithstanding, a review article by Yoo et al.³⁰ concluded that accessibility measures in the air transport context remain heavily infrastructure-centric, commonly neglecting temporal and travel behavioral factors.

The potential added value offered by the joint consideration of HSR and air transport services has been the subject of investigation in a few recent studies. Qi et al.¹⁰ demonstrated that a multi-layered transport network incorporating both airports and rail hubs maintains significantly better connectivity and efficiency under targeted attacks than single-mode systems. The need to capture real-world operational realities within these assessments was emphasized by Zhou et al.²⁵, who demonstrated that incorporating flight frequencies and seat capacities fundamentally alters the identification of critical nodes and vulnerabilities to targeted attacks. In operational settings, Li et al.³¹ moved away from purely topological metrics in favor of service-based metrics like travel time and frequency. They showed that the Chinese HSR network provides a spatiotemporal complementary effect that preserves connectivity for non-hub airports during disasters. Exploring this multi-modal dynamic in the European context, Ippolito and Cats²² conducted a comparative analysis of air and rail networks across 124 metropolitan areas. By applying an iterative node removal strategy based on centrality metrics, the study revealed a significant disparity in robustness: the air network experienced only a 10% performance loss under worst-case disruptions, whereas the rail network

suffered a 71% loss. To address this disparity, a new metric was introduced to assess cities' reliance on aviation during rail failures, identifying a critical sub-graph of nodes whose protection is vital for maintaining the connectivity of the integrated European transport system.

While individual studies have explored how HSR can support aviation during localized shocks, it remains unknown how the two regions - a unified network topology (China) versus a decentralized one (Europe) - maintain regional accessibility for long-distance travel when faced with the same types of disruptions. This study bridges this gap by conducting a quantitative, comparative robustness analysis of the aviation-only network against the integrated aviation-HSR network for both Europe and China. Using a consistent set of topological metrics and robustness simulations - which include operational airline shutdowns alongside random airport failures and adaptive targeted hub attacks - we model the impact of large-scale airport closures to investigate how well the corresponding rail networks protect long-distance accessibility under stress. We employ accessibility-based metrics of Generalized Travel Time (GTT) which are obtained using a schedule-based routing algorithm. To ensure a reliable baseline, the transport layers are filtered by performance: the aviation layer consists of short-haul commercial passenger flights, while the rail layer focuses on premium high-speed services (the Chinese G-series and algorithmically speed-filtered European intercity services). By moving beyond single-mode or corridor-specific analysis, our approach allows for a direct comparison of how different network planning models contribute to continental transport robustness. An overview of the methodological framework is displayed in Figure 1.

2 Results

2.1 Baseline network topology and accessibility

The comparative analysis of the European and Chinese transport networks reveals fundamentally different operational architectures. While the European network encompasses fewer Functional Urban Areas (FUAs), i.e. 384 versus 672 in China, it possesses a higher absolute number of airports (238 versus 182). Conversely, the Chinese network relies heavily on its HSR infrastructure, featuring 593 stations compared to Europe's 375. These infrastructural differences dictate the distinct routing strategies and accessibility outcomes observed in the baseline multi-layer networks.

A mono-layer unweighted analysis of the aviation networks (i.e. only airports and flights) reveals that topological indicators demonstrate a rigid hub-and-spoke system in China. The network is characterized by strong disassortativity and a heavily concentrated diamond topology anchored by mega-hubs (which can be observed in Figure 2b). This structure funnels domestic traffic efficiently, resulting in short average path lengths: 2.49 in Europe versus 2.00 in China. The European aviation network shown in Figure 2a shows a softer hierarchy. Driven by the prevalence of Low-Cost Carriers (LCCs), Europe favors point-to-point regional connections. This yields a structurally sparser network that, despite its dense core around legacy hubs, imposes a slightly higher transfer penalty for cross-continent travel.

The mono-layer unweighted P-space representation of HSR services presents an even starker topological contrast. The Chinese HSR network (Figure 2d) operates as a large unified grid with a non-assortative routing strategy that distributes shortest-paths uniformly across parallel routes and major trunk-line junctions. Conversely, the European HSR network (Figure 2c) is severely fragmented into multiple disconnected components and relies on a rich-club topology where major hubs preferentially connect, frequently leaving secondary stations isolated and heavily dependent on specific structural bottlenecks.

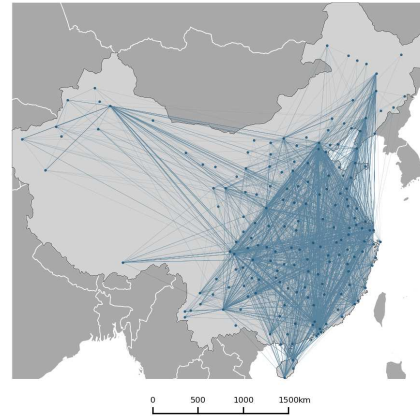
Transitioning to the integrated Air-HSR multi-layer networks highlights how these topological foundations impact Generalised Travel Time (GTT) and hence accessibility. In an aviation-only baseline, the two regions exhibit a clear trade-off between spatial coverage and travel speed (Fig. 3a and 3b). China achieves a higher average initial node coverage (91.36% compared to Europe's 88.13%). However, Europe achieves significantly lower average travel times (769 minutes GTT versus 830 minutes in China) mostly due to its smaller geographical footprint and regional density. Geographically, European accessibility is highly concentrated within the densely populated "Blue Banana" corridor and scattered national capital cities, leaving peripheral FUAs in Eastern Europe and Scandinavia with poor travel times. Conversely, Chinese aviation efficiency is concentrated strictly around the coastal hubs and the corners of its diamond-shaped topology, leaving the highly populated interior (e.g. the city cluster west of Zhengzhou) relatively disconnected.

The integration of the HSR layer fundamentally reshapes these dynamics, triggering a performance leap in China that outpaces Europe's more modest gains. While both regions see improved node coverage, the Chinese average multi-layer GTT drops sharply by 11.3% to 736 minutes, overtaking Europe (which drops only by 2.5% to 750 minutes). This integration reverses the baseline travel time advantage, driving the Chinese average travel time below that of Europe.

