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Robustness assessment of urban road networks in densely populated cities

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Abstract
This paper presents a robustness assessment in terms of inducing damage to the functioning of real-world urban road networks via a comparative analysis of the efficacy of various network perturbation strategies. Specifically, we assess the network robustness through an iterative node removal process considering five targeted (deterministic) and two random (stochastic) strategies. The targeted node removal strategies are based on different centrality measures. We study the robustness of 10 road networks of densely populated cities using three different metrics: the size of the largest connected component, global efficiency, and local efficiency. Our findings suggest that targeted disruptions utilizing centrality measures are more effective in disrupting the network than random ones. However, some centrality measures have a strong correlation with each other and thus, requiring combinations of different removal orders to gain more comprehensive insights into the ability of the network to withstand perturbations. We find centrality measures considering shortest paths are more effective in degrading the robustness of the network as a whole while centrality measures that only consider directly connected neighbours are better in disrupting the local effectiveness of the network. Interestingly, we also find that removing nodes can counter-intuitively increase the local efficiency of the network.

Keywords Network robustness, Urban road networks, Largest connected components, Global efficiency, Local efficiency

Introduction

In the past thirty years, the global urban population has risen from 39 to 52% and is projected to reach approximately 66% of the total population by 2050 (Habitat, 2022). One critical infrastructure to sustain this trend in urban areas is the road networks which are vital in facilitating economic activities and growth by supporting efficient movement of people and goods. They are also important in enhancing the overall quality of life by connecting communities and fostering social interactions. It is then not surprising that huge impact and significant costs are incurred when these road networks do not function well. The various consequences of inadequate road infrastructure can range from minor delays due to increased traffic congestion to disruptions or reduced accessibility to essential and emergency services (e.g., ambulance, fire, police), causing both life and

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economic losses (Ben 2019; Zhang and Cheng 2023). To illustrate, Transport for London (2022) reported that congestion costs the London economy £5.1bn a year (equivalent to £1,211 per driver). On average, drivers in India, one of the most populous countries in the world, waste 135 h per year in traffic congestion per year, costing USD$22bn involving fuel waste, high air pollution, and productivity loss (ESCAP UN 2021). The collapsed Zijin Bridge in Heyuan City in June 2019 led to significant direct and indirect economic losses, limited mobility, and incalculable ecological imbalances (Tan et al. 2020). Another, more recent bridge collapse in Baltimore has led to severe consequences, greatly impacting commuters preparing for significantly longer travel times lasting three to four times as long as usual (Craig et al. 2024).

Road networks are, unfortunately, susceptible to various perturbations such as accidents and road closures due to construction/maintenance work.[1] There could also be more severe perturbations due to natural events/disasters (e.g., extreme weather conditions– extreme heavy rainfall in Zhengzhou city (Stanway 2021) or human activities (e.g., a day-long urban mobility strike in Delhi (The Economic Times 2024)). Severe perturbations could incapacitate some parts of the road networks. Hence, it is important to understand the ability of the network to withstand failures (e.g., for transportation maintenance and planning endeavors). As such, the focus of our study here is on the robustness assessment of urban road networks. Specifically, we choose ten road networks from densely populated cities and subject them to different and increasing perturbations. We then monitor how the network responds to such disturbances. These cities are often identified as second-tier (Brian and Peter 2014; Wong 2019) or emerging cities (Wood 2018) in their respective countries. Their rapid economic and infrastructure development has driven their rise as industrial and economic hubs, though they have yet to be globally recognized as top-tier cities like Beijing, Shanghai, Delhi, or Mumbai. They are critical for regional economies, often specializing in particular industries (e.g., Dongguan for electronics, Surat for textiles, Harbin for heavy industry, and Qingdao for shipping and trade). Geographically, they share the common trait of located in close proximity to water sources such as coastlines (e.g., Quanzhou, Fuzhou and Dalian are coastal cities with access to sea and major ports) or rivers (e.g., Surat, Ahmedabad, Harbin and Shenyang lies near to Tapti, Sabarmati, Songhua and Hun rivers respectively). Dongguan is in the Pearl River Delta, giving it access to a waterway network that connects to the South China Sea.

In this paper, we adopt concepts from network science (Barabási 2013) in which the networks are first abstracted as graphs and we evaluate the network performance degradation using robustness metrics based on graph theory that are commonly used in the literature (cf. Section 2 for the review of related work). We introduce the relevant concepts and our methodology in Sect. 3 in which we systematically introduce perturbations to the network based on different network perturbation patterns representing scenarios including random incidents (e.g., road accidents) and strategic removals based by node importance. We discuss our results and analysis in Sect. 4, highlighting how the networks respond to different perturbation patterns. We see random disruptions are, in general, less effective than targeted disruptions and the different targeted disruption

[1] For the rest of the paper, we use the term "perturbation" to refer to any event, both planned and unplanned, that cause the non-functioning of the node or more specifically, the blockage/inaccessibility of the road). Further, we follow the literature (e.g., Trajanovski et al. (2013); Buhl et al. (2006)) to use the term "node removal" as the method of which we use to represent such events.

strategies could offer very different results. We find that removing nodes based on ranking using path-based centrality measures (e.g., betweenness) offers the greatest impact to the network. We find that removing nodes based on ranking using immediate connectivity (e.g., degree) can have high impact on local regions but not the network as a whole. We find that due to similarity/correlation of some centrality measures, there is a need to use a combination of disruption strategies to comprehensively study the robustness of road networks. Finally, we summarize our findings in Sect. 5.

Related work

Network robustness has been a staple topic of study in network science over the past decades and has been applied to various types of complex real-world networks. While the concept can be easily intuited, a formal standardized definition proved to be more elusive and highly dependent on the type of network or application of interest (Smith et al. 2011). Additionally, scholars have encountered challenges in reaching a consensus on the definition of robustness within the realm of networked systems. Various terms such as reliability, survivability, safety, and resilience have similar meanings to robustness, further complicating consensus-building among researchers. In Immers et al. (2004), robustness is described as "the extent to which a system can operate in line with its design specifications even during significant disruptions". Meanwhile, Boccaletti et al. (2006) defined robustness as a network's capacity to function despite damage to some of its components. Robustness in Schillo et al. (2001) appears as the capability to uphold "safety responsibilities", while also linking it broadly to system performance. In the context of road networks and for our study, we will adapt the definition by Mieghem et al. (2010), where robustness is the network's ability to withstand perturbations under node disruptions.

Several studies have explored the evaluation of network robustness in various disaster scenarios, aiming to enhance the robustness of urban road networks. In particular, researchers have introduced different methodologies and indices to analyze the robustness of urban road networks under different conditions, with a focus on minimizing the isolation of districts during disruptive events. Sakakibara et al. (2004) introduced a topological index grounded on the concentration of links in a network to evaluate robustness in disaster scenarios, with the goal of reducing the network breaking into multiple components during these events. Similarly, Scott et al. (2006) defined and applied the network robustness index, for evaluating the critical importance of a link in three hypothetical road networks. They measure robustness by calculating the change in travel time when a link is completely removed. Zhou et al. (2017) have introduced a framework for evaluating the robustness of urban road networks, consisting of two layers. The framework includes variations for measuring robustness against random failures and intentional disruptions and is validated using a real-world urban road network in Hong Kong.

Disruptive scenarios were studied through random or targeted disturbances. The random strategy removes random network edges or nodes, whereas the targeted strategy removes network nodes based on a classification of their centrality values (Scardoni and Laudanna 2012; Casali and Heinimann 2020; Iyer et al. 2013; Bellingeri et al. 2020; Ma et al. 2020; Kumar and Singh 2020). In Buhl et al. 2006, the authors investigated the robustness of the road network by progressively removing nodes in a random way and by decreasing the order of node degree in 41 urban settlements. Another study by Albert et al. (2000) utilizes metrics like variations in diameter, the size of the largest cluster, and the average size of isolated clusters to evaluate how networks respond to intentional or random disruptions. A study in Duan and Lu (2014) analyzing six city road networks globally found that the diversity in betweenness centrality distribution of the network plays a key role in its robustness, more than geographical features (e.g., rivers and mountains) and inherent spatial attributes (e.g., road length and width). The authors of this work found that the studied cities exhibit similar robustness under disruptions due to shared topological structures and when different representation granularities (i.e., different network abstraction approaches) are used, the cities show different robustness. The authors considered three granularities– road segment granularity, stroke granularity (i.e., a series of linearly connected road segments) and community granularity (i.e., a group of highly clustered road segments). These studies have contributed to the development of a detailed analysis of how road network robustness properties may change under a broad range of alterations. Our work here follows the same line of approach but focuses on road networks in densely populated cities which have some specific but prevalent properties such as lack of degree diversity due to the physical spatial constraint in the construction of road infrastructure.

Robustness of road networks

For our robustness assessments of urban road networks, we utilize tools and metrics from network science. For this purpose, we abstract the road networks and represent them as an undirected graph, *G*(*V*, *E*) with $V = v_1, ..., v_N$ the set of nodes and $E = e_1, ..., e_L$ the set of links where $N = |V|$ and $L = |E|$. In the context of this paper, the nodes represent the road intersections/junctions while the links represent road segments connecting two nodes. *G* can be represented by *A*, the $N \times N$ symmetric adjacency matrix, with $a_{i,j} = 1$ if there exists a link between nodes v_i and v_j and 0 otherwise. In this work, we assume the input unperturbed network is connected (i.e., there is a path between any pair of nodes in the network) so that *A* is irreducible.

Robustness metrics

As mentioned in Sect. 2, we follow the definition of robustness as the ability of the network to sustain adequate functionality under network perturbations. In this study, we focus on node removals. To measure robustness, we employ three real-valued metrics, namely the size of the largest connected component (*LCC*), S_{LCC}, global efficiency, E_{Glob}, and local efficiency, E_{Loc}. We normalize them into range [0, 1] where a higher value indicates a higher functioning network (i.e., 1.0 indicates an unperturbed network implicitly assuming that the original input network has 100% functionality). We compute and track the performance of these metrics over the increasing amount of perturbations introduced to the network under study and gain insights into the behaviour of the network until the networks are fully dismantled.

Size of the largest connected component

The *LCC* is a fundamental and widely used metric for assessing network robustness. It is defined as the size of the biggest component of a network:

$$S_{LCC} = \max(S_j) \tag{1}$$

where S_j is the size (number of nodes) of the *j*-th component. S_{LCC} is simple to compute and has been used in various works for assessing the global topological connectedness of the network (e.g., Bellingeri et al. 2020; Albert et al. 2000; Duan and Lu 2014; Kozhabek and Chai 2025; Diop et al. 2022).

Global efficiency

The global efficiency of a network, *G*, is the average of efficiency between all pairs of nodes whereby the efficiency between nodes *i* and *j* is simply the reciprocal of the shortest path length between them. Following this definition, global efficiency of network *G*, E_{Glob}, can be written as follows (Latora and Marchiori 2001):

$$E_{Glob}(G) = \frac{1}{N(N-1)} \sum_{i \neq j \in V} \frac{1}{H_{i,j}} \tag{2}$$

where H_{ij} denotes the shortest path distance between node (in hopcount) v_i and v_j. Generally, E_{Glob} provides an indication of the effectiveness of traffic exchange within a network. In the context of our work, E_{Glob} signifies the effectiveness with which destinations are accessible across the entire network. It is a measure that assesses how well vehicles on the road flow through a network from one point to another. Specifically, it indicates how easily vehicles can travel between any two points in the road network. A higher value of E_{Glob} signifies, on average, it is faster or requires fewer steps to get from one point to another across the network, as illustrated by Latora and Marchiori (2001). Similar to S_{LCC}, E_{Glob} has been commonly used in assessing network robustness (e.g., Latora and Marchiori 2001; Barabasi 2014; Koulakezian et al. 2015; Manzano et al. 2012).

Local efficiency

While E_{Glob} takes the entire network as a whole into consideration, local efficiency instead focuses on the immediate neighborhood of each node. Specifically, the local efficiency of node *i* is the average efficiency of the local subgraph consisting of all nodes adjacent to node *i*, but not the node itself. We can then compute the network's local efficiency by taking the average of the local efficiency of all nodes in the network as follows (Latora and Marchiori 2001):

$$E_{Loc}(G) = \frac{1}{N} \sum_{i \in V} E(G_i) \tag{3}$$

where

$$E(G_i) = \frac{1}{k_i(k_i-1)} \sum_{l \neq m \in G_i} \frac{1}{H'_{lm}}. \tag{4}$$

G_i is the local subgraph of node *i*. If node *i* has k_i neighbors, then G_i has k_i nodes and at most $k_i(k_i-1)/2$ edges. There, H'_{lm} is the shortest distance between nodes *l* and *m* calculated on the graph G_i. As opposed to S_{LCC} and E_{Glob}, to the best of our knowledge, E_{Loc} is not a commonly used metric in the literature. However, we find interesting insights with regard to this metric (cf. Section 4). Having introduced the above, we would also like to note that the choice of robustness metrics is dependent on the specific application domain and our study and approach here can naturally be extended to accommodate any other metrics.

Perturbation models

A common approach to assess the robustness of a network is by determining how the network responds to different kinds of disruptions. In this paper, we consider two types of perturbations: (1) random disruptions corresponding to random events such as accidents and (2) targeted disruptions, aimed at stress-testing the network by removing nodes considered most critical based on some metrics. This approach seeks to maximize the damage or impact inflicted to the network.

Random disruptions

A road junction may be blocked due to various unplanned reasons (e.g., traffic accidents, fallen trees, landslides). For such events, the sites of occurrence are usually not predictable and they can be modeled as random events. For this, we consider two types of random node removal strategies.

- Random Point (R_P)– A node is selected at random from all remaining nodes in the network, with each node having an equal probability of being chosen. For this, a node can be removed at any part of the network at each iteration, reflecting well the randomness of events such as accidents.
- Random Area (R_A)– Start by randomly removing a node in the network. In the next iteration, choose to remove a random neighbor of the last removed node. Repeat the process of removing random neighbors iteratively until the desired fraction of node removals is achieved. Such a process reflects a scenario where an area is impacted by events such as flooding or strike actions which usually start at one point in the network and gradually spread from the initial affected location. In real-world scenarios, the spreading may not be purely random and influenced by various factors but for the purpose of illustrating the potential impact, we follow the literature (Kirby 1969; Dong et al. 2022; Wang et al. 2019) to simplify and model the spreading as a stochastic process.

Targeted disruptions

It is often important to understand how much disruptions a network can withstand (i.e., worst-case scenario). For such purpose, disruption must be introduced with the aim of maximizing damage to the network. The rationale is that a malicious attacker will logically attempt to target nodes which are deemed to be the most critical to the network first to cause the most disruption. To achieve this,

1. We first rank all the nodes in the network based on their importance based on some centrality metrics (see below) in descending order (i.e., the most important node at the top of the list which should incur the most impact to the network if removed).
2. We then iteratively remove the node from the top of the list one at a time and compute the robustness metrics detailed in Sect. 3.1 after each removal to assess the impact after each removal.

Note that we do not recalculate the centrality values after each removal; instead, the nodes are removed based solely on the initial centrality ranking list. This approach allows us to maintain a consistent evaluation framework throughout the disruption process.

To compute the node ranking, we consider different centrality measures, conventionally used in network robustness studies (Mieghem et al. 2010; Kumar and Singh 2020; Trajanovski et al. 2013; Chai et al. 2016).

- Degree centrality (c_D) (Wasserman and Faust 1994)– Measures the number of direct neighbors each node has. In the context of road networks, it represents the number of road segments (link) meeting at an intersection (node). An intersection with many roads converging towards has a higher degree and has more influence on the local connectivity.
- Betweenness centrality (c_B) (Wasserman and Faust 1994)– Measures the involvement of a node between all node pairs in the networks (i.e., lies in the shortest path, acting as a bridge between the two nodes). An intersection with high betweenness implies that the location lies on many shortest paths between other nodes and thus, is likely to see a high volume of traffic across this node.
- Closeness centrality (c_C) (Wasserman and Faust 1994)– Assesses how proximate a node is, on average, to all other nodes in the network. Applied to road networks, a node with high closeness centrality would mean that it can reach other nodes with fewer hops.
- Katz centrality (c_K) (Newman 2018)– Computes the centrality for a node based on the centrality of its neighbors. It assesses the impact of a node in a network by taking into account both its direct neighbors and all other nodes in the network that connect to the node under consideration through these immediate neighbors. In the realm of road networks, Katz centrality can pinpoint nodes with indirect ties to prominent nodes, shedding light on their secondary level of significance.
- Load centrality (c_L) (Song et al. 2015)– Assumes that every node in a network sends an equal amount of a specified commodity to every other node in the network, without considering any capacity limits of edges or nodes. It measures the total amount of flow passing through a node in a network. As opposed to betweenness centrality which ranks node based on its position in the shortest paths between node pairs, load centrality looks at the total flow passing through a node assuming an equal distribution.

The definitions of the above-mentioned centrality measures are given in Table 1.

Table 1 Centrality measures used to rank nodes for targeted disruptions

Degree	$c_D(v_i) = \frac{d_i}{N-1}$
Betweenness	$c_B(v_i) = \sum_{v_j, v_k \in V} \frac{\sigma(v_j, v_k \mid v_i)}{\sigma(v_j, v_k)}$
Closeness	$c_C(v_i) = \frac{N-1}{\sum_{j=1}^{N-1} H_{i,j}}$
Katz	$c_K(v_i) = \beta(I - \alpha A)^{-1}$
Load	$c_L(v_i) = \sum_{v_j, v_k \in V} \frac{1}{\sigma(v_j, v_k \mid v_i)}$

d_i is the degree of node v_i; $\sigma(v_j, v_k)$ is the number of shortest paths between nodes v_j and v_k; $\sigma(v_j, v_k|v_i)$ is the number of those paths between v_j and v_k passing through node v_i; H_{ij} denotes the shortest path distance between node v_i and v_j; α is a constant (damping factor), usually $\alpha < 1/\lambda_{\max}$ where $\lambda_{\max}$ is the largest eigenvalue of the adjacency matrix, *A*. When $\alpha \geq \lambda_{\max}$, the centrality tends to diverge; β is a bias constant (exogenous vector) used to avoid the zero centrality values; *I* is the identity matrix

Network perturbation analysis

Our analysis involves the introduction of perturbations to the network under study. For this, we sequentially remove an increasing fraction of nodes from the network following the perturbation models described in Sect. 3.2. For random disruptions (i.e., R_P and R_A), since they are stochastic, we repeat the experiment for each network 100 times and present the mean value along with their 95% confidence interval using error bars.

We track the gradual degradation of the robustness metrics introduced in Sect. 3.1 (i.e., the resulting S_{LCC}, E_{Glob}, and E_{Loc}) after each node removal and recompute the *LCC*. We consider this new *LCC* for the next removal. Algorithm 1 presents the pseudocode for our node removal process.

Input : Network $G = (V, E)$, X=$\{R_P, R_A, c_D, c_B, c_C, c_K, c_L\}$
Output: S_{LCC}, E_{Glob}, E_{Loc}
Initialization:
  Compute and record S_{LCC}, E_{Glob} and E_{Loc} of G;
  Let $LCC = G$
  if $X == R_P$ **then**
    while $S_{LCC} \neq 0$ **do**
      Node = getRandomNode(LCC);
      remove Node from LCC;
      record new S_{LCC}, E_{Glob}, E_{Loc} of G;
    end
end
else if $X == R_A$ **then**
    Node = getRandomNode(LCC);
    while $S_{LCC} \neq 0$ **do**
      remove Node from LCC;
      record new S_{LCC}, E_{Glob}, E_{Loc} of LCC;
      Node = getNeighbor(Node);
    end
end
else
    nodeList = rankNodes(G,X) //put nodes in LCC in decreasing order based on X;
    index=0;
    while $S_{LCC} \neq 0$ **do**
      remove nodeList(index);
      index=getNextNode(nodeList);
      record new S_{LCC}, E_{Glob}, E_{Loc} of LCC;
    end
end

Algorithm 1 Node disruption algorithm

Figure 1 provides an illustration of the removal process following node ranking based on betweenness centrality. For each step, the node with the highest c_B(node in red color) is removed. Note that after four nodes were removed, the network disconnected into two components (see Fig. 1e). When this happens, following the literature (e.g., Trajanovski et al., 2013), we continue to consider only the new *LCC* and ignore the small component(s).

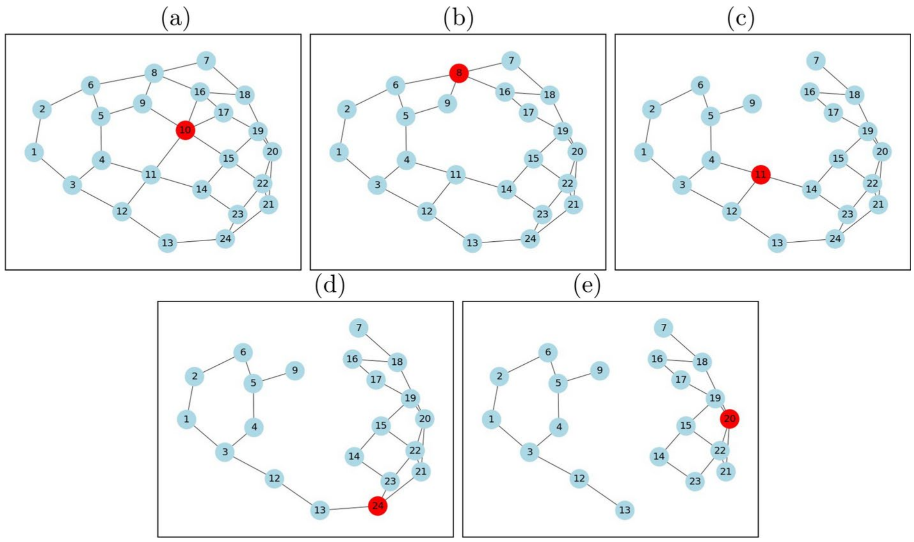

Fig. 1 Illustration of node removal process based on c_B for a sample 24-node road network where the node with the highest c_B for each *LCC* is indicated in red

Robustness assessment

Dataset

For this paper, we have chosen road networks from ten densely populated cities. There are two Indian cities (i.e., Surat and Ahmedabad), and eight Chinese cities (i.e., Quanzhou, Dongguan, Zhengzhou, Harbin, Fuzhou, Shenyang, Dalian, and Qingdao). These cities share a strategic geographical advantage (near water bodies like coastlines or rivers) and are classified as second-tier (Brian and Peter 2014; Wong 2019) or emerging cities (Wood 2018), with fast-growing economies and infrastructure. This combination has fueled their development as industrial and economic centers, though they are not yet at the level of the most prominent global cities.

Our dataset, sourced from Karduni et al. (2016), incorporates the GIS Features 2 Edgelist (GISF2E) tool, which was applied to the road networks of 80 major cities worldwide using data from OpenStreetMap. This tool converts shapefiles into network representations, generating a Comma-Separated Values (CSV) file containing all nodes and the corresponding edge list. The extracted data also includes the geospatial coordinates of nodes, the length of each road segment, and information on which each link within the network connects nodes. Table 2 provides a summary of some basic quantities for these networks.

Correlation and similarity of different targeted disruption strategies

Before we present our robustness assessment, we first offer some insights into the different targeted disruptions (i.e., the node rankings based on different centrality measures). For this, we first investigate the extent to which different centrality measures result in the removal of similar nodes. We compute the Spearman coefficient as a full-rank correlation proxy (see Fig. 2). We see a strong correlation between c_B and c_L and between c_D and c_K, implying that one from each pair could be redundant in future analysis as they almost provide the same node removal sequences. At the other end of the spectrum, we find c_D and c_C to have the lowest correlation while others fall between these two extremes.

