407

Local Modularity, a measure that characterises street neighbourhood connectivity

STEPHEN LAW, YAO SHEN, TAO YANG, KAYVAN KARIMI, & ALAN PENN,

UCL, LONDON, UK

ABSTRACT

Recent research in space syntax has shown the use of community detection methods on the street network dual graph can identify isolated local areas. Leveraging on this characteristic, we propose a new measure called local modularity that tries to capture street neighbourhood connectedness. We examine the measure visually for a number of cities where we found the measure can identify more neighbourhood connectivity. We also then validated the measure by running a network stability experiment where we simulate a network under different forms of attacks; a random attack scenario versus a targeted attack scenario. We found more stable behaviour when removing streets that have higher neighbourhood connectivity than attacking the same network randomly. These results have implications on the spatial design and planning of neighbourhoods and in measuring community severances.

KEYWORDS

Connectivity, Community detection, neighbourhoods, space syntax, street network

1 INTRODUCTION

The concept and the definition of a local area or a neighbourhood is complex and can be defined as a spatially contiguous region whose morphological, socio-economic and perceptual characteristics are more homogenous within (Lebel et al., 2007; Galster 2001; Kearns and Parkinson, 2001). A strand of recent research in space syntax proposed the use of community detection methods (Girvan and Newman 2002 and Blondel et al 2008) on the street network dual graph to identify street-based local areas (Law et al 2015; Law 2017). These local areas were argued to more accurately capture subtle perceptual differences in urban environments, where people living in the same spatial neighbourhood will by chance more easily bump into each other, cluster together and share information with each other. An observation from these earlier research is that more gridded or connected areas have fuzzier definitions. Leveraging on this observation, we propose a new neighbourhood measure called local modularity that tries to capture street neighbourhood connectivity. We intend to validate the measure through a visual description and a street network experiment where we simulate different edge removal scenarios. We conjecture targeting edge removal in more connected areas as defined by the new measure will result in more stable network components when compare to random edge removal.

2 RELATED WORKS

Early research in space syntax suggests local areas can be defined using its spatial morphology. Hillier et al. (1987), for example, found that space-and-movement correlations can differ between local areas (Penn 2003). Peponis (1988) found that highly accessible routes act as boundaries between neighbourhoods, while Read (1999) suggest that cores of neighbourhoods are often found in places of high local integration. These early ideas led to the conjecture of syntactical local area (Yang2007; Dalton2006). Yang (2007), for example, proposed the embeddedness measure that defines neighbourhoods as fuzzy areas whose node count density differs between radii, while Dalton (2006) proposed the point intelligibility measure which calculates a local intelligibility where neighbourhoods are being defined by how global and local covaries. Both research studies found visual correspondence to named local areas in London.

In the network science literature, a related area of research is community detection, whose aim is to partition a graph into subgraphs, or group/cluster of edges/nodes, that are densely connected internally and weakly connected externally (Girvan and Newman, 2002). A large volume of literature were written proposing algorithms to detect natural communities/subgraphs. A very popular measure in evaluating the quality of partitions is modularity, which are often optimised to identify subgraphs or detect communities that maximises internal connections and minimise external connections (Girvan and Newman 2002; Blondel et al 2008).

Inspired from this line of research, Law et al. (2015, 2017) applied modularity optimisation as a community detection methods on the street network dual graph in defining street based local area. These local areas were found to qualitatively correspond to named local areas that were topologically isolated. This research propose a related measure that instead aims to measure local connectivity using the modularity as a quality measure at the local scale, not dissimilar to the neighbourhood quality measures proposed by Yang (2007) and Dalton (2006). We call this neighbourhood connectivity measure local modularity.

3 LOCAL MODULARITY

Local modularity combines the concepts of street neighbourhood from urban planning and space syntax as well as the modularity quality function from the community detection literature. In general, given a street network $G(V, E)$ with a set of junctions $v \in V$ and set of street edges $e \in E$; select a root street e, identify its street neighbourhood subgraph SG, generate an optimal partition c_e using a community detection algorithm and assign the modularity score (equation 1) of the optimal partition back to the root street. Repeat for every street to calculate local modularity LQ. The inverse of local modularity can be seen as a Street neighbourhood connectivity measure. A description of the algorithm can be seen below and illustrated in figure 1.

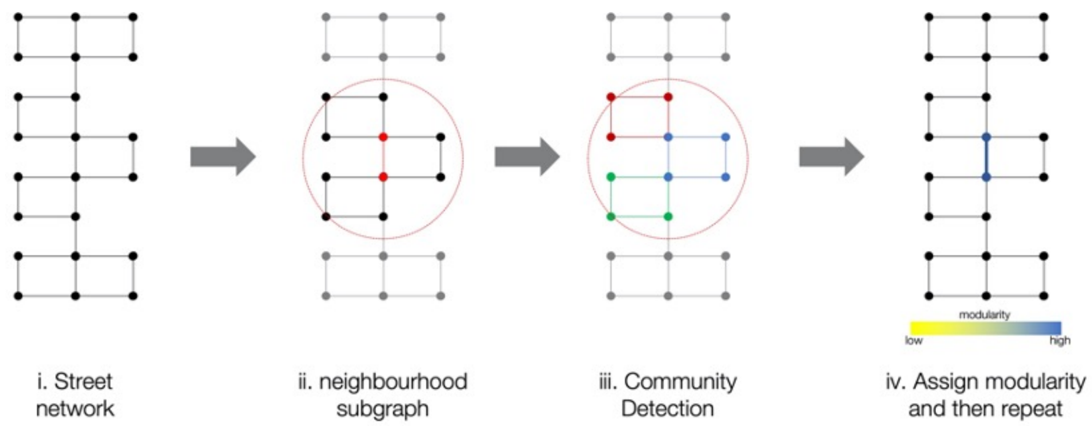

Figure 1: Local modularity algorithm

Steps in calculating Local Modularity

Step i. Given a street network, select a street as its root street.

Step ii. A street neighbourhood subgraph is defined as the ego-graph expanded from the root street. In general, the street neighbourhood subgraph can be defined by a cut-off radius as either the number of topological steps away, some crow-fly or network distance away or as the K^{th} nearest streets away from the root street. In the space syntax literature, the street neighbourhood subgraph, is commonly defined by either the number of steps away in a local topological analysis (R3,R5,R7) or the metric distance away in a local angular segment analysis (R400,R800,R1200). In this research we will use the K^{th} nearest neighbour approach. After retrieving a K^{th} nearest neighbours for the root street, which we call street neighbourhood subgraph, we can then apply a community detection algorithm to find a local partition.

Step iii. To identify the optimal partition in a computationally feasible manner, we will use the highly popular and effective hierarchical (multi-level) modularity optimisation (Blondel et al 2008) as the community detection algorithm. The heuristic algorithm joins adjacent node/vertices if the partition gets a higher modularity score. The joining of adjacent nodes/vertices happens hierarchically and repeats until convergence. Modularity, being the a popular quality function used in community detection (Girvan and Newman, 2002), calculates the difference between the observed number of edges within a subgraph and the expected number of edges. The greater is the observed number of edges relative to its expected number, the higher is its modularity, and the more separated or isolated the subgraphs are. More formally stated: Modularity Q is defined where A is the adjacency matrix, m is the total number of edges in the graph, ki and kj are the degrees for vