Assessing Node Importance and Network Resilience in Chicago's Transportation Network

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This research paper identifies the key intersections in the Chicago transportation network through the commonly used measure of closeness centrality and local betweenness centrality (LBC), a variant of the more common betweenness centrality. Furthermore, the tolerance of this city network to intersection closures was assessed by measuring how the diameter of the network increased in response to the removal of nodes, a method that has been developed but not applied to the Chicago transportation network. We find that the Chicago city network fragments catastrophically at a critical threshold of 40% of nodes removed. Our findings are useful for urban city planners to analyze how intersection closure may impact traffic and travel time across the city of Chicago and therefore which intersections are the most important to keep open.

Significance Statement

This study contributes to the field of network analysis by demonstrating how local betweenness centrality can effectively pinpoint crucial nodes in urban transportation networks. It offers insights into enhancing urban connectivity and resilience to traffic disruptions.

Local betweenness centrality | Chicago transportation network | Road network analysis | Urban planning | Traffic optimization | Network resilience

Transportation networks in large cities are complex systems that require efficient design and management to ensure smooth flow and resilience in the face of disruptions. In particular, identifying the most crucial intersections and roads within a network is essential for improving traffic flow and minimizing congestion. Centrality measures, such as betweenness centrality, play an important role in identifying these key nodes in the network.

Betweenness centrality is widely used to find important roads that act as bridges, connecting various regions of a city. Similar studies in other cities, such as those by Yamaoka et al. (1) and Zhao et al. (2), have shown that roads with high betweenness centrality are vital for maintaining the flow of traffic and connecting different parts of the city. For example, in their analysis of European cities, Yamaoka et al. (1) demonstrated that high betweenness centrality roads are main connectors, while low centrality roads tend to be smaller or older roads that play a lesser role in facilitating traffic.

Zhao et al. (2) incorporated road-specific features like length, type, and traffic volume into their centrality analysis, providing a more nuanced understanding of how certain roads can affect traffic flow. Similarly, other studies (3) have emphasized the importance of considering physical features, such as lane count and road type, when evaluating the traffic efficiency of a road network. By utilizing these insights, our research focuses on using local betweenness centrality to assess the Chicago transportation network, with a particular focus on how the network would be affected if these central roads were disrupted.

In addition to centrality analysis, our research investigates the vulnerability of the Chicago transportation network. Previous work by Albert et al. (4) and Latora and Marchiori (5) has shown that scale-free networks exhibit different levels of resilience to random errors and targeted attacks. The Chicago transportation network is not scale-free, suggesting it may be more susceptible to targeted disruptions. By evaluating the impact of removing critical roads, we provide valuable insights into the potential risks posed by traffic disruptions and propose strategies for improving the resilience of the city's transportation system.

We also applied Louvain community detection to examine the modular structure of the Chicago road network. After removing degree-one nodes, the algorithm revealed clusters of densely connected intersections that often align with real-world neighborhoods. Visualizations of these communities highlight smooth transitions between central zones and greater isolation at the periphery, offering insights into urban structure and resilience planning.

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Dataset Information

The dataset used for this research represents the road network of Chicago, with each node corresponding to an intersection or endpoint and each edge representing a road connecting two nodes. The dataset includes a variety of attributes for each road segment, such as road capacity, road length, and road type, which are used to assign weights to the edges. This weighted network allows us to better capture the real-world importance of each road segment in facilitating traffic flow. The network consists of 1,467 intersections and approximately 1,298 roads, making it a comprehensive representation of Chicago's transportation infrastructure.

The data for the road network was sourced from publicly available transportation datasets, and the edge weights were derived based on factors such as road length and capacity, which reflect the actual importance of the roads in the city's overall connectivity. By analyzing this data with centrality measures like local betweenness centrality, we can identify key intersections and evaluate the network's resilience by simulating disruptions to high-centrality roads.

Mathematical Background

In graph theory, the diameter of a network is defined as the average length of the shortest paths between any two nodes in a network. This value characterizes the ability of an actor to travel between two nodes: the smaller d is, the shorter the expected path between them.

To determine the importance of nodes within a network, centrality is used. There are several types of centrality, each providing different perspectives on what makes a node significant in the structure of the network. The three most commonly used centrality measures are betweenness centrality, closeness centrality, and Katz centrality.

Betweenness Centrality. Betweenness centrality quantifies the importance of a node based on the number of shortest paths that pass through it. A node with high betweenness centrality lies on many of the shortest paths between other nodes, meaning it plays a critical role in connecting different parts of the network. This measure is particularly useful for identifying nodes that act as bridges, facilitating the flow of information or traffic between different regions of the network.

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma(s,t \mid v)}{\sigma(s,t)} \quad [1]$$

Here, $\sigma(s,t)$ is the total number of shortest paths between nodes s and t, and $\sigma(s,t \mid v)$ is the number of those paths that pass through node v.

Closeness Centrality. Closeness centrality measures how close a node is to all other nodes in the network. It is calculated as the inverse of the sum of the shortest path distances from the node to all other nodes. A node with high closeness centrality can reach other nodes more quickly, making it important for the spread of information or traffic.

Katz Centrality. Katz centrality takes a more holistic approach by not only considering direct connections (edges) to other nodes but also including paths through intermediary nodes. It assigns weight based on both direct and indirect connections, making it especially useful in networks where indirect influence matters.

Local Betweenness Centrality. In this research, local betweenness centrality (LBC) is the primary measure used to identify the most important intersections in the Chicago transportation network. Unlike global betweenness centrality, which considers all node pairs in the network, LBC focuses only on the local neighborhood of a node, considering its connections and role within a specific region of the network.

This local measure helps identify intersections that are crucial for maintaining connectivity and efficient traffic flow within specific urban areas. By analyzing these centrality measures and their applications to the Chicago transportation network, this paper aims to better understand how the structure of urban road systems influences traffic flow and the city's overall connectivity.

Materials and Methods

Link to Code. Google Colab Notebook for Reproducibility

Goals. Our goal was to rank key intersections using local betweenness centrality (LBC), while optionally comparing to degree and closeness centralities. LBC was weighted by road capacity to better reflect real-world conditions. We also examined how the diameter of the network increases as critical nodes are removed, comparing random removals with those based on centrality rankings, following the methodology of Albert et al. (2000).

Models. The Chicago transportation network was modeled using the `ChicagoSketch_net.tntp` dataset. Each node in the network represents an intersection or endpoint, and each edge corresponds to a directed road segment between two nodes.

The dataset was loaded using the `pandas` library, and a directed graph was created using `NetworkX`. To focus on overall connectivity rather than directionality, the graph was converted to an undirected form using the `to_undirected()` method. All analyses were performed in Python. The main tools included:

- `NetworkX` for graph operations and centrality metrics
- `Matplotlib` for plotting
- `random` module for shuffling nodes during simulations

Centrality and Importance Research.

Preprocessing the Graph. To prepare the network for analysis, we began by cleaning up peripheral noise that could skew centrality metrics. We noticed that every node in the original dataset had an extra leaf node,an additional node connected by a single edge,which likely represented driveways, cul-de-sacs, or other non-essential endpoints. To eliminate these artifacts, we removed all nodes with degree 1 from the network. This step helped us isolate meaningful intersections that play a more substantial role in urban connectivity. Following this, we graphed the degree distribution of the cleaned network to examine whether it followed a power-law distribution, as is common in many real-world networks (citation for class material or external reference can be added here).

Centrality Research. Our centrality analysis focused on two metrics that are particularly applicable to road networks: Local Betweenness Centrality (LBC) and Closeness Centrality. These metrics are useful because they highlight nodes that are highly trafficked, either by being centrally located or by appearing in many shortest paths. Nodes that are closer to most others or serve as frequent connectors tend to be more critical for maintaining flow in the network.

To compute LBC, we implemented a custom algorithm. For each node v, we identified its immediate neighbors (nodes directly connected to it) and evaluated all $\binom{k}{2}$ shortest paths among these k neighbors. We then counted how many of those paths passed through node v, giving us a localized version of betweenness that focuses on the node's role within its neighborhood.