Table 2 Statistics of road networks

Road networks	*N*	*L*	Network Diameter	Average path length	Degree diversity, κ	Population (million)
Surat	2593	7340	73	29	3.10	7.86
Quanzhou	5672	15234	125	43	3.09	1.83
Dongguan	8315	22256	135	46	3.05	7.52
Zhengzhou	9162	25730	114	42	3.13	5.74
Harbin	10727	29422	162	53	3.09	6.7
Fuzhou	12333	32338	128	46	3.01	3.86
Ahmedabad	12859	36406	129	49	3.11	8.5
Shenyang	13000	38052	117	41	3.23	7.57
Dalian	13605	35794	186	70	3.01	5.92
Qingdao	13894	38036	183	63	3.15	5.89

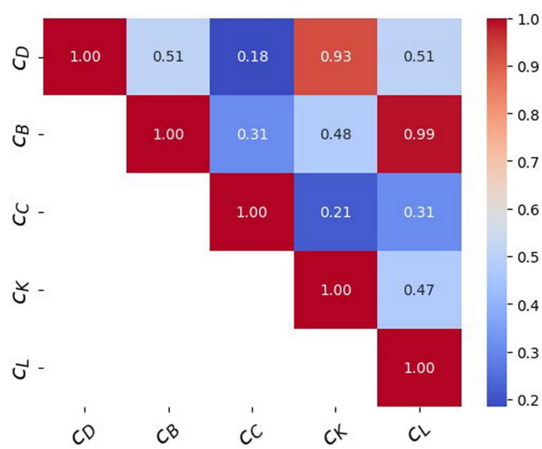

Fig. 2 Spearman correlation heatmap of the centralities (the targeted disruptions). The heatmap represents the average of all ten networks

We further compute the pairwise similarity of the centrality measures to understand how similar are the rankings when an increasing fraction of nodes are removed. To achieve this, we consider the following process. For two node rankings, $C_a = [c_{a_1}, c_{a_2}, \ldots, c_{a_N}]$ and $C_b = [c_{b_1}, c_{b_2}, \ldots, c_{b_N}]$, $U_{C_a,C_b}(k)$ is the percentage of nodes in $\{c_{a_1}, c_{a_2}, \ldots, c_{a_{\lfloor kN \rfloor}}\}$ that also appear in $\{c_{b_1}, c_{b_2}, \ldots, c_{b_{\lfloor kN \rfloor}}\}$. In this way, when $k = 100\%$, complete overlap is achieved, resulting in $U_{C_a,C_b}(100\%)$=1. Essentially, $U_{C_a,C_b}(k)$ indicates the proportion of shared nodes from the top $k\%$ of nodes in the rankings C_a and C_b. The results of $U_{C_a,C_b}(k)$ for studied road networks are given in Fig. 3. Five different centrality measures give us ten possible combinations of centrality pairs. From the figure, we observe that $U_{Betweenness,Load}(k)$ generally has the highest overlap across increasing *k*. This is expected, as both betweenness centrality and load centrality are closely related, with both metrics being based on shortest path values. It is followed by $U_{Degree,Katz}(k)$. The remaining eight pairs perform closely with $U_{Closeness,Katz}(k)$ and $U_{Degree,Closeness}$ showing the lowest values for all networks. Since $U_{C_a,C_b}(k)$ is low when C_a and C_b have few overlap (i.e., C_a and C_b consider node importance differently), then pairs of centrality measures with low $U_{C_a,C_b}(k)$ have distinct impacts to the road network. Considering this, with $U_{Closeness,Katz}(k)$ and $U_{Degree,Closeness}(k)$ showing relatively few overlaps between their node rankings, they

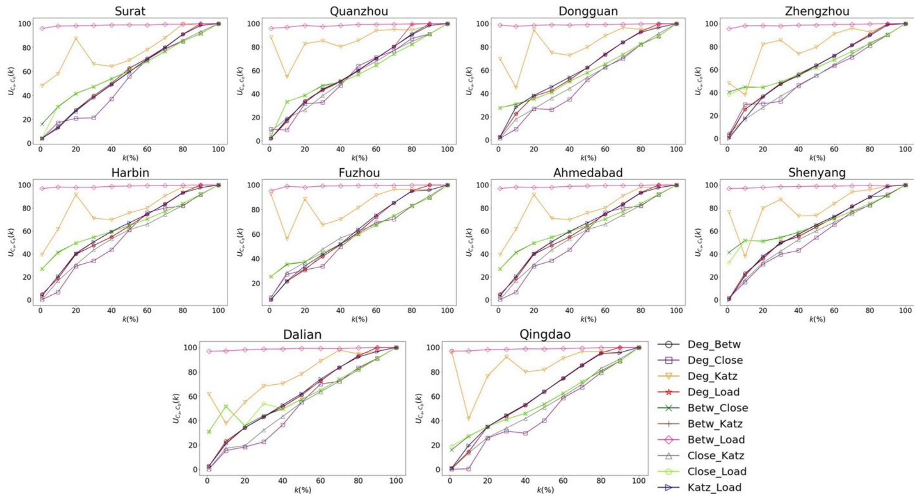

Fig. 3 Similarities of centrality rankings for road networks. Each plot shows the overlap of nodes (y-axis in %) from the first nodes (x-axis) ranked according to centrality ranking C_a and the first nodes ranked according to centrality ranking C_b for a given network

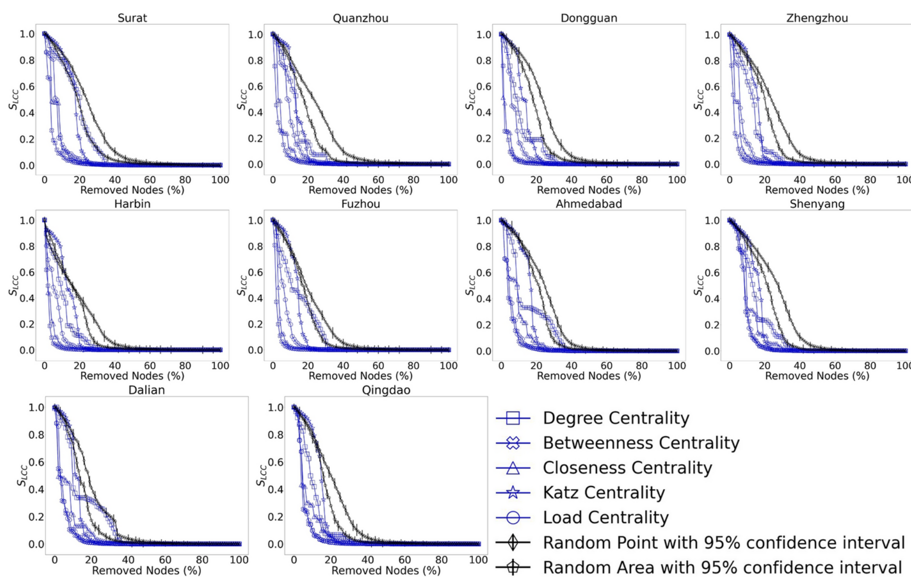

Fig. 4 The evolution of S_{LCC} curve (normalized) for different disruption strategies in the ten road networks

should be considered to gain insights into the impact to the network following different node disruption sequences.

Impact of perturbations on size of the largest connected component

We begin our assessment focusing on LCC and present in Fig. 4 the evolution of S_{LCC} in our experiments. Not surprisingly, as we increase the number of perturbations, S_{LCC} decreases monotonically for all networks. However, in general, random perturbations (i.e., R_P and R_A) are less effective in disrupting the network (shown by the slower degradation of S_{LCC}) compared to targeted perturbations based on centralities. Between R_P and R_A, our results suggest disruptions spreading around a neighbourhood region in the network, R_A, incur a higher detrimental impact than disruptions occurring at random locations in the network. This is likely due to the fact that R_A removes nodes focusing in one area and thus manages to disconnect the network into components more effectively.

Proceeding to consider the targeted disruptions, we first observe that, for all networks, c_K is the least effective in disintegrating the network. This implies that for road networks, a node directly connected to or near important major junctions does not necessarily inflate the importance of the node of interest and c_K is a poor choice to degrade S_{LCC}.

