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WHAT WOULD HAPPEN WHEN THE UNDERGROUND NETWORK IS UNDER ATTACK?

—— ROBUSTNESS EXPLORATION OF LONDON UNDERGROUND NETWORK

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Abstract. Contemporary society increasingly depends on the resilience of a complex network of interconnected infrastructure systems, particularly in metropolitan areas. London, as one of the largest cities in the world, serves as a vibrant hub, supporting the lives and work of millions of residents. In 1863, London inaugurated the world's first underground railway system, marking a groundbreaking achievement in urban transportation. However, as the city has grown and transformed significantly over the decades, can the London Underground still effectively support the demands of modern urban commuting? More importantly, how well can it withstand unexpected failures and interruptions? In this study, we conduct a comprehensive exploration of the resilience of the London Underground network, from both macroscopic and microscopic perspectives. By leveraging network science and agent-based modeling approaches, we uncover its performance under various attack scenarios, providing valuable insights into the robustness of this iconic transportation system. Additionally, dynamic simulation such as Agent-based modeling is also widely used for testing different scenarios of the system .

Keywords: London underground system, Robustness, Complex system, network analysis, Agent-Based Modeling.

1. Introduction

The resilience of urban transportation networks plays a critical role in ensuring the stability and functionality of cities, particularly in mitigating the impacts of disruptions on mobility and economic activity[1]. A robust transportation network enhances a city's ability to adapt to unexpected events, safeguarding the continuity of essential services and supporting long-term urban development[2]. The London Underground, one of the busiest metro systems in the world, accommodates over 5 million passenger journeys daily across its extensive network of 402 kilometers and 11 lines, underscoring its vital role in urban mobility. This immense demand highlights the challenges of ensuring operational efficiency and resilience in a transportation system that serves as the backbone of daily commutes for millions of residents and visitors[3]

As one of the world's most utilized metro systems, London Underground frequently faces disruptions caused by a variety of factors, including infrastructure failures, overcrowding, and external incidents such as strikes or adverse weather conditions. For instance, delays due to signal failures alone accounted for a significant portion of service disruptions, affecting thousands of commuters daily and underscoring the need for continuous investment in maintenance and modernization. These disruptions can have cascading effects on the city's overall mobility and economic productivity while also impacting the efficiency of subway operations and influencing passenger travel demand. Therefore, in recent years, there has been growing academic interest in the resilience of the London Underground system. Scholars have increasingly used it as a case study to explore the robustness of metro networks and their potential for future development[4][5][6]. In 2010, Transport for London (TfL) also introduced the Review of TfL Resilience Management Policy Framework[7], proposing measures to mitigate the impact of disruptions.

Over the past decade, research on transportation networks has made substantial progress in understanding the structural properties that underpin their reliability and robustness. Network analysis has become a key approach for evaluating these systems, enabling the exploration of how topological configurations influence resilience[8][9][10]. Additionally, dynamic simulations, such as Agent-Based Modeling and System Dynamics, are widely used to test different system scenarios[11][12][13]. Our objective in this study is to thoroughly examine the robustness of the London Underground network. Specifically, we address two key questions:

Q1. Is the London Underground network vulnerable?

Q2. What are the exact impacts when a specific station is disrupted?

To address Q1, we performed a macro-level analysis of the network's structure, focusing on its small-world properties and robustness. This involved evaluating the network's ability to maintain connectivity under different disruption scenarios, including random