In addition, we computed Closeness Centrality as a global measure to determine how quickly a node can reach all others. This was done using NetworkX's built-in function`closeness_centrality(G)`. To compare results on a consistent scale, we normalized both LBC and closeness values using `sklearn.MinMax`, ranked the nodes by importance, and visualized the results on the graph. This dual approach provided complementary perspectives on node influence at both local and global levels.

Diameter Experimentation. To evaluate how resilient the Chicago road network is to disruptions, we conducted a simulation-based experiment that progressively degraded the network through node removal. Two strategies were employed: random removal and targeted removal. In the random removal strategy, nodes were shuffled and then deleted in equal-sized batches across 50 steps. This approach simulates accidental or unpredictable failures, such as those caused by construction or natural events. In contrast, the targeted removal strategy ranks nodes by their betweenness centrality using NetworkX's `betweenness_centrality()` function and removes the highest-ranked nodes first. This simulates deliberate attacks on the most critical intersections and follows the methodology of Albert et al. (2000).

After each batch of node removals, we performed three key analyses. First, we extracted the largest connected component (LCC) from the updated undirected graph. Second, we computed the diameter of the LCC using `nx.diameter()`. Third, we normalized the LCC's size by dividing it by the original number of nodes to track how much of the network remained intact.

To visualize the results, we generated two plots: one showing how the diameter changes as a function of the fraction of nodes removed (f), and another showing the normalized LCC size as f increases. Following the approach of Albert et al., we defined the critical threshold f_c as the point where the LCC shrinks to below 50% of its original size. This threshold marks the moment when the network loses global connectivity.

A higher value of f_c indicates that the network can withstand the removal of a large portion of its nodes before breaking apart, whereas a lower value suggests the network is fragile and susceptible to fragmentation. To further illustrate this process, we took network snapshots at five key stages, $f = 0$, 0.2, 0.4, 0.6, and 0.8,showing the progression of fragmentation over time. To ensure consistency across these visualizations, we used a spring layout with a fixed random seed so that node positions remained stable between snapshots.

All simulations were conducted using modular Python code. We ensured reproducibility by fixing random seeds wherever randomness (such as node shuffling) was involved. We opted for batch-wise removal instead of removing nodes one at a time to make the overall trends clearer and to reduce the computational cost of the simulation.

Results

Centrality Importance and Hubs.

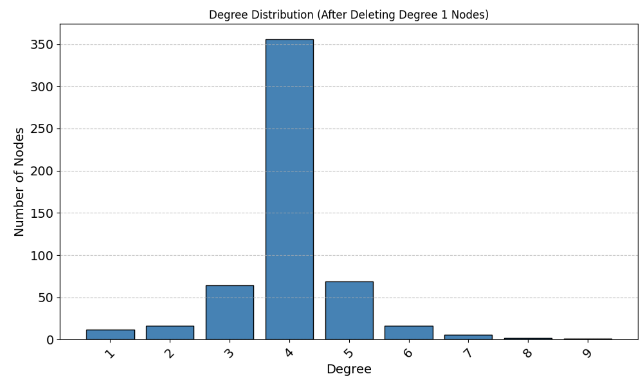


Figure 1. Degree Distribution (After Deleting Degree 1 Nodes)

Figure 1 shows the degree distribution of the Chicago transportation network after removing all nodes with degree 1. The histogram reveals that the vast majority of intersections have degrees of 3, 4, or 5, with degree 4 being the most common. Intuitively, this makes a lot of sense since the network reflects the grid-like structure of Chicago's urban planning, where intersections typically connect to four surrounding streets. The distribution exhibits a steep drop-off for nodes with degrees higher than 5, indicating that highly connected intersections (i.e., hubs in the traditional sense) are rare. This supports the earlier conclusion that the network does not exhibit a strong scale-free structure, but rather a constrained and uniform layout typical of planned urban grids.