This is followed by c_D. While many real-world networks exhibit scale-free properties with power-law degree distributions (Barabási 2013) we found that urban road networks do not possess such degree distribution (Porta et al. 2006; Barthelemy 2021). Rather, since they are spatial networks, they have a small deviation of average degree (between 2.7 and 2.95 with an average standard deviation of 0.94 and average variance of 0.89). This observation has also been found by previous works (e.g., Kozhabek and Chai 2025; Reza et al. 2022; Lee and Jung 2018; Akbarzadeh et al. 2018) that urban road networks do not exhibit large variation in degrees due to planar constraints (Lämmer et al. 2006 and Viana et al. 2013). In our case, we see that the road networks have a majority of junctions (nodes) inter-connecting two or three roads. Hence, with many nodes having similar degrees, the c_D disruption strategy ultimately does not differentiate most of the nodes. Moreover, we observe clear knee points for the S_{LCC} curves in Fig. 4, indicating removal of some nodes with similar degrees has a small impact on S_{LCC}.

At the other end of the spectrum, we found that disruption based c_B to be the most effective and this is consistent across all networks. This aligns with previous research in Albert et al. (2000) where it was also found that node removal based on c_B leads to the worst-case scenario for the robustness of complex networks. In the context of transportation, Duan and Lu (2014) found that c_B-based disruption strategy is the most harmful. In Vaca-Ramírez (2019), only ≈10% of nodes removed based on c_B ranking is needed to incur significant deterioration of the road network of Quito city.

Meanwhile, the effectiveness of disruption strategies, c_C and c_L, vary between different networks but overall, c_C appears to be more disruptive for smaller networks while c_L to be more effective for bigger ones. However, the differences are marginal. Based on the above discussion, we could broadly summarize the effectiveness of the different disruption strategies in the following order: $c_B \succ c_C \approx c_L \succ c_D \succ c_K \succ R_A \succ R_P$.[2]

In Fig. 5, we present the percentage of nodes needed to be removed to achieve 25%, 50% and 90% reduction of S_{LCC} for the considered road networks. From this figure, we can make several further observations. First of all, we can see that, overall, Shenyang appears to have the most robust road network when most disruption strategies are less effective on it than other networks. This could be due to the physical landscape and geographical features allowing better overall connectivity such that the closure of roads incurs less disruption to the network. Delving further into this, we found that Shenyang has the highest degree diversity among all the cities considered here, suggesting high degree diversity offers better robustness in terms of S_{LCC}.[3] City planner for this city may have strategically improved the network in terms of improving the number of

[2] To simplify discussion and presentation, we use $X \approx Y$, $X \succ Y$, and $X \prec Y$ to indicate that X inflict similar, higher, and lower degradation to the network than Y respectively.

[3] Degree diversity, $\kappa = \frac{\sum_{i=1}^{N} d_i^2}{\sum_{i=1}^{N} d_i}$.

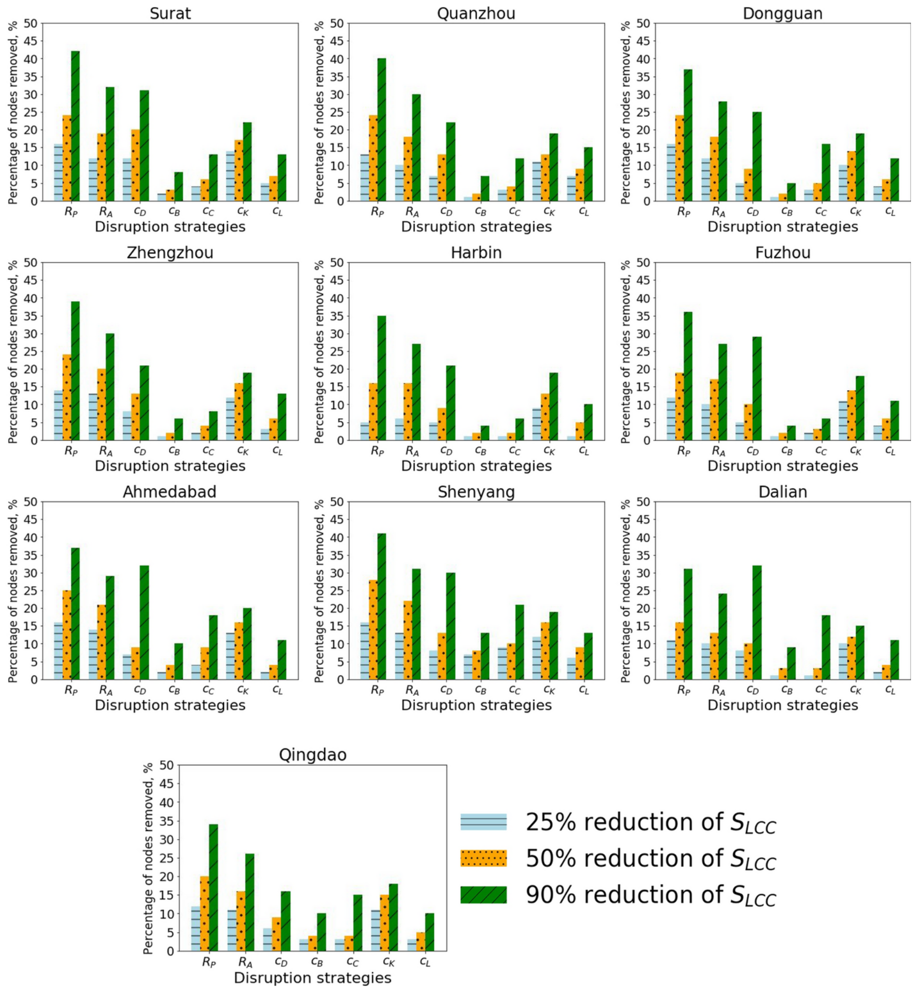

Fig. 5 Reduction of S_{LCC} based on types of perturbation strategies to achieve 25%, 50%, and 90% decrease

alternative routes and eliminating "dead-end" roads[4] and thus, mitigating potential disruptions. Second, while c_D-based disruption is generally more effective than random removal strategies, (i.e., R_A and R_P), there are cities (i.e., Fuzhou, Ahmedabad, and Dalian) where a higher number of nodes are needed to be removed to achieve $90\% S_{LCC}$ reduction even though much lower number of nodes are needed to achieve 25% and $50\% S_{LCC}$ reduction. This indicates that disruption based on node degree has smaller impacts when the S_{LCC} is small. Third, c_K disruption strategy seems to need a similar number of nodes removed to achieve the three 25%, 50% and $90\% S_{LCC}$ reduction; forming a more linear relationship between node removal and decrease of S_{LCC} at the end of the node removal process compared to other strategies. Finally, the least effective R_A require ≈30–40% removal to achieve 90% S_{LCC} decrease.

Impact of perturbations on global efficiency

We present in Fig. 6 the evolution of E_{Glob} with increasing perturbations for all the cities. Similar to S_{LCC} in Fig. 4, we can still set apart random and targeted disruption strategies where random ones are less effective in decreasing the E_{Glob} with $R_A \succ R_P$.

[4] https://www.shenyang.gov.cn/english/aboutshenyang/shenyangnews/202312/t20231212_4571802.html

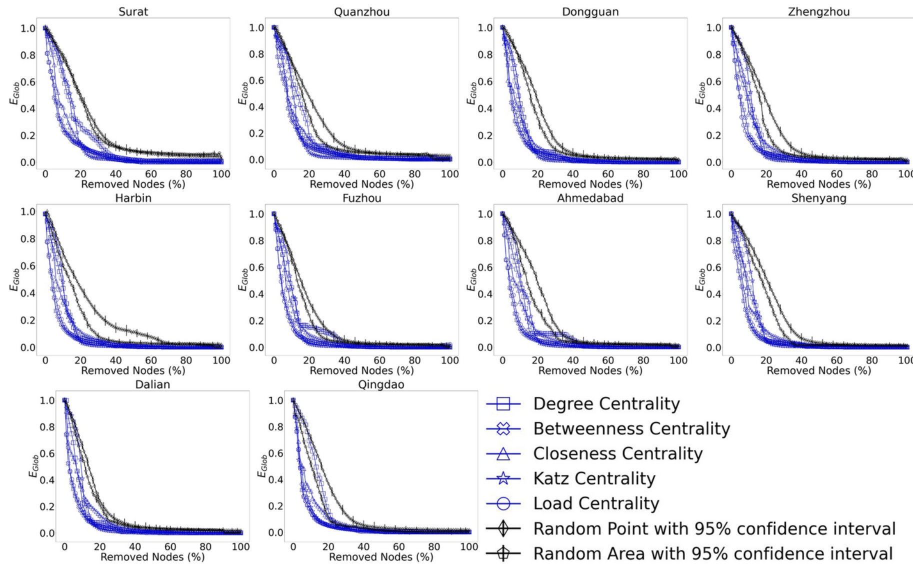

Fig. 6 The evolution of E_{Glob} curve (normalized) for different disruption strategies in the ten road networks

Broadly, random node disruption leads to a more gradual deterioration until the network eventually collapses when $\approx 40\%$ of nodes are removed. Our findings align with other studies (Trajanovski et al. 2013), where similar percentage of nodes were removed to cause a collapse in the complex networks (i.e., industrial networks (Alrumaih and Alenazi 2023), metro networks (Zhao et al. 2018), and power grid (Trajanovski et al. 2013)). However, we observe an exception for Qingdao when R_A is actually more effective than c_D. In fact, compared to S_{LCC}, the curves for E_{Glob} are closer, indicating the smaller differences in impact for the different strategies. Disruption based on c_B and c_L appear to be the most effective ones with both performing similarly ($c_B \approx c_L$). The rest are close and dependent on the city with c_D marginally worse than others.