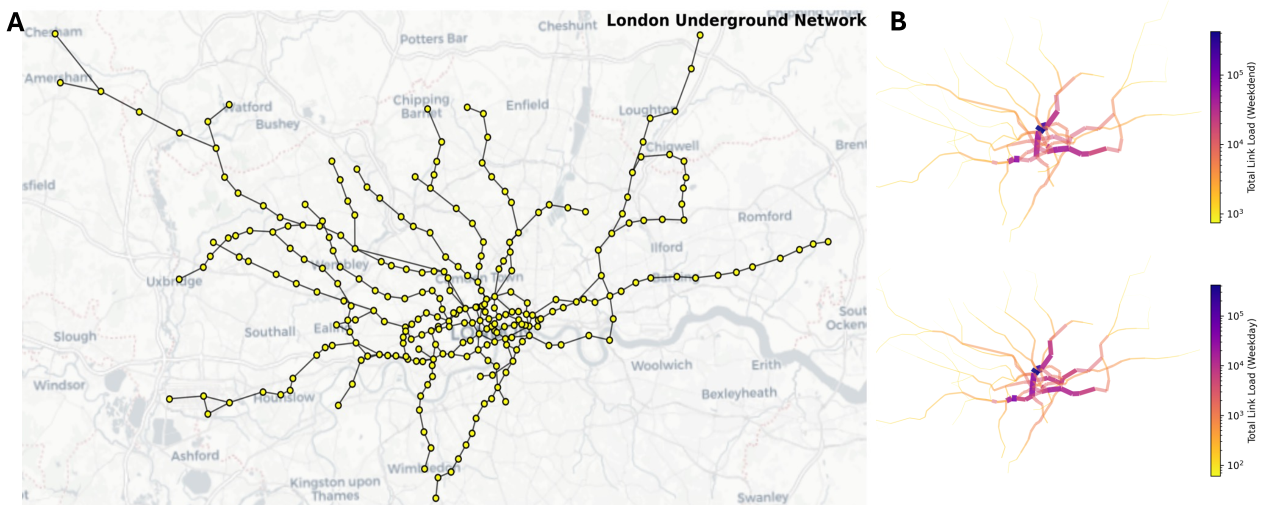


FIGURE 1. London Underground Network Construction. **(A)** Topological structure. **(B)** Weighted network for a typical weekend and weekday (Edges below this value are semi-transparent with alpha=0.5, while edges above are opaque with alpha=0.9. The threshold is defined as one-third of the global maximum edge weight.)

failures and targeted attacks, to assess its overall resilience.

For Q2, we shifted focus to the micro-level impacts of specific station disruptions. Our analysis explored two key aspects: (1) network operation efficiency, examining how the effects of a disruption vary depending on its duration and start time; and (2) passenger travel demand, estimating the proportion of London's population affected and the percentage of passengers unable to meet their travel needs during the disruption. To address these questions, we employed Agent-Based Modeling to simulate passenger behavior and interactions under various disruption scenarios, alongside demand analysis to quantify the broader consequences for urban mobility[1].

2. Methods

2.1. Data and Network Construction

All data used in this study are sourced from Transport for London (TfL), the authority responsible for managing London's transportation system (`https://crowding.data.tfl.gov.uk/`). The dataset provides a detailed representation of travel demand across the TfL network during a typical autumn week, covering weekdays and weekend. Data are recorded at 15-minute intervals throughout the day, capturing the dynamics of passenger movement and network usage. Key metrics include link load, which tracks the number of passengers traveling between stations, station entry and exit totals, and origin-destination O/D demand.

Topology definition is important for network analysis. Here, We followed the method outlined by Chopra et al.[14], which merges sub-graphs of individual metro lines into a unified metro network, ensuring that no multiple edges exist between consecutive nodes served by more than one line. Figure 1.A shows the topological network of London underground, comprising 270 stations from 11 lines, spanning zones 1 to 6. The network exhibits a hub-and-spoke structure[15], with a dense central core surrounded by sparser peripheral branches extending outward.

In addition to the topological network, we construct weighted networks for typical weekdays and weekends using link load data between connected stations (Figure 1.B). On weekdays, higher link loads (represented by darker and thicker edges) are concentrated in the central part of the network, reflecting increased passenger activity during commuting hours. In contrast, the weekend network shows relatively lower link loads overall, with a more evenly distributed pattern of usage across the network. This highlights reduced demand and less concentrated travel activity during weekends.

In subsequent sections, we further leverage the 15-minute station entry data and origin-destination (O/D) demand data for network shocks simulation and passenger travel demand analysis. The detailed methodologies and findings will be presented in the following discussions.

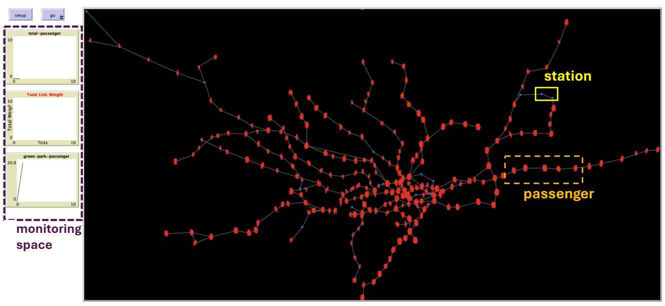
2.2. Network Robustness Analysis

2.2.1. Small-World Properties Evaluation

Understanding whether the London Underground exhibits small-world properties is critical for evaluating its structural resilience. Networks with small-world characteristics—marked by high clustering coefficients and short average path lengths—are often more robust to random failures, although they may remain vulnerable to targeted disruptions[16][17]. Most small-world analyses primarily focus on the topological structure

[1] Source code: `https://github.com/Qin99113/robustness_analysis_of_London_underground_network`

A



B

Attribute Category	Attribute Name	Description
Model Background	Research Objective	Simulate the impact of station closures on network efficiency.
	Agent Types	Passengers (agents), Stations (agents)
	Agent Properties	Passengers: target-station, ticks-to-next; Stations: station-id, passenger-count.
Agents	Agent Rules	Passengers move toward their target stations; reroute or disappear when encountering closed stations.
	Network Topology	Underground network composed of stations and links created from OD data.
	Spatial Embedding	Each station has real-world latitude and longitude coordinates.
Environment	Global Variables	E.g., station-closure, closure-start-tick, closure-end-tick, total-passengers, etc.
	Time Granularity	Each tick represents one time unit; agent behavior and system state evolve with each step.
Time Steps	Simulation Period	Simulates multiple time periods covering pre-closure, closure, and recovery phases.
Input Data	Station Entry Data	Number of passengers entering stations during each 15min time intervals.
	Station Coordinates	Coordinates of stations used to place them in the simulation environment.
Output Data	Global Metrics	Network efficiency, cumulative link weight, affected passenger counts, etc.
	Link load (weight)	Link load after a specific station closure at a defined time and duration
	Passenger Behavior	Passengers move to their targets or reroute; may fail to reach targets if rerouting is impossible.
Dynamic Processes	Greater Impact During Peak Hours	Assumes higher passenger volumes during peak hours result in greater impacts on network efficiency.

FIGURE 2. Agent-Based Modeling Framework for Station Disruption Simulation. **(A)** Network setup and passenger flow visualization. **(B)** Key model attributes and processes.

of networks, whereas many real-world networks incorporate edge weights. Consequently, recent studies have increasingly explored small-world properties in weighted networks[18][19]. In this study, we examine not only the small-world characteristics of the topological structure of the London Underground network but also those of the weighted subway networks across different representative days of the week.

We adopted the classical small-world criteria introduced by Watts and Strogatz, which include a small characteristic path length (CPL), representing the average shortest path length in the network, and a high clustering coefficient (CC), which measures the degree of local clustering. Since real-world networks rarely follow the ideal logarithmic relationship between the averagSie path length L and network size N, a more common approach involves constructing a corresponding Erdős-Rényi random graph (ER)[20][21] for comparison[22]. For the topological network of the London Underground, a random graph was generated using the Erdős-Rényi (ER) model with the same number of nodes and edges as the original network. The largest connected component (LCC) of the random graph was extracted to ensure comparability in structural analysis. For weighted networks, we followed a similar approach: an unweighted random graph with the same number of nodes and edges as the original network was first generated, and then the edge weights from the real weighted network were randomly redistributed across the edges of the unweighted random graph. To ensure the stability and reliability of the results, all random graph metrics were calculated as the average over 50 iterations.

To evaluate the robustness of the London Underground network, we conducted simulations of both random and targeted attacks to quantify the impact of node removals on the network's overall performance. One key metric was used: global efficiency.

Random attacks involved removing nodes uniformly at random, simulating scenarios such as equipment failures or unforeseen disruptions. Targeted attacks, by contrast, prioritized the removal of high-betweenness nodes, representing deliberate disruptions aimed at maximizing network damage. High-betweenness nodes are critical for maintaining network connectivity and passenger flow, as they often function as major transfer hubs.