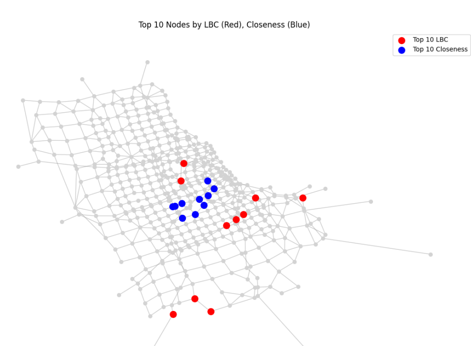


Figure 2. Top 10 Nodes by LBC (Red), Closeness (Blue)

Figure 2 displays the top 10 nodes ranked by Local Betweenness Centrality (LBC, shown in red) and Closeness

Centrality (blue) on the Chicago transportation network. The distribution of high-LBC nodes is scattered across multiple regions, particularly near the network periphery, indicating their role as critical connectors within localized subgraphs. In contrast, nodes with high Closeness Centrality are tightly clustered near the geometric center of the network, reflecting their structural importance in providing efficient access to other intersections. This spatial distinction illustrates the complementary nature of the two centrality measures: LBC identifies locally influential nodes that help maintain neighborhood-level flow, while Closeness Centrality highlights intersections with broad citywide accessibility.

Community Detection.

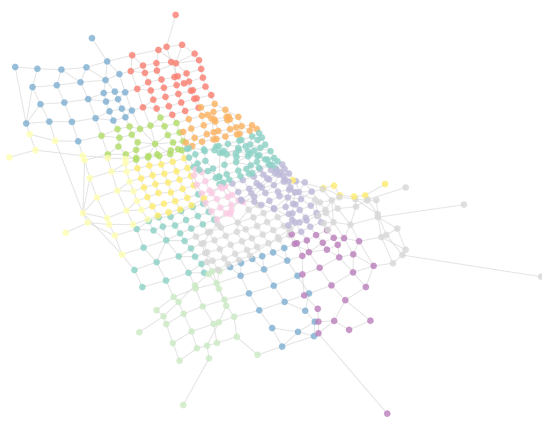


Figure 3. Chicago road network with Louvain community detection visualized using the Kamada-Kawai layout

To explore the structural organization of the Chicago road network, we applied the Louvain community detection algorithm, which identifies clusters of nodes that are more densely connected internally than with the rest of the graph. These communities often correspond to functional or geographic neighborhoods, providing insight into how the city self-organizes beyond individual intersections and roads.

Before applying the algorithm, we pruned the graph by removing all nodes with degree one (e.g., cul-de-sacs) to focus on the city's main transportation backbone. The Louvain method, implemented using the `community_louvain.best_partition()` function, partitions the network to maximize modularity, effectively revealing natural substructures in the urban grid.

Figure 3 shows the community-labeled network using the Kamada-Kawai layout, where color-coded clusters reveal a clear modular structure. Intra-community connections are visibly denser than inter-community links, reflecting localized connectivity typical of urban neighborhoods. Additionally, several regions exhibit smooth transitions between clusters, suggesting that neighborhood boundaries in Chicago are often gradual rather than abrupt—an expected result in organically developed cities.

To further examine the internal composition of each community, we decomposed the network into its individual communities and visualized them as separate subgraphs. This is shown in Figure 4, where each plot represents a single detected community arranged in a grid layout.

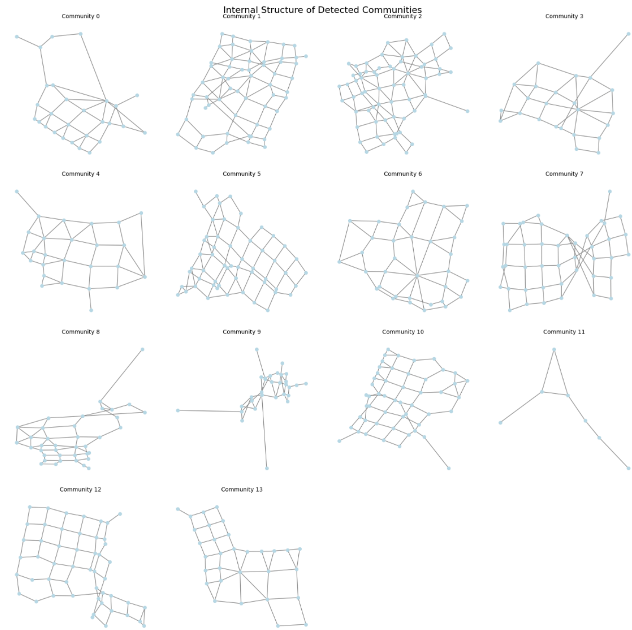


Figure 4. Subgraph decomposition of individual communities detected in the Chicago road network