We present in Fig. 7 the percentage of nodes needed to be removed to reduce E_{Glob} by 25%, 50%, and 90%. From the figures, Surat and Quanzhou are generally the most robust against random failure R_P and R_A for 25%, 50%, and against targeted disruption strategies. However, for R_P at 90% reduction of E_{Glob}, Harbin is the most robust compared to all studied road networks. Overall, Dalian appears to be the least robust to the R_P and R_A based on E_{Glob}.

We now focus on the initial phase of disruption where only small perturbations are introduced as this is the most important in assessing how a network may maintain it's function. A fast deterioration at the initial phase would indicate that the network's function can be severely disrupted with minimal perturbations. For this purpose, we look at the robustness metrics discussed so far.

We present the results in Fig. 8. In this figure, we compare the difference between the decrease of S_{LCC} and E_{Glob} at 5%, 10% and 15% node removal. The shaded area indicates the difference between the two metrics. In general, we see increasing differences between S_{LCC} and E_{Glob} for R_P, R_A and c_D when N is increasing. However, the converse is true for c_B and c_C where we see bigger differences for smaller networks and vice versa. For instance, we note that 15% removal of nodes with the highest c_B or c_C already incur almost 100% of S_{LCC} for smaller networks such as Surat and Quanzhou though

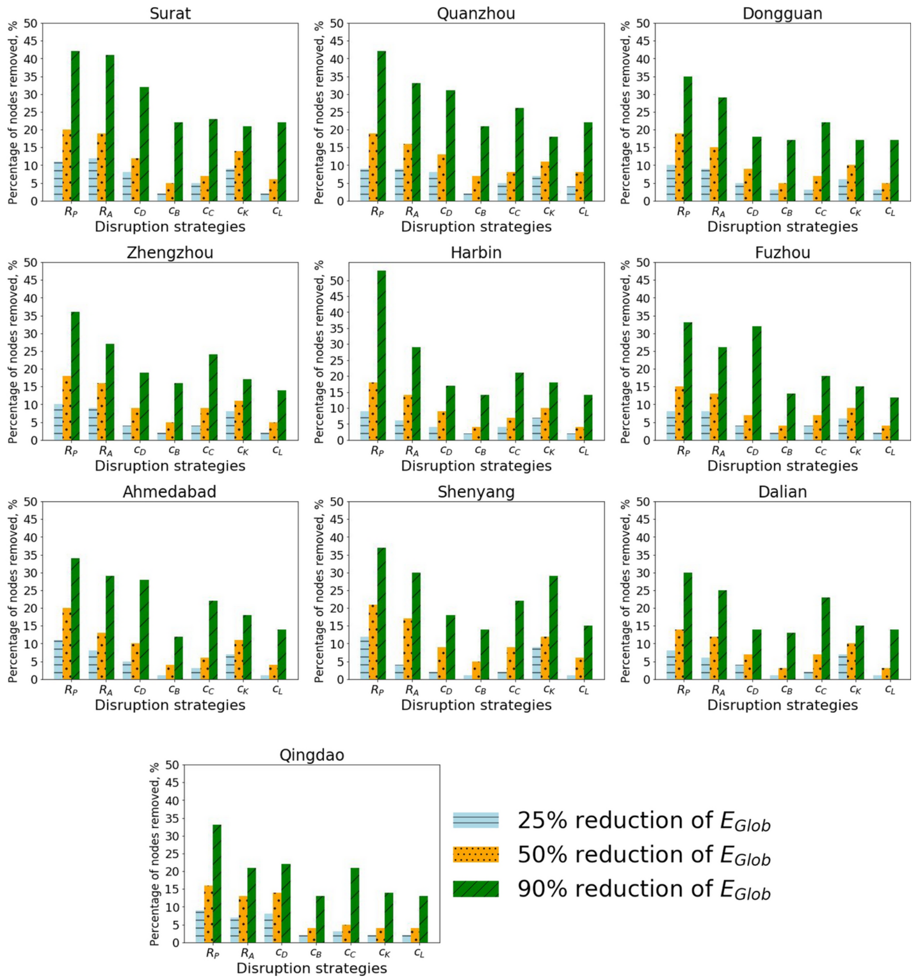

Fig. 7 Reduction of E_{Glob} based on types of perturbation strategies to achieve 25%, 50%, and 90% decrease

E_{Glob} appears to be affected less. Finally, the differences observed for c_K and c_L remain stable across the 10 road networks.

Impact of perturbations on local efficiency

In this section, we focus on a less explored metric, i.e., local efficiency E_{Loc}. Instead of viewing the efficiency of the entire network as a whole, E_{Loc} focuses on the efficiency within the immediate neighborhood of each node. This is relevant to local traffic as many car trips in big cities have been found to be short or within small localities (i.e., a third of car trips in London are shorter than 1 km (Transport for London 2012); in 2019, 17% of UK car journeys were between one and two miles (Carlton 2023); nearly 25% of car trips were shorter than five minutes in Sydney (Sugiyama et al. 2012); less than 5 km car trips made up more over 40% of all car trips in 2010 in Beijing (Ming et al. 2014). There are various initiatives to discourage short car trips to reduce environmental impacts (e.g., replacement with micromobility modes (Fan and Harper 2022; Scotland 2022; Lang and Herrmann 2022)).

Figure 9 shows the evolution of the average E_{Loc} when the network is perturbed based on the seven different perturbation strategies. From the results, we can clearly see three groups of strategies. The first group consists of the random perturbation strategies, R_P