Global efficiency (E_{global}) was chosen as the primary metric to evaluate the network's performance under these attack scenarios due to its ability to quantify the overall efficiency of information or passenger flow across the entire network. For unweighted networks, global efficiency is calculated as:

$$E_{\text{global}} = \frac{1}{n(n-1)} \sum_{u \neq v} \frac{1}{d(u,v)},$$

where n represents the total number of nodes, and $d(u,v)$ denotes the shortest path distance between nodes u and v, measured as the number of edges along the path. While this metric is effective for topological analyses, it assumes all edges are equal in importance and therefore does not capture the heterogeneous nature of real-world networks, where edges often have weights representing factors such as passenger flow or travel time.

To address this limitation, we adopted a weighted version of global efficiency for the London Underground network, where edge weights reflect passenger flow. This adaptation allows for a more realistic assessment of the network's performance, as it considers the relative importance of each connection. In the weighted formulation, the shortest path distance $d(u,v)$ is redefined as:

$$d(u,v) = \min_{P \in \mathcal{P}(u,v)} \sum_{(i,j) \in P} \frac{\sum_{(x,y) \in E} w_{xy}}{w_{ij}},$$

where $\mathcal{P}(u,v)$ represents the set of all possible paths between nodes u and v, and w_{ij} is the weight of edge (i,j), normalized by the total edge weight $\sum_{(x,y) \in E} w_{xy}$. This formulation ensures that paths with higher passenger flow are prioritized, reflecting the capacity and importance of key connections in maintaining network efficiency.

In our simulations, nodes were sequentially removed according to the attack type, and global efficiency was recalculated after each removal to quantify the degradation in network performance.

2.2.2. Network Shocks Simulation Under Real-World Scenarios

Agent-Based Modeling (ABM) is a powerful tool for analyzing complex systems by simulating the interactions of individual agents within their environment. In the context of urban transit networks, ABM enables us to model passenger behavior, travel decision-making, and the cascading effects of disruptions in a highly detailed and dynamic manner. Unlike traditional network analysis that focuses on static or aggregated metrics, ABM provides a bottom-up perspective by capturing the heterogeneous responses of individual agents to shocks and their interactions with the system as a whole. Building on the previous macro-level evaluation of the London Underground's structural properties and resilience to disruptions, we transitioned to a micro-level analysis to better understand the localized and temporal impacts of specific station disruptions.

We aim to quantify the impacts of station closures or disruptions on the overall efficiency of the London Underground network. Specifically, we investigate how the timing and duration of a disruption influence the magnitude of its effects. Our hypothesis is that disruptions occurring during peak hours will have significantly larger impacts on network efficiency due to higher passenger volumes and greater demand for connectivity, while longer durations will exacerbate the system's inability to recover, amplifying delays and disruptions for both passengers and operations. These assumptions align with findings in previous studies. For instance, Zhang et al.[23] analyzed the vulnerability of urban metro systems and found that central stations are more susceptible to disruptions during peak periods due to higher passenger densities.

In this model, we utilize the geographical coordinates and topological structure of the London Underground stations to construct a spatially embedded network representing the transit system, as shown in Figure 1A. The setup integrates stations as nodes and passenger movement paths as weighted links. Entry data, recorded at 15-minute intervals for each station, is used to simulate the dynamic flow of passengers entering the network over time. Specifically, the system operates based on predefined rules for passengers and stations, as shown in Figure 1B. Passengers enter the network every 15 minutes based on entry data and are assigned a random travel time between 2 and 30 minutes, which decreases by 1 at each time step. When the travel time reaches 0, passengers exit the system, indicating they have reached their destination. Link weights update dynamically to reflect passenger flow. Based on Transport for London (TfL) data, the average travel time between two stations is 2 minutes, so one time tick in the model represents 2 minutes. If a station is disrupted, passengers attempt to reroute; if no alternative path exists, they are removed from the system. Monitoring spaces track key metrics such as passenger counts, link weights, and flow changes. In this study, we selected Green Park station, which has the highest betweenness centrality, as a representative case to simulate disruptions. Specifically, we conducted 30 simulations covering 10 disruption durations (ranging from 15 to 150 minutes) and 3 starting times: 07:00 (morning peak), 10:00 (off-peak), and 16:00 (afternoon peak).