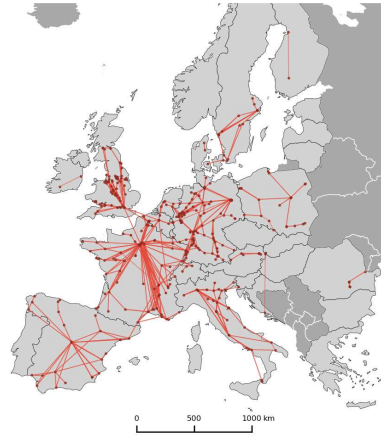
The relative difference maps (Figure 3c and 3d) unravel the varying network effects of this HSR integration. While the benefits of HSR remain geographically bounded by physical infrastructure constraints in both systems (leaving unconnected peripheral nodes almost completely unaffected) the functional role of the rail differs between the two regions. In Europe, most cities experience only marginal GTT improvements. HSR effectively acts as a local feeder to major aviation hubs, transforming the regional accessibility of specific well-positioned nodes like Poitiers and Tours, which gain crucial intermodal access to large airport hubs. In China, HSR serves as a strong stand-alone backbone. Entire clusters of inland cities experience transformative



(a) European Aviation Network



(b) Chinese Aviation Network



(c) European HSR Network



(d) Chinese HSR Network

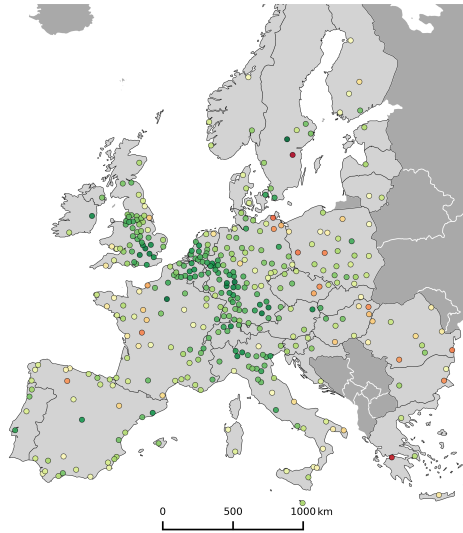
Figure 2– The aviation and HSR network baselines in Europe and China. For visualization purposes, HSR configurations are depicted via route sequences rather than projecting all FUAs between which there is at least one operating service, i.e. P-space.

travel time savings of up to 40%. Rather than primarily feeding airports, the Chinese rail grid acts as a high-speed substitute for regional aviation, significantly increasing the connectivity of the domestic interior.

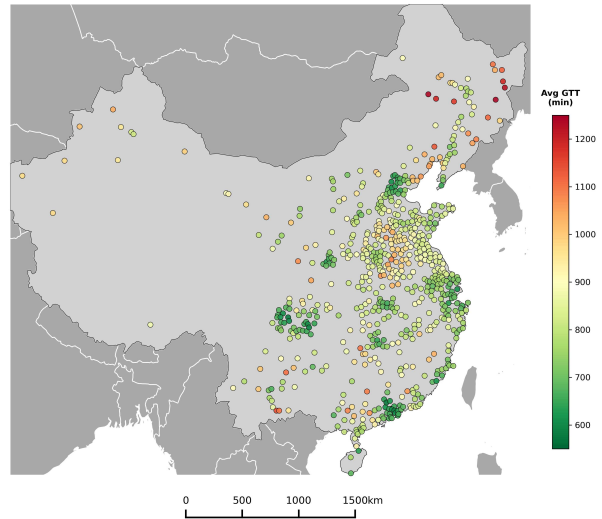
The modal share of schedule-based shortest paths and route-based centrality of the multi-layer model further expose critical network dependencies. Long-distance travel in Europe remains heavily air-dominated, accounting for 88% of fastest routes for all Origin Destination (OD) pairs in the network. European HSR functions primarily as a localized feeder to major aviation gateways: For none of the FUAs in Europe HSR emerges as the absolute dominant mode for any single European FUA for reaching its destinations. In contrast, the Chinese HSR system is much more prevalent in offering the prime connection between OD pair routes. Intermediate satellite cities (such as Zhumadian, Shancheng and Shangqiu) in China rely on HSR for over 60% of their fastest routes (i.e. HSR direct and indirect route share), explicitly demonstrating how the Chinese HSR network operates as the primary high-density backbone rather than a supplementary feeder.

2.2 Robustness against random and targeted airport disruptions

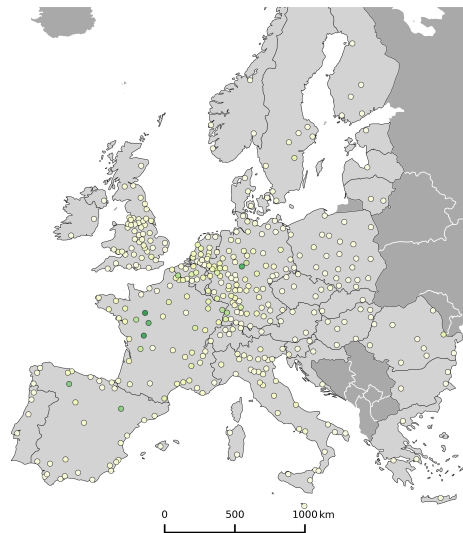
To evaluate network robustness, the baseline configurations were subjected to two distinct degradation simulations (Figure 4): a Random Failure (RF) scenario, which simulates uncoordinated, stochastic airport closures through Monte Carlo replications, and a Targeted Attack (TA) scenario, which simulates intelligent, adaptive disruptions by sequentially removing airports based on dynamic route Betweenness Centrality (BC). Network robustness was tracked across three dimensions: Network Average FUA Coverage (R_C), Weighted Global Efficiency (R_E), and service availability as measured by Effective Service Frequency (R_S).