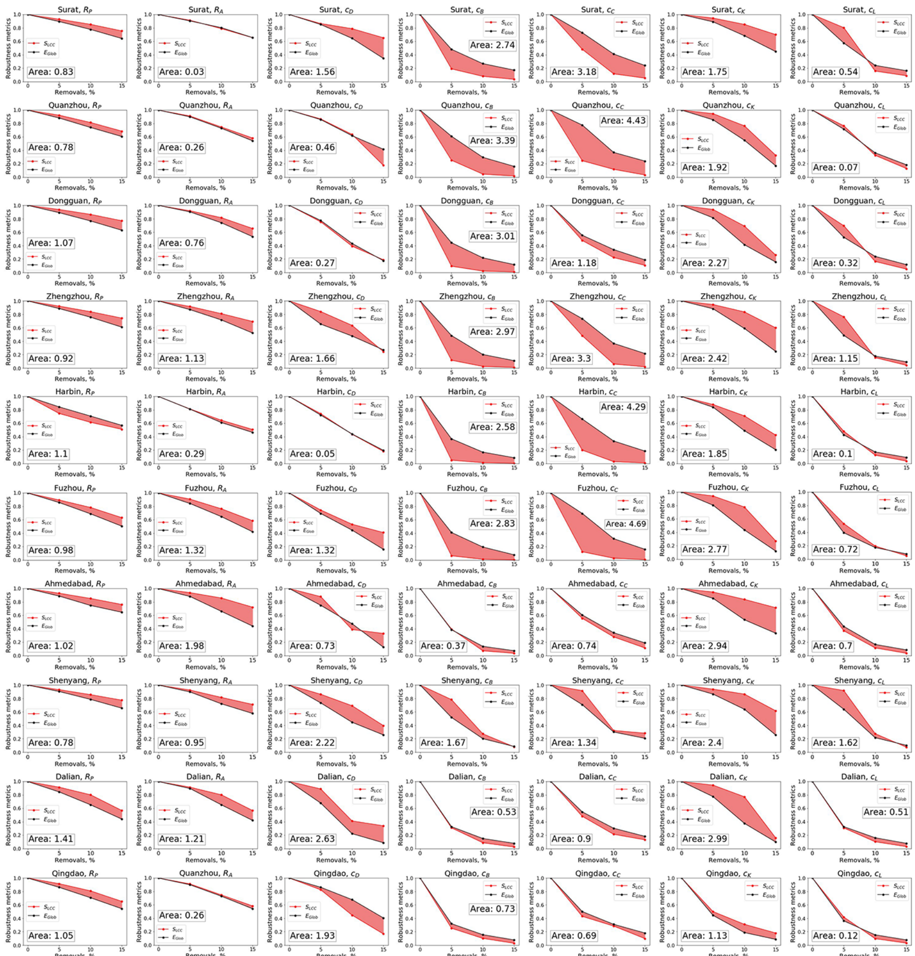

Fig. 8 Comparing the decrease of S_{LCC} and E_{Glob} with 5%, 10%, 15% of nodes removed

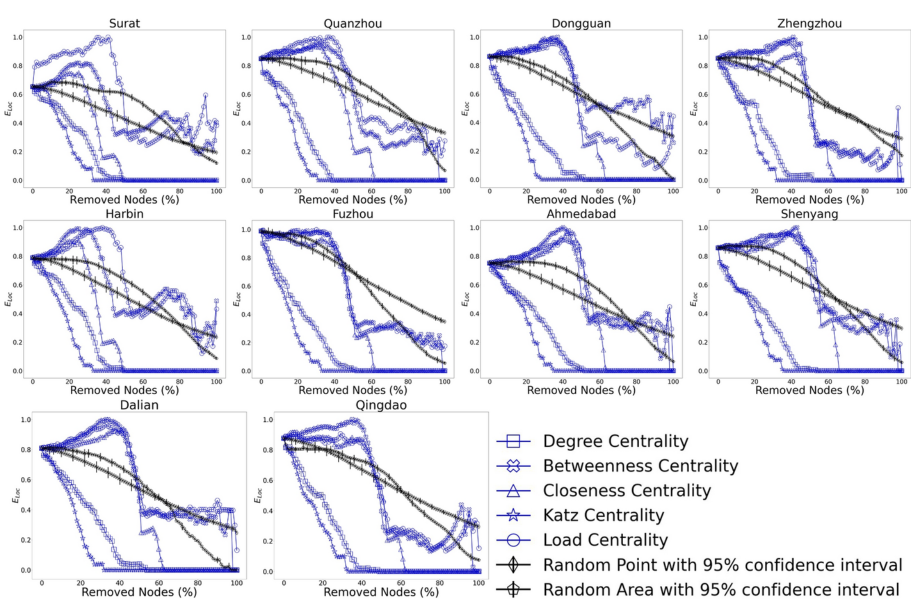

Fig. 9 The evolution of E_{Loc} curve (normalized) for different disruption strategies in the ten road networks

and R_A, showing smoother gradual degradation of E_{Loc}. In the case of R_A, it is relatively steady until $\approx 20-30\%$ of nodes are removed, followed by a rapid decline.

The most impactful disruption strategies, c_K and c_D, form the second group where we see a steeper decline in E_{Loc}. This is opposite to the S_{LCC} and E_{Glob} metrics where c_K and c_D are the less disruptive ones. Networks collapse when $\approx 30\%$ of nodes are removed based on c_K and $\approx 40-45\%$ nodes based on c_D. From these observations, we can deduce that c_K and c_D offer strong disruption to the local region but not the overall network where other centrality measures (e.g., c_B) can incur greater damage to the network as a whole.

The third group consisting of three removal strategies based on c_B, c_L, and c_C is perhaps the most interesting one. In contrast with previous metrics, we observe an initial *increase* of E_{Loc} for these removal strategies, implying an improvement of local efficiency after node removals. The increase continues until $\approx 33-45\%$ of the nodes removed from the network (e.g., the E_{Loc} increases for 0.05 in Fuzhou and 0.25 in Surat when removing nodes based on the highest ranked c_L). However, when more than $\approx 45\%$ of the nodes are removed, the network begins to lose its structural integrity and ability to maintain efficient paths between nodes. We illustrate the possibility of such a counter-intuitive phenomenon in Fig. 10 with a small 12-node network. In this illustration, when node 1 is removed, we see the average E_{Loc} is increased from 0.411 to 0.485. Specifically, we see the E_{Loc} of node 0 is increased from 0.33 to 1.00 due to the removal of node 1 causing the resulting neighborhood of node 0 to consist only of nodes 2 and 6 which are directly connected. Referring to the definitions of the c_B, c_L, and c_C(Table 1), perturbations based on these centralities decrease the number of shortest paths, which in turn, can lead to an increase in network connectivity within local subgraphs. Hence, we observe the initial increase pattern in our results. However, the E_{Loc} eventually falls faster than the random perturbation strategies after the initial increase. In short, we find $(c_K, c_D) \succ (R_P, R_A) \succ (c_B, c_L, c_C)$.

Figure 11 shows the percentage of nodes needed to be removed to reduce E_{Loc} by 25%, 50%, and 90%. In general, more nodes are needed to be removed to achieve the equivalent level of reduction of E_{Loc} than S_{LCC} and E_{Glob}. The c_K node removal strategy appears to be the fastest in disrupting the road networks, followed by c_D.

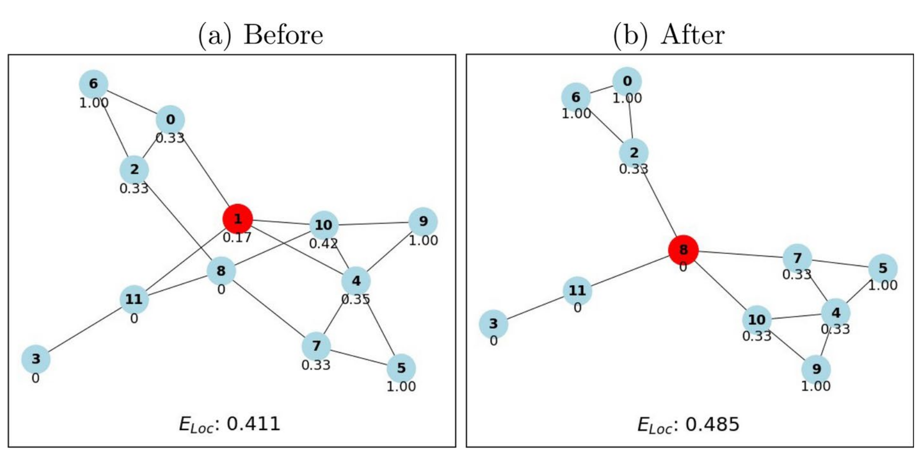

Fig. 10 Illustration of a node removal increasing E_{Loc} in a sample 12-node network. In this case, removing node 1 increases E_{Loc} from 0.411 to 0.485