2.2.3. Passenger Travel Demand Analysis Under Disruptions

While previous analyses provide insights into network-wide performance under disruptions, this section focuses on the impact of disruptions on passenger travel demands, offering a user-centric perspective.

To analyze the impact of node disruptions on passenger travel demands, we evaluated two key aspects: the proportion of unmet demands and the extent of inconvenience experienced by passengers. This analysis was based on the assumption that all passengers prefer the shortest path (in terms of distance or travel time) between their origin and destination under normal conditions, and will reroute to the next shortest available path if disruptions occur. Passenger travel demands were modeled using a fixed origin-destination (O-D) matrix, where each element D_{ij} represents the number of trips from origin node i to destination node j. A demand was classified as unmet if the disrupted node served as the origin, destination, or an intermediate transfer point along the shortest path, with no feasible alternative route available. The proportion of unmet demands (U_d) was calculated as $U_d = \frac{\sum_{i,j} D_{ij}^{\text{unmet}}}{\sum_{i,j} D_{ij}} \times 100\%$, where D_{ij}^{unmet} represents the total unmet demands under the disrupted network.

For passengers whose trips were rerouted, we quantified inconvenience using metrics such as additional stops and increased travel time. The number of additional stops for each rerouted trip was calculated as $S_{\text{add}} = S_{\text{rerouted}} - S_{\text{original}}$, where S_{rerouted} is the number of stops on the rerouted path, and S_{original} is the number of stops on the original shortest path. The average additional stops per passenger were then determined as $S_{\text{avg}} = \frac{\sum_k S_{\text{add},k}}{N_{\text{rerouted}}}$, where N_{rerouted} denotes the total number of rerouted trips. Similarly, the increase in travel time was calculated as $T_{\text{add}} = T_{\text{rerouted}} - T_{\text{original}}$, where T_{rerouted} and T_{original} represent the travel times for the rerouted and original paths, respectively. The total increase in travel time across the network was obtained by summing T_{add} over all rerouted trips, from the dataset, we calculated that the average time at one stop is around 2 minutes.

To simulate targeted attacks, nodes were removed sequentially based on their betweenness centrality, and the unmet demands and passenger inconvenience metrics were recalculated after each removal. This methodology offers a comprehensive framework for un-

Network	Actual Clustering Coefficient	Random Clustering Coefficient (Avg)	Actual Shortest Path Length	Random Shortest Path Length (Avg)	Results (Is or Not Small-World Properties)
Topological Network	0.031040	0.005448	13.954151	6.282330	**NOT Small-World**
Weighted Weekdays Network	0.006092	0.000775	0.000375	0.000167	**NOT Small-World**
Weighted Weekend Network	0.005998	0.000820	0.000322	0.000161	**NOT Small-World**

TABLE 1. Small-world Properties of Three Networks

derstanding how disruptions impact passenger travel demands and highlights the practical implications of network vulnerabilities.

3. Results and Discussion

3.1. Small-World Properties

As shown in Table 1, the topological network considers only the presence or absence of connections between stations, without accounting for passenger flow. As shown in the results, the actual clustering coefficient (0.031040) is significantly higher than the random clustering coefficient (0.005448), indicating strong local cohesion. However, the average shortest path length (13.95) is considerably higher than that of a random network (6.28). This discrepancy suggests that while the network exhibits localized clustering, it lacks the global efficiency typically associated with small-world properties. This is a characteristic limitation of unweighted networks, where all connections are treated equally regardless of their real-world significance. Such a model is insufficient for understanding real-world network behavior, particularly in public transportation systems where flow intensity is critical to connectivity. These findings motivate the need for weighted analysis to capture the functional implications of passenger flow patterns.