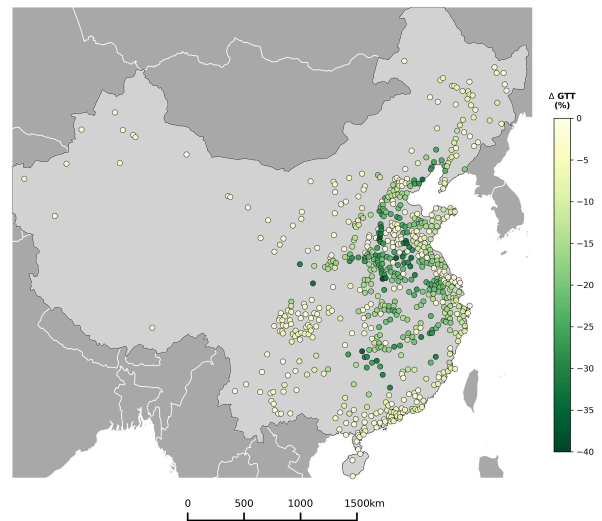
(a) Europe: Aviation-only GTT



(b) China: Aviation-only GTT



(c) Europe: Relative GTT decrease (Air-HSR)



(d) China: Relative GTT decrease (Air-HSR)

Figure 3— Spatial distribution of baseline accessibility. The top row depicts the absolute Generalized Travel Time (GTT) in the mono-layer aviation network. The bottom row displays the relative decrease in GTT experienced by each Functional Urban Area (FUA) upon the integration of the High Speed Rail (HSR) layer.

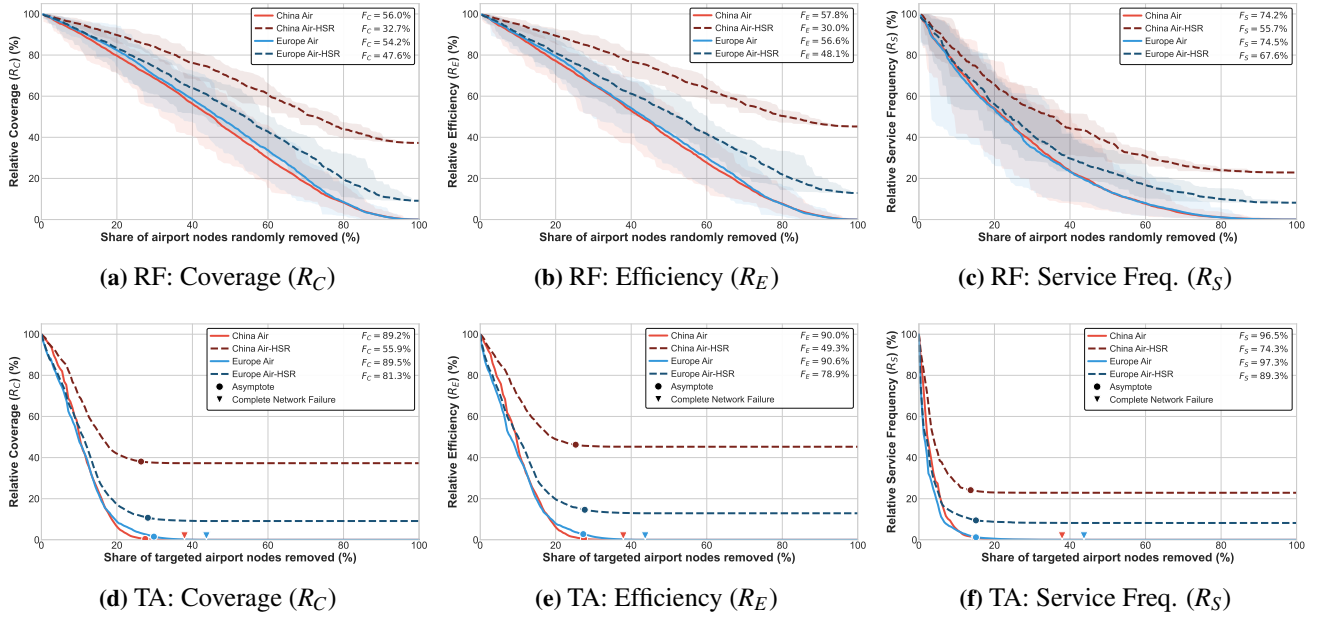


Figure 4—Comparative degradation profiles across topological and operational metrics. The top row depicts Random Failure (RF) scenarios, where shaded areas represent the min–max range across Monte Carlo simulation runs. The bottom row depicts adaptive Targeted Attack (TA) scenarios tracking the sequential removal of critical structural hubs, with their asymptotic behavior and complete network degradation points depicted in the lines. Solid lines indicate aviation-only Multi-Layer Network; dashed lines indicate integrated Air-HSR networks. The cumulative loss in performance F of each network is shown in the legend.

Across both degradation models, a stark divergence emerges between topological connectivity and actual service capacity, see Figure 4. While R_C and R_E degrade gradually, Effective Service Frequency (R_S) collapses more rapidly. This confirms that while a single surviving route can nominally maintain city-to-city coverage, the practical service capacity relies heavily on a small fraction of high-frequency major hubs.

Evaluating the FUA-aviation networks reveals distinct structural vulnerabilities. Under random failure, the European and Chinese air networks degrade at highly similar rates. However, under targeted attacks, the Chinese aviation network reaches a state of total topological collapse (a completely disconnected network) after just 37.9% of its nodes are removed, compared to 43.7% in Europe. Despite having fewer airports, China’s air system relies far more heavily on a highly concentrated set of core gateways to maintain cohesion. Once those fail, regional Chinese cities are instantly disconnected from the broader network.

The integration of the HSR layer changes these degradation trajectories considerably, serving as a safety net. In Europe, the integration of HSR provides a modest buffer, yielding roughly a 10 percentage point reduction in cumulative performance loss (F_C) under random failure. Conversely, the structural benefit of the Chinese rail grid is transformative. In China, HSR cuts the topological vulnerability almost in half under random failure (F_C drops from 56.0% to 32.7%) and heavily dampens the shock of targeted attacks (F_C drops from 89.2% to 55.9%). The residual capability of the networks further highlights this difference: in the event of 100% airport blackout scenario, Europe’s rail network alone maintains only 9.1% of baseline FUA coverage, whereas China’s large, highly interconnected HSR grid manages to preserve 37.3% of its initial OD pair connections.