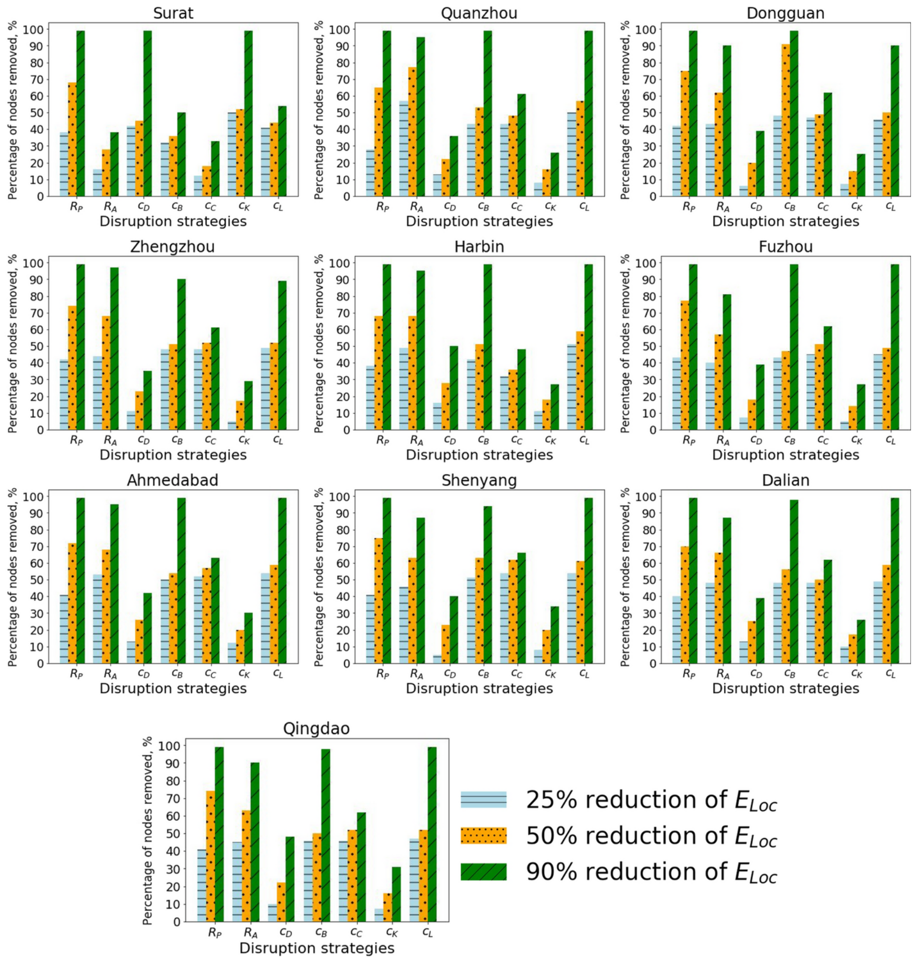

Fig. 11 Reduction of E_{Loc} based on types of perturbation strategies to achieve 25%, 50%, and 90% decrease

In order to provide a comprehensive comparison of the networks' response to the considered robustness metrics to the different node removal strategies, we present the scatter plots of the normalized metrics in Fig. 12. In these figures, the red bisector line indicates a perfect correlation between the two robustness metrics (i.e., the network response is the same for both metrics). We see a relatively good correlation between S_{LCC} and E_{Glob} with c_D and c_C mostly appearing above the bisector line indicating that there is a higher decrease of S_{LCC} than E_{Glob} while the rest recorded the opposite (i.e., faster degradation of E_{Glob}). We see that R_P and R_A are the closest to the bisector line (Fig. 12 the first and the fourth columns), implying a higher correlation between S_{LCC} with E_{Glob} based random removals. On the other hand, the relationship between S_{LCC} and E_{Loc} showed a weak correlation with sharper S_{LCC} decrease (Fig. 12 the second and fifth columns). This is most apparent for c_B, c_L and c_C and mainly due to the initial increase of E_{Loc} discussed above. Similarly, the comparison of E_{Glob} vs E_{Loc} pair indicates a faster decline of E_{Glob}(Fig. 12 the third and sixth columns).

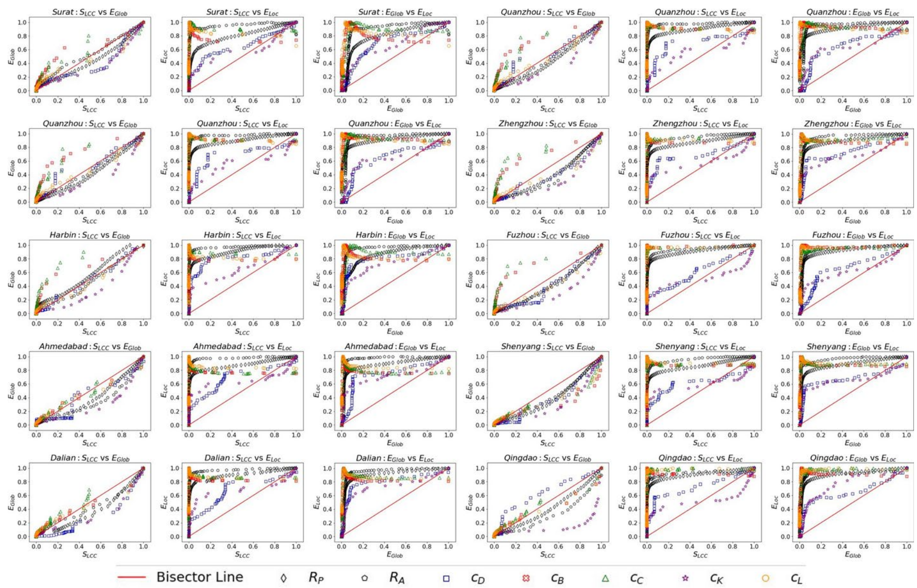

Fig. 12 Networks functioning comparison. The bisector line indicates the perfect correlation between the pair of two metrics

Conclusion

In this paper, we investigate the robustness of urban road networks in densely populated cities. We use real-world data of these networks and conduct the robustness assessment via an iterative node removal process, monitoring the degradation of the network in terms of the size of the largest connected component, global efficiency, and local efficiency. We considered seven node removal strategies; two of which are stochastic in nature based on random selection and five are deterministic where nodes are ranked based on different centrality measures, namely degree, betweenness, closeness, Katz, and load centrality. Our results show that the introduction of an increasing amount of perturbations degrades the considered robustness metrics but in different magnitudes. For the size of the largest connected component and global efficiency, random disruption strategies are almost always the least damaging compared to targeted disruption strategies based on centrality measures. We found that random area disruption (where a random neighborhood of the network is gradually disrupted) inflicts higher degradation of S_{LCC} and E_{Glob}. Among the different targeted disruption strategies, we found c_B to be the most disruptive, closely followed by c_L due to the fact that both of them rely mainly on the same measure (i.e., the length of shortest paths). While they generally provide very similar node rankings, they are not equivalent and in some cases (e.g., for Quanzhou, Zhengzhou and Harbin in S_{LCC} curve), c_C is found to be second most disruptive in place of c_L. Meanwhile, c_K was the least disruptive, though the difference in effectiveness was smaller for E_{Glob} than for S_{LCC}.

While the centrality-based disruption strategies are more effective, they impact the network differently for different robustness metrics. From our analysis, removing nodes with the highest betweenness centrality appears to be the most damaging while c_D and c_K are the least effective according to S_{LCC} and E_{Glob}. Meanwhile, based on our similarity analysis, some disruption strategies correlate with each other. As such, we suggest the combination of c_C with c_K, and c_D with c_C strike a good balance between differences in disruption sequences. The degradation of local efficiency offers a different picture where we find interestingly an initial increase after perturbations for removal strategies based on c_B, c_C, and c_L. From our results, c_K, and c_D inflict greater degradation to local efficiency than other targeted disruption strategies while stochastic removal strategies (i.e., R_P and R_A) lie in between. Synthesizing the results, for assessing the robustness of road networks, we recommend using c_B as the first choice for studying the worst-case scenario, R_P and R_A to gain insights into average robustness degradation behavior on random events (e.g., accidents) and finally, using c_D and c_K for finding the impact of the localized impact of perturbations. Considering the entire network as a complex system, removal strategies based on centrality that take into account paths are more disruptive.

As future work, we would like to use the insights gained from this study and develop strategies on how to protect the road network to minimize disruptions in the face of perturbations (e.g., targeting critical nodes that can incur the greatest damage based on our results). Furthermore, another research direction we would like to explore is on how urban road networks can recover and adapt after perturbations. This should provide useful insights for city planners when attempting to recover from unplanned events.

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Both authors contributed equally.

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Availability of data and materials
The used data is publicly available at: https://figshare.com/articles/dataset/Urban_Road_Network_Data/2061897.

Declarations

Ethical approval and consent to participate
Not applicable.

Consent for publication
All authors have given their consent for publication of the manuscript. The manuscript is not being considered or submitted to any other journal for review.

Competing interests
The authors declare that they have no Conflict of interest.

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