The Weighted Weekday Network introduces passenger flow as edge weights, capturing the intensity of connections between stations during commuter-heavy weekdays. The results reveal a significant reduction in the actual clustering coefficient (0.006092) compared to the topological network (0.031040), along with a notable decrease in the average shortest path length (0.000375) from 13.95. These reductions reflect the dominance of high-flow connections between central business district hubs, where commuter demand is concentrated. This prioritization of high-volume links enhances global efficiency, as passengers rely on direct, well-utilized routes, but comes at the cost of localized clustering, as peripheral and intermediate nodes become less integrated. As a result, it does not exhibit a small-world property.

Similar to the weekday network, the weekend network incorporates passenger flow as weights but reflects a different demand pattern. The clustering coefficient (0.005998) and average shortest path length (0.000322) show marginal differences from the weekday network. The similarity suggests that the London Underground maintains a consistent structural efficiency despite variations in passenger flow patterns. However, subtle changes in clustering may indicate differences in local cohesion due to altered travel behaviors during weekends, such as leisure-oriented travel versus commuter-dominated flow on weekdays.

Building on the findings from the Weighted Weekday Network, the Weighted Weekend Network reflects the shift in travel behavior, where commuter flows diminish, and leisure-oriented, dispersed travel patterns emerge. This shift results in a slightly lower clustering coefficient (0.005998) and average shortest path length (0.000322) compared to weekdays, as central hubs become less dominant and peripheral areas see increased connectivity. The reduced clustering highlights weakened local cohesion, as leisure travel is less concentrated around tightly connected nodes. However, the network maintains consistent global efficiency, demonstrating its adaptability to varying demand patterns. These results emphasize how the London Underground accommodates diverse travel behaviors while retaining overall functionality, though at the cost of further reduced small-world characteristics on weekends.

3.2. Random and Targeted Attack Performance

Figure 3 illustrates the impact of random and targeted node attacks on the global efficiency of the topological network. The results reveal a clear distinction between the two attack strategies, emphasizing the structural vulnerability of the network under targeted attacks.

Targeted attacks, which remove nodes based on their importance, high betweenness in this research, result in a steep decline in global efficiency as nodes are progressively removed. This sharp decrease is attributed to the removal of highly connected or strategically critical nodes, which act as key hubs in the network. These nodes are central to maintaining both local and global connectivity, and their removal disrupts the shortest paths between numerous node pairs, causing a cascading failure in network efficiency.