The sequence of hub failures during the targeted attacks explains why this shielding effect differs so drastically. In Europe, the network’s primary bottlenecks (airport nodes with the highest route-based BC) do not change when adding the HSR layer. The top four target airports (Frankfurt, Paris Charles de Gaulle, Munich, and Vienna) remain completely identical whether the HSR layer is integrated or not. The European rail network cannot bypass the inter-city traffic concentrated at these aviation gateways. In China, however, the presence of HSR completely rewrites the network’s internal stress lines. In the mono-layer air network, the failure of Beijing shifts systemic load to coastal mega-hubs like Shanghai Pudong, Guangzhou, and Shenzhen. In the multimodal Air-HSR network, the critical bottlenecks shift inland. Remarkably, central airport hubs like Changsha Huanghua and Xi’an Xianyang become the second and third most critical targets in the country, acting as vital intermodal hinges. Simultaneously, traditional coastal gateways like Shanghai Pudong are stripped of their bottleneck status, as the rail corridors along China’s eastern seaboard provide enough structural redundancy to bypass them during disruptions in the aviation network.

2.3 Robustness against airline disruptions

In addition to physical infrastructure disruptions, the network can be evaluated through the lens of operational failures. By simulating the sequential shutdown of the five largest airline operators in each region (corresponding for example to labor strikes or severe cybersecurity attacks) the analysis shifts from removing a single node to removing a sub-network.

The market structures of the two regions dictate the scale of this disruption. Europe's aviation market is highly fragmented; its top five operators in terms of number of flights offered (namely Ryanair, Lufthansa, Air France, SAS and easyJet) account for 39.5% of the network. In contrast, China's aviation sector is heavily consolidated around the "Big Three" carriers (China Southern, China Eastern, and Air China), meaning the removal of its top five airlines (with the addition of Shenzhen Airlines and Hainan Airlines) strips the majority, i.e. 53.6%, of all flights from the network.

Evaluating the topological metrics Coverage and Efficiency (Figure 5a and 5b), the FUA-aviation only networks exhibit surprisingly identical degradation patterns. By the fifth removal step, terminal coverage falls to roughly 90% and efficiency to roughly 86% in both regions. This similarity is striking given the disparity in grounded flights (53.6% in China vs. 39.5% in Europe). This reveals that Europe possesses a higher structural dependency on its top operators to maintain fundamental spatial connectivity, whereas China's topological grid remains cohesive even after more than half of its flights are removed.

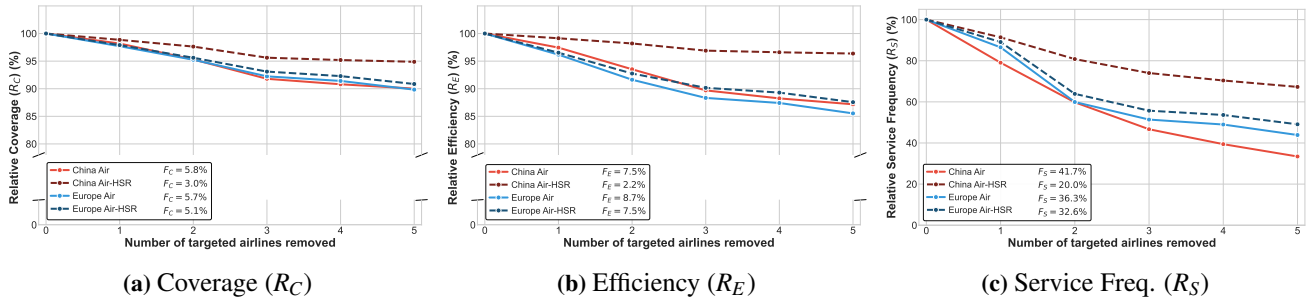


Figure 5— Operational degradation profiles simulating the sequential removal of the five largest airline operators in Europe and China. Solid lines indicate unimodal aviation; dashed lines indicate integrated Air-HSR networks. The y-axis of the left and middle plot, Coverage and Efficiency, are cut-off to improve readability.

Tracking the Effective Service Frequency (R_S) in Fig. 5c exposes a critical operational vulnerability unique to hub-and-spoke architectures. In Europe, the removal of the largest operator (Ryanair, 15.3% of flights) causes a proportional R_S drop of 13.5%. In contrast, the subsequent removal of Lufthansa (9.1% of flights) triggers a much greater reduction of 26.6% in total network service capacity. Because Lufthansa operates a hub-and-spoke model in the geographical center of Europe, grounding its fleet severs the bottleneck capacity for thousands of multi-leg itineraries across the continent. Ryanair's Low-Cost Carrier (LCC) point-to-point model, despite being physically larger in flight volume, serves far fewer connective itineraries, resulting in a much softer systemic shock when removed.

The inclusion of the HSR networks highlights a significant divergence in the mitigative capacity of the two regions. In Europe, the HSR network provides only a marginal operational buffer, raising the greatly severed R_S slightly from 43.9% to 49.1% after all five airlines are grounded. In China, in contrast, the HSR network fundamentally rescues the system. Even after the complete grounding of its five largest airlines, the Chinese Air-HSR multi-layer network maintains 67.3% of its service frequency supply (compared to just 33.4% in the aviation-only network). This performance is attained despite being subject to the removal of a considerably larger share of the flights volume. Furthermore, the Chinese rail grid almost entirely neutralizes the efficiency loss, keeping R_E above 96.3%. This clearly demonstrates that China's deeply integrated HSR system acts as a highly effective, high-capacity operational safeguard against catastrophic aviation failure, a systemic redundancy that the European network currently lacks.

3 Discussion

This work developed a Multi-Layer Network (MLN) model to analyze long-distance travel by evaluating several accessibility based metrics. A framework for simulating degradation of the networks was proposed by applying random failure, targeted attacks and event-based disruption scenarios. This approach was then applied to the European and China aviation-only and aviation-HSR multi-model network to assess and compare the robustness of these networks.

While the aviation networks in China and Europe differ in size and topological structure, their degradation under random and targeted airport node removal is remarkably similar in terms of network coverage, efficiency, and service frequency. However, China's aviation-only MLN is more vulnerable; removing fewer airport nodes leads to an earlier complete loss of connectivity in both relative and absolute terms. Furthermore, China's aviation network relies more heavily on a few major

airlines, which have a relatively larger share of flights, making its supply capacity less robust against airline failures than its European counterpart.

Once HSR connections are considered, stark topological differences are revealed. While Europe's HSR network is severely fractured into 14 disconnected national components, China operates in contrast a highly unified, meshed national grid that provides structurally shorter and more efficient travel pathways. When the HSR layers are integrated into each region's MLN, the similarities observed in the aviation-only networks all but disappear. While accessibility improves for some HSR-oriented cities in Europe, many inland FUA clusters in China experience substantial performance gains, including a greater than 40% improvement (decrease) in GTT for certain areas. Consequently, the full Chinese MLN outperforms the European Air-HSR MLN across nearly all global and local network indicators. For many Chinese FUAs, average connectivity and average OD-pair GTTs show substantial improvements compared to the aviation-only baseline.

Under both random and targeted airport node removal scenarios, the robustness of the Chinese Air-HSR MLN is strikingly high, and considerably higher than the counterpart performance level retained in Europe in the event of such disruptions. Although service frequency drops significantly, nearly 40% of all OD pairs in China remain connected even after a complete aviation network failure, compared to barely 10% in Europe. This difference is most pronounced in the event of airline disruptions where the operations of airlines are shutdown.

Ultimately, the findings demonstrate that a strong, well-integrated HSR network is a highly effective way to improve the robustness of long-distance travel accessibility. While China's state-coordinated grid successfully leverages this complementary robustness potential, Europe's fragmented, more nationally bounded HSR network fails to provide sufficient robustness to keep the continent well connected in terms of long-distance travel under aviation network disruptions.

Network topologies heavily reflect their regulatory environments. Europe's liberalized aviation market has fostered a decentralized, point-to-point architecture driven by Low-Cost Carriers. In contrast, China has a rigid hub-and-spoke aviation architecture dominated by state-owned carriers. While efficient for daily traffic, this consolidation creates severe structural fragility under systemic disruption. The contrast in rail governance is equally stark. China operates a unified, top-down HSR mega-grid that provides exceptional redundancy during aviation crises, acting as an effective safety net. Conversely, the European HSR network remains fractured into isolated national sub-networks. Instead of a fluid cross-border backbone, it relies on severe structural bottlenecks, failing to keep the continent connected during systemic aviation crises.

Based on our findings, we outline several additional planning implications for both European and Chinese contexts. In the European context, it is essential to prioritize cross-border rail infrastructure: policymakers should shift funding from isolated domestic expansions to identifying and resolving critical cross-border missing links, connecting fragmented national networks into a cohesive European grid. Infrastructure managers should therefore eliminate physical and operational barriers through the synchronized deployment of ERTMS, gauge unification, and transparent capacity allocation. In addition, to safeguard peripheral connectivity and ensure substitution capacity, peripheral airports may be stimulated to connect to multiple primary hubs rather than depend on a single one. Moreover, regulatory bodies are advised to refrain from enacting short-haul flight bans without first verifying that a high-performing, high-capacity HSR alternative is fully operational.

In the Chinese context, our planning implications include the development of targeted central intermediate airports (such as Changsha and Xi'an) for strategic expansion to enable absorbing very large traffic shifts in the event of aviation disruptions. Another related measure should focus on increasing the number of connected airports per FUA to distribute structural risk away from single gateway hubs. Finally, the dramatic expansion of the HSR network in China forces lower-tier cities to rely on high-cost assets and imposes significant travel time penalties due to remote station placements. Regional governments should prioritize improving local access to remote HSR stations, mitigating the travel-time penalties caused by their placements.

Future work may address key study limitations. First, the path-finding logic evaluates Generalised Travel Time (GTT) but omits monetary costs, departure time choice, and vehicle or terminal capacity constraints. Future iterations can address these shortcomings by integrating empirical passenger demand data, fares, and temporal period-of-day frequencies (peak/off-peak hours) alongside physical throughput caps on nodes and links to simulate realistic passenger gridlock. Second, the model relies on fixed catchment thresholds from population centroids and assumes free-flow driving, frictionless borders, and complete flight cancellations upon airport closure. These assumptions could be refined by introducing dynamic, frequency-dependent catchment areas, integrating urban traffic and public transit schedules for more precise ground access, and modeling operational flight rerouting mechanisms. Third, the data used in this study introduced temporal and modal constraints stemming from multi-source integration across different baseline years—specifically aligning 2019 Chinese HSR, 2023 global aviation, and 2024–2026 European HSR data into a single representative day. This approach assumes timetable compatibility and omits recent infrastructure expansions in China, while regional modal definitions vary. Future iterations should address these boundaries by utilizing more synchronized datasets and refining modal filtering strategies.

Beyond these direct improvements, this study opens up several broader, independent research avenues. The model can evaluate future regional infrastructure evolutions, such as explicitly quantifying the structural robustness gains of the completed Trans-European Transport Network (TEN-T)³² core HSR lines, or systematically applying the localized failure methodology

to smaller sub-regions to identify regional accessibility gaps. This design framework could also stress-test real-world policy instruments, such as evaluating the structural redundancy lost during environmental short-haul flight bans or testing the impact of air-rail partnerships. Furthermore, future studies should ultimately transition from network robustness diagnosis to prescriptive network design using optimization algorithms to strategically locate new airports or determine where adding specific flight or rail services maximizes overall network coverage and systemic robustness.

4 Method

4.1 Multi-layer network construction

Following the structural classification proposed by Sfiligoj et al.³³, the transport system is modeled as a mode-layered structural multilayer public transport network. To accurately capture intra-city transfers and terminal-specific accessibility, airports and rail stations are treated as distinct nodes rather than aggregate city centroids. The three-layer layout coupling population demand centers and air and rail transport nodes - airports and HSR stations, respectively - is illustrated in Figure 6.

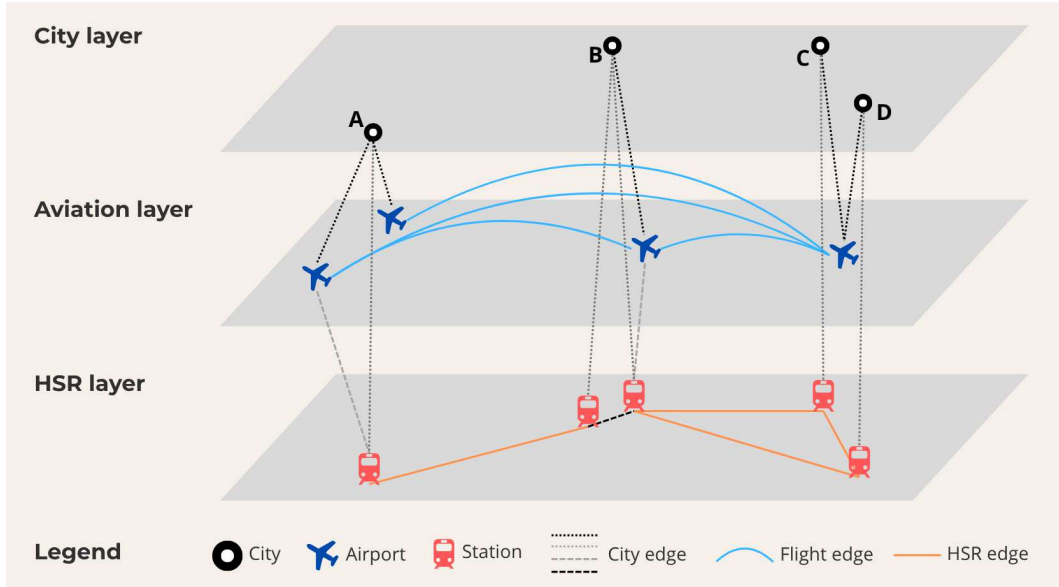


Figure 6– Schematic representation of the multi-layer graph layers and connection types.

The MLPTN is mathematically defined as a directed multilayer multigraph $G = (V, E)$ with layers $\mathcal{L} = \{C, A, H\}$ representing Cities (C), Aviation (A), and HSR (H). A node i in layer $\alpha \in \mathcal{L}$ is denoted as v_i^α , yielding the total vertex set $V = \bigcup_{\alpha \in \mathcal{L}} V^\alpha$. The edge multiset E contains intra-layer links $e_{ij}^\alpha = (v_i^\alpha, v_j^\alpha)$ and inter-layer couplings $e_{ij}^{\alpha\beta} = (v_i^\alpha, v_j^\beta)$ ($\alpha \neq \beta$). To integrate operational timetables, the network is implemented as a NetworkX³⁴ `nx.MultiDiGraph` in Python, accommodating parallel edges $e_{ij,k}^\alpha$ for distinct scheduled trips k with unique temporal stamps and graph labels.

The node set V consists of Functional Urban Areas (FUAs) (V^C), individual airports (V^A), and HSR stations (V^H). Transport layers use a service-based P-space topology, where a directed link connects any node pair sharing at least one direct scheduled route without transfers³⁵, mapping service connectivity rather than physical transport trajectories (e.g. track layouts). The edge set E differentiates between scheduled aviation services (E^A), timetabled HSR routes (E_{train}^H), local intra-FUA HSR station transfers (E_{trans}^H), and inter-layer access, egress and transfer connections ($E^{C,A}$, $E^{C,H}$, $E^{H,A}$). Local ground connections are unified into a single city edge set: $E^C = E^{C,A} \cup E^{C,H} \cup E^{H,A} \cup E_{\text{trans}}^H$.

Coordinate-to-coordinate free-flow driving times for E^C are computed using the Open Source Routing Machine (OSRM) on OpenStreetMap (OSM) data^{36,37}. Table 1 reports the threshold values deployed for algorithmically generating the edges included in E^C . If a city cannot be connected to any airport within 2 hours driving, it is connected to its absolute nearest airport with a longer access time to prevent becoming completely disconnected from the networks. Isolated terminal nodes are removed from further analysis.

4.2 Network path construction and routing Logic

To model long-distance continental trips, paths are restricted to a maximum of two long-distance transit legs (at most one HSR to HSR, HSR to air, air to HSR or air to air transfer), thereby allowing for path configurations composed of flight-only,

Table 1. Local city edges time thresholds

Edge Type	Threshold	Rationale
City to Airport ($E^{C,A}$)	2 hours	Standard airport catchment area; isolated cities use nearest-hub coupling.
City to HSR station ($E^{C,H}$)	45 min	Connects peripheral HSR infrastructure across municipal boundaries.
HSR station to Airport ($E^{H,A}$)	20 min	Limits intermodal substitution and feeder routes to close-proximity hubs.
Inter-HSR-Station (E_{trans}^H)	20 min	Direct intra-city transfers between terminal hubs using transit or taxi.
Airport to Airport	N/A	Excluded due to excessive transfer penalties and customs complexities.

Note: The final threshold values applied in this study were primarily determined through sensitivity analysis and bounded using practically-reasonable bounds. The following references were consulted as background literature during the process of defining these parameters:^{31,38–41}.

HSR-only, and multimodal topologies, next to local public transport access and egress connections (Figure 7).

To prevent short-range trips from distorting the continental model, origin-destination (OD) pairs are filtered using an open-source routing machine (OSRM) travel-time hybrid approach: OD pairs under 100 km geodesic distance are excluded; pairs between 100–300 km are retained only if free-flow driving times equal or exceed 2.5 hours; and all pairs over 300 km are included.

Total journey duration is calculated as follows. Direct journeys sum local access from the origin to the long-distance transport terminal ($t_{FUA \rightarrow term}$), fixed terminal access processing ($t_{term,acc}$), in-vehicle timetable duration (t_{iv}), terminal egress ($t_{term,egr}$), and local egress from the long-distance transport terminal to the destination ($t_{term \rightarrow FUA}$):

$$T_{direct} = t_{FUA \rightarrow term} + t_{term,acc} + t_{iv} + t_{term,egr} + t_{term \rightarrow FUA} \quad (1)$$

For journeys involving a connection, whether intra-modal or inter-modal, the formulation expands to incorporate the transfer phase. The total duration is modeled by splitting the journey into two sequential travel legs separated by the transfer components:

$$T_{transfer} = T_{leg1} + t_{term1 \rightarrow term2} + t_{term,trans} + t_{wait} + T_{leg2} \quad (2)$$

Here, T_{leg1} comprises the initial origin access and first in-vehicle segment ($t_{FUA \rightarrow term1} + t_{term,acc} + t_{iv,1}$), while T_{leg2} covers the second in-vehicle segment and final destination egress ($t_{iv,2} + t_{term2,egr} + t_{term2 \rightarrow FUA}$). The intermediate transfer phase consists of inter-terminal access time ($t_{term1 \rightarrow term2}$, which is zero for transfers within the same facility), fixed mode connection buffers ($t_{term,trans}$), and schedule-dependent waiting intervals (t_{wait}). Table 2 summarizes the mode (combination)-specific values specified for each of the terminal processing and transfer time components.

To account for the difference in perceptions between different travel time components, we consider the Generalized Travel Time (GTT):

$$GTT = t_{iv} + \beta_a \cdot t_a + \beta_w \cdot t_w + \beta_n \cdot n_t \quad (3)$$

where t_{iv} is the baseline in-vehicle time duration (scheduled station-to-station or flight block time). The nominal travel time components extracted by the routing algorithm are mapped onto the perceived GTT variables based on their behavioral characteristics:

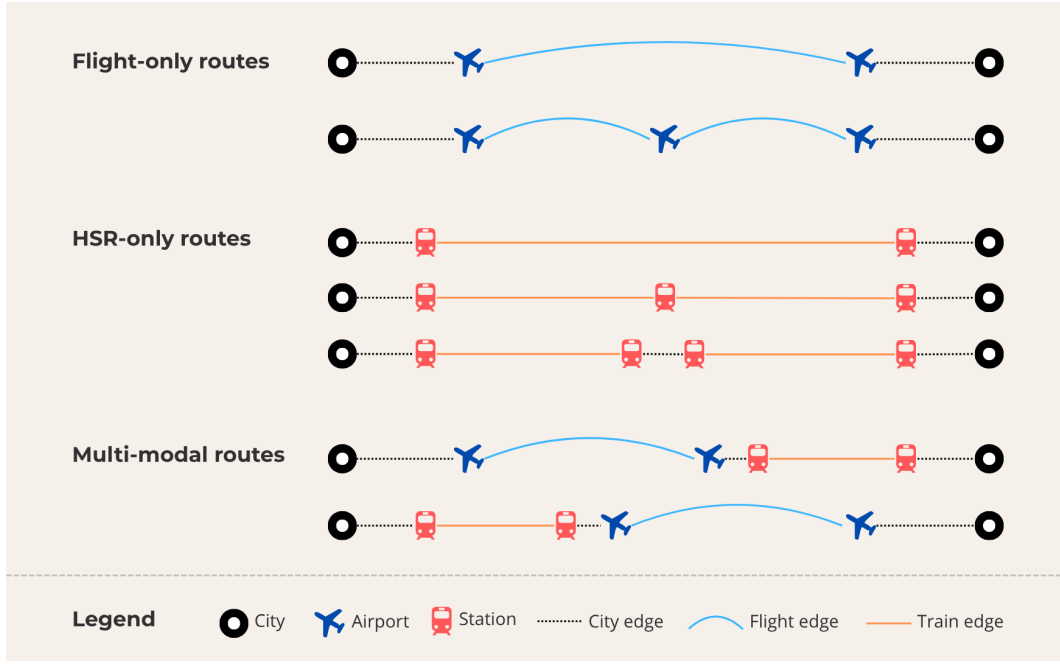


Figure 7– Allowed routing configurations within the multi-layer transport network.

- Access time (t_a) aggregates all local connection movements and facility egress phases ($t_{\text{FUA} \rightarrow \text{term}}$, $t_{\text{term} \rightarrow \text{FUA}}$, $t_{\text{term.egr}}$, $t_{\text{term1} \rightarrow \text{term2}}$, $t_{\text{term.trans}}$).
- Wait time (t_w) captures stationary periods, including the mandatory pre-departure buffer time at the initial terminal ($t_{\text{term.acc}}$) and schedule-dependent connection gaps (t_{wait}), i.e. transfer wait time.
- The transfer count (n_t) applies a flat penalty (β_n) based on the connecting destination mode which reflects the additional dislike/discomfort associated with transferring above-and-beyond the associated additional time components.

Multipliers are specified based on the findings reported in the meta-analysis by Wardman et al.⁴⁴ and adapted by Bruno et al.⁴³, setting the access coefficient to $\beta_a = 1.87$ and the waiting coefficient to $\beta_w = 1.76$. The transfer penalty (β_n) represents the standalone disutility of a connection and is set to 30 minutes for HSR-bound connections and 70 minutes for aviation-bound connections, synthesized from Allard and Moura⁴⁵ and Cao et al.⁴⁶.

The routing engine is executed in two phases. Phase 1 isolates active terminals for an OD pair and evaluates timetables. Departure times from FUAs are set so as to minimize terminal wait time before the first transport leg. Overlapping catchments are resolved via a vehicle-first strategy, mapping unique trip identifiers to preserve only the path that minimizes GTT. Phase 2 groups matching individual vehicle combinations into distinct terminal sequences and sorts the final outputs by minimum GTT up to a 24-hour itinerary ceiling.

4.3 Robustness and accessibility metrics

To capture realistic passenger utility rather than binary graph connectivity⁴⁷, network robustness is measured as the capability of the multi-layer system to preserve accessibility under systematic degradation^{31,48}. Let N_i^s be the successfully reached destinations from origin i under scenario (network state) s , and N_i^{OD} denote the original set of long-distance destinations from origin i . Indicators are split into local and global levels³³:

Local location-based accessibility is measured using Average Generalized Travel Time (GTT_i) to destinations:

$$GTT_i = \frac{1}{N_i^s} \sum_j GTT_{ij} \quad \forall i \in V^C \quad (4)$$

To investigate the share of reachable destinations, local FUA Coverage (C_i) quantifies the share of reachable nodes for FUA origin i :

$$C_i = \frac{N_i^s}{N_i^{OD}} \quad \forall i \in V^C \quad (5)$$

Table 2. Terminal processing and transfer times

Trip phase	Component	Variable	Time [minutes]	Sources
Terminal Access	FUA → HSR	$t_{\text{term_acc}}$	20	18,42,43
	FUA → Flight	$t_{\text{term_acc}}$	110	17,18,31
Terminal Egress	HSR → FUA	$t_{\text{term_egr}}$	5	43
	Flight → FUA	$t_{\text{term_egr}}$	30	18
Transfers	Flight → Flight	$t_{\text{term_trans}}$	75	17,43
	HSR → HSR	$t_{\text{term_trans}}$	60	17,31
	Flight → HSR	$t_{\text{term_trans}}$	90	43
	HSR → Flight	$t_{\text{term_trans}}$	110	31,43

At the global network level, Network Average FUA Coverage ($\bar{C}$) calculates the mean coverage across all valid origins. Weighted Global Efficiency (E) tracks network-wide directness using GTT as link weights, remaining stable when nodes become isolated ($GTT_{ij} \rightarrow \infty, 1/GTT_{ij} \rightarrow 0$)^{25,28}:

$$E = \frac{1}{\sum_i N_i^{OD}} \sum_{i \neq j} \frac{1}{GTT_{ij}} \quad (6)$$

Effective Service Frequency (S) measures overall operational supply, discounting the frequency f_p of path $p \in P_{ij}$ by its total leg count k_p (1 or 2) to penalize more indirect routes:

$$S = \frac{1}{\sum_i N_i^{OD}} \sum_{i \neq j} \sum_{p \in P_{ij}} \frac{f_p}{k_p} \quad (7)$$

In our analysis we employ three global metric changes which are all scaled as a relative robustness ratio (R_x) comparing a given disrupted scenario (s) against baseline conditions (0)⁴⁹:

$$R_C = \frac{\bar{C}^s}{\bar{C}^0}, \quad R_E = \frac{E^s}{E^0}, \quad R_S = \frac{S^s}{S^0} \quad (8)$$

To evaluate full degradation profiles over a continuous failure spectrum, the scalar Cumulative Performance Loss (F_x) calculates the area above the robustness curve across the removed (airport) node fraction $q = i/K$, where $K = |V^A|$ ²¹:

$$F_x = \int_0^1 (1 - R_x(q)) dq \quad (9)$$

The index F_x resolves to an absolute percentage (%), where higher values signify structural fragility and lower values indicate better systemic robustness.

4.4 Simulation of network disruptions and experimental design

Simulations follow a two-step framework: first disrupting the FUA-Air only MLN, and then repeating the process for the full FUA-Air-HSR MLN to isolate inter-modal benefits. Simulation profiles are compared across geographic regions (Region X vs. Region Y) and network structures (standalone aviation vs. aviation-HSR). This setup evaluates: (1) cross-regional performance under identical disruptions to isolate the impact of different regional network topologies, and (2) intermodal contributions to measure the marginal robustness and fallback capacity added by HSR integration.

4.4.1 Random Failure (RF)

Stochastic disruption profiles are modeled using sequential Monte Carlo simulations characterized by random airport node removals. To ensure statistical validity across different network configurations, an adaptive sampling equation determines the required replication count $N(m)$ based on a pilot sample of $m = 10$ runs for each studied network scenario.

4.4.2 Targeted Attacks (TA)

Adaptive targeted disruptions simulate sequential attacks targeting central airports. The simulation executes an iterative recalculation loop: route-based Betweenness Centrality (BC) is initially computed for all active nodes using fastest path profiles^{22,49}. The airport node exhibiting the highest instantaneous BC is removed, triggering an update of the graph topology and fastest paths to recompute global robustness ratios. This process repeats, with BC scores for the remaining airport nodes recalculated prior to each subsequent deletion step.

4.4.3 Airline Failures

Operational capacity shocks simulate sudden carrier shutdowns due to system breakdowns like strikes, telecommunication or cybersecurity failures. The algorithm sequentially removes the five largest airlines per network based on regional flight frequency market share in the model. Disruptions propagate via bottleneck capacity rules: multi-leg itineraries fail completely if carrier cancellations force the operational frequency of any single leg to zero.

4.5 Case study scope and data acquisition

To empirically evaluate the structural properties and robustness of long-distance multimodal travel, we construct MLN graphs for Europe and China. The geographic, transport, and temporal boundaries defining the case study are structured to ensure an equivalent baseline for cross-regional network comparison (Table 3).

Table 3. Case study scope overview

Dimension	Europe	China
Geographic	UK, Ireland, and 29 Schengen states (excl. Iceland)	China, including Hong Kong and Macau
Transport	Regional aviation & speed-filtered fast intercity rail	Domestic / SAR aviation & G-series HSR
Temporal	2023 Air; 2023–2026 Rail composite	2023 Air; 2019–2020 Pre-pandemic rail

Urban centers are designated as Functional Urban Areas (FUAs) to establish catchment boundaries based on commuter flows rather than arbitrary administrative borders. We consider all FUAs which have 200,000 inhabitants or more. This yields 385 nodes for our European network. To allow for a meaningful comparison, Chinese urban nodes are delineated using the FUA framework from the European Commission’s Joint Human Settlement Layer (GHSL)⁵⁰, yielding 672 nodes⁵¹. Other studies focusing on China frequently use the prefecture-level city system, which Chen et al.⁵² point out to be unsuitable for representing actual urban areas, preferring the FUA method to more realistically analyze regional spatial interactions. Details regarding the data processing and filtering rules applied are provided in the associated public repository⁵³.

Operational transport schedules are compiled using the following repositories: (i) European aviation data is extracted from the Eurocontrol R&D Archive⁵⁴, tracking flight-level trajectories; (ii) Chinese aviation data is sourced from the VariFlight database⁵⁵, providing pre-refined commercial schedules; (iii) European rail schedules are derived from aggregated General Transit Feed Specification (GTFS), and; (iv) Chinese rail operations are extracted from a verified station-to-station schedule log encompassing over 2.7 million stop events from Zhang et al.⁵⁶. The final parsed configurations are visualized side-by-side in Figure 2. The compiled data is available at the aforementioned public repository⁵³.

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Data and Code Availability

Related datasets and code are available in the following public repository: <https://doi.org/10.4121/fc909e93-4959-4fb4-aebf-9227a31e048d>.

Author Contributions

M.M. and O.C. conceived the method and experiments. M.M. curated the data, conducted the experiments and analysed the results. J.G., A.B., B.D. and O.C. analysed the results and supervised this research. O.C. is responsible for project administration and funding acquisition.

Competing Interests

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