This granular view reveals the diversity in community structure. Some communities, like Community 1, 5, and 12, resemble well-ordered grids, suggesting a highly regular street layout likely found in planned residential or downtown zones. Others, such as Community 9 and 11, appear more irregular or sparse, which may reflect less structured road systems—possibly due to natural boundaries, zoning constraints, or lower-density development.

Community 11, for instance, is tree-like and poorly connected, which could indicate a suburban or peripheral region. In contrast, Community 7 shows a denser, more complex mesh of connections with potential overlapping paths—possibly indicating a high-traffic junction or transit hub.

By decomposing and visualizing these communities individually, we gain not only structural insight but also a means of associating form with function. This approach allows urban planners to identify zones of vulnerability or redundancy and compare neighborhood-level design patterns across the city. Moreover, it enhances the interpretability of centrality-based findings by placing key roads within their broader modular context.

Together, Figures 3 and 4 reinforce the value of community detection as a tool for understanding how transportation infrastructure is spatially organized, interconnected, and potentially optimized.

Diameter Experimentation.

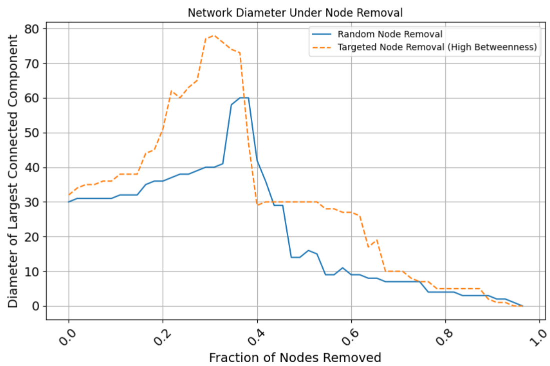


Figure 4. Network Diameter Under Node Removal

Figure 4 above shows how the network diameter changes as an increasingly large fraction of nodes are removed. The targeted node removal leads to a much steeper and earlier increase in diameter of the network as opposed to random node removal, which causes a slower, more gradual breakdown as shown by its lower absolute diameter values. Around a fraction of 40% of node removal, both curves drop sharply, indicating that the critical threshold f_c where the network fragments is around 0.4. At this point, the largest connected component shrinks drastically.

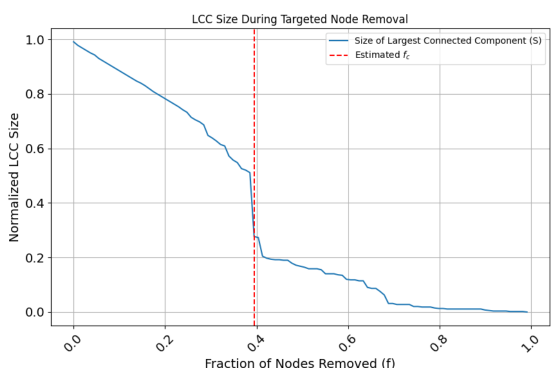


Figure 5. Network Diameter Under Node Removal

The breakdown of the network may also be visualized through the change in the size of the LCC as a function of the fraction of nodes removed. In the case of targeted removal of nodes, Figure 5 demonstrates that the network exhibits a sharp decrease in size at $f_c = 0.39$. This indicates network fragmentation that is particularly large at this critical threshold.

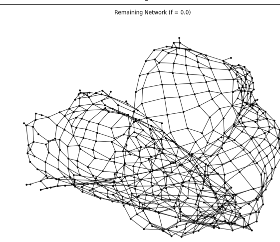
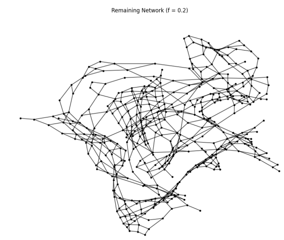
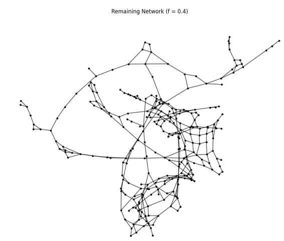
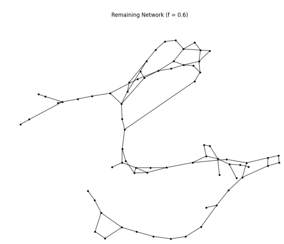
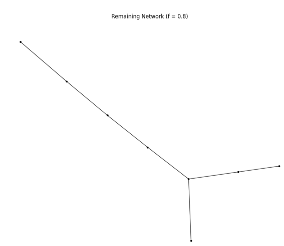
Fraction f	Snapshot
0.0	
0.2	
0.4	
0.6	
0.8	

Table 1. Snapshots of the network as a function of removed node fraction f.

Figure 6 visualizes the breakdown of the network at each 0.2 increment of fraction of nodes removed f. One can observe that between $f = 0.2$ and $f = 0.4$, the network becomes more sparse, and above $f = 0.4$, the connectivity of the network clearly drops greatly. As f increases, connectivity decreases dramatically.

Conclusions & Discussion

Centrality. The degree distribution of the Chicago road network loosely resembles a power-law but deviates in the tail. This makes sense, as most nodes have degree 4 or 5, reflecting the grid-like structure of urban street design where intersections commonly connect four roads.

Nodes ranked highly by Local Betweenness Centrality (LBC) are typically local hubs, meaning they sit at critical junctions within smaller neighborhoods or subnetworks. These intersections may not be central to the whole city, but they are essential for maintaining local flow. Thus, LBC is useful for applications like traffic management in residential zones or detecting local bottlenecks.

In contrast, nodes ranked highly by Closeness Centrality are more likely to be globally important, acting as major city-wide hubs. These intersections are positioned to reach most other intersections quickly, which aligns with our intuitive understanding of urban cores. Closeness centrality is therefore more appropriate for identifying strategic intersections in city-level planning and emergency response.

Node Removal. With regards to node removal, this paper suggests that Chicago's road network may be resilient to random failures. It appears able to maintain connectivity and short travel paths around local areas despite random removal of intersections, which may happen if certain intersections need to be closed in the case of construction, accidents, etc. However, it seems to be vulnerable to targeted removal of key intersections, which can cause fragmentation and a sharp rise in travel path lengths across the city. For individuals who need to move across larger swaths of the city, this could be an issue.

Interestingly enough, for both random and targeted removal of nodes, the critical threshold f_c in which the network breaks down was the same, happening around $f_c = 0.39$. This suggests that the road network's connectivity may be heavily reliant on having a certain fraction of intersections intact.

This node removal experimentation connects to the findings of Albert et al., which show that scale-free networks are especially vulnerable to targeted node removal, often leading to sharp drops in global connectivity near a critical point. Although our analysis of the degree distribution indicates that the Chicago road network is not truly scale-free, it still shows a similar pattern of vulnerability when key nodes are removed. This suggests that even networks without a scale-free structure can behave like one in certain scenarios, particularly when a few intersections play a large role in maintaining connectivity.

Limitations

With regards to limitations of node removal, this paper only investigates how this particular road network in Chicago responds to node removal. This paper also does not take into account road length. A path consisting of many longer roads may naturally be a longer path than a path consisting of shorter road lengths with the same number of edges. Therefore, future research could weight the network by road length and road capacity. Assessing how the maximum total path length changes could also be an interesting lens to assess how traffic is affected by road closure.

Similar to what Zhao et al. (2017) does, incorporating point-of-interest (POI) analysis could also be interesting to assess how road closure impacts the distances between common places of commute, particularly within the densest areas of the city. This could help road planning to prioritize keeping certain intersections open to maximize traffic flow.

Acknowledgements

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