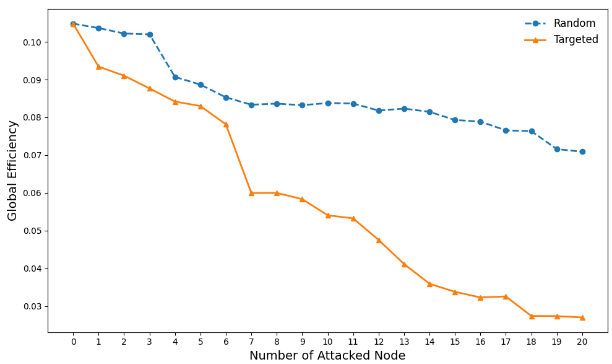


FIGURE 3. Attack performance of topological network

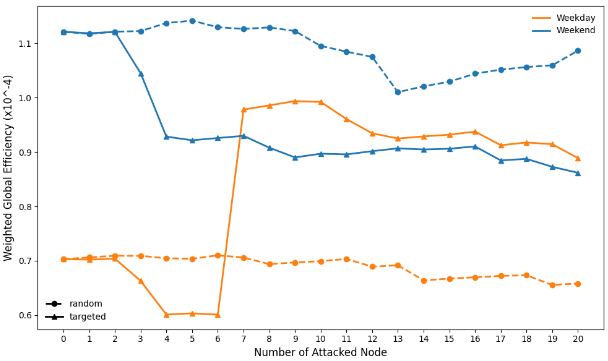


Figure 4. Attack performance of passenger flow weighted network

The analysis of the global efficiency performance for the two weighted networks, namely the weekday and weekend passenger flow networks, reveals a notable anomaly in the weekday network under targeted attacks. Specifically, as shown in Figure 4, the global efficiency unexpectedly increases when the 6th node is removed in the targeted attack scenario. This behavior deviates significantly from the overall decreasing trend typically observed in such attacks. This anomaly can be systematically explained using the weighted global efficiency formula, The 6th station has an exceptionally high passenger flow, contributing significantly to the total edge weight of the network $\left(\sum_{(x,y)\in E} w_{xy}\right)$. Its removal leads to a substantial reduction in the total flow, thereby reducing the normalized weights w_{ij} for the remaining edges. This sharp decrease in the denominator outweighs other impacts, resulting in an overall increase in global efficiency. Although the 6th station exhibits relatively high betweenness centrality, its removal does not dramatically disrupt the connectivity of the network. Consequently, the shortest path distances between node pairs $(d(u, v))$ remain relatively stable. The numerator, therefore, does not decrease as significantly as the denominator, further amplifying the increase in global efficiency.

This unique interplay between the flow-weighted nature of the network and the mathematical structure of global efficiency highlights the sensitivity of efficiency metrics to both passenger flow distribution and network topology. In contrast, the weekend network demonstrates a more consistent performance trend, as its flow distribution is less concentrated on specific nodes.

3.3. Temporal Impact of Station Closures on Network Efficiency

The figure illustrates the temporal variations in network efficiency under station closures or disruptions, with different starting times and durations. The x-axis represents the disruption duration, ranging from 15 to 150 minutes, while the y-axis shows the magnitude of efficiency loss. Each line corresponds to a specific disruption starting time (e.g., morning, noon, and evening rush hours).

During the first 60 minutes of disruption, the network efficiency decreases significantly across all scenarios. This sharp decline can be attributed to the immediate loss of connectivity and rerouting caused by the closure of a central station. The network attempts to redistribute passenger flows, but the increased travel distances and congestion on alternative routes exacerbate the overall efficiency loss. Beyond 60 minutes, the rate of efficiency reduction stabilizes and reaches a plateau. This phenomenon occurs because the network has already absorbed the impact of the disruption, and the redistribution of flows has reached a state of equilibrium. Essentially, the network's capacity to reroute passengers is exhausted within this time frame, and additional disruption duration does not lead to further significant losses in efficiency. The efficiency loss varies with the time of day. Disruptions starting during the evening rush hour (after 4 PM) have the most pronounced impact. This is due to the high passenger demand during peak hours, where a station closure intensifies congestion and amplifies the network's inefficiency. In contrast, disruptions occurring during off-peak hours exhibit relatively lower impacts.

This analysis underscores the critical temporal sensitivity of network disruptions, highlighting the disproportionate impact of closures during peak hours. Additionally, the stabilization of efficiency loss after 60 minutes suggests that the duration of closures beyond this threshold has diminishing marginal effects on the overall network performance.

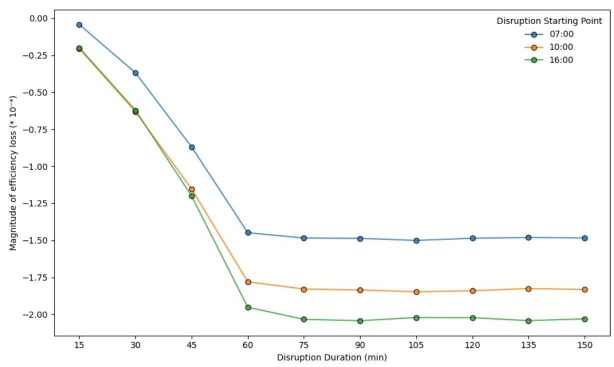


Figure 5. Trending of network efficiency when the closue or attack happened in different time period and lasted for different duration ("Green Park" Station)

3.4. Passenger Demand and Rerouting Effects Under Targeted Attacks

Building on the analysis of targeted attacks, the results highlight two critical aspects of network performance: the percentage of unmet travel demands and the impact on rerouted passengers. Together, these metrics provide a comprehensive view of how disruptions affect passenger flow and network efficiency:

As illustrated in Figure 6, targeted attacks on critical nodes result in a significant proportion of travel demands remaining unmet, particularly when these nodes function as origins, destinations, or vital transfer points. The weekday network is notably more vulnerable, with unmet demands reaching up to 3% in top betweenness nodes, highlighting its higher dependency on key nodes compared to the weekend network. Nevertheless, the network demonstrates considerable resilience, with 97% travel demands still being fulfilled, underscoring the overall robustness of the underground system despite targeted disruptions.

As shown in Figure 7, path adjustments are inevitable under disruptions, especially when high-betweenness nodes are targeted. Disruptions to major transfer stations (e.g., Green Park, Westminster) affect up to 20% of passengers, requiring rerouted paths. However, the inconvenience is relatively minor, with passengers averaging no more than 2 additional stops, as alternative routes are readily available. In contrast, disruptions to nodes with lower betweenness centrality (e.g., Northwick Park) have a more limited impact on the overall network but impose significant inconvenience, with rerouted passengers averaging up to 11 additional stops. This is due to the limited availability of alternative shortest paths for nodes with lower betweenness.

These results collectively underscore the dual challenges posed by targeted attacks: unmet demands and increased passenger inconvenience. While the network demonstrates resilience by maintaining connectivity for most passengers, protecting critical nodes is essential to minimize the broader impacts of disruptions.

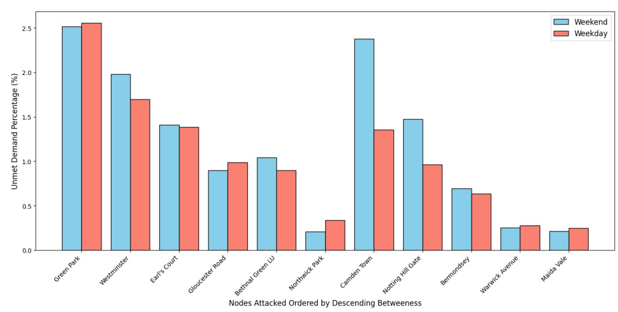


FIGURE 6. Comparison of unmet passengers' travel demand: weekday vs weekend

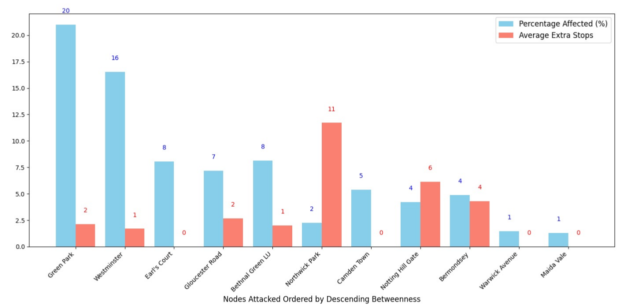


FIGURE 7. Impact of targeted attack on path changes

4. Conclusions

This study investigated the robustness of the London Underground network under both random and targeted disruptions, providing a comprehensive analysis of its structural properties, performance metrics, and the impact on passenger travel demands. Through simulations of random and targeted attacks, we demonstrated that high-betweenness nodes, which play critical roles as transfer hubs, disproportionately affect network connectivity and efficiency when disrupted. Our findings confirmed that the network exhibits certain topological vulnerabilities, as evidenced by significant reductions in global efficiency under targeted attacks, highlighting its reliance on a few critical nodes for maintaining overall functionality.

In addition to structural analysis, this study adopted a passenger-centric perspective to evaluate the practical implications of disruptions. By analyzing unmet travel demands and passenger inconvenience metrics, such as additional stops and increased travel time, we provided insights into how disruptions affect passenger experience. Results showed that while the network maintains relatively high resilience in meeting most travel demands under some targeted disruptions, targeted attacks on some critical nodes lead to a higher proportion of unmet demands and rural nodes lead to substantial inconvenience for rerouted passengers. These disruptions are especially impactful during weekday operations, where passenger flow is concentrated, underscoring the importance of safeguarding high-betweenness nodes.

Finally, the real-world London Underground network benefits from a more efficient structure for passenger flow, but its reliance on critical nodes also makes it more vulnerable to targeted disruptions. This duality highlights the need for proactive measures to enhance the network's resilience, such as decentralized routing strategies or capacity enhancements at critical nodes. Future research could extend this framework by incorporating multi-modal transportation networks to provide a broader perspective on urban transit resilience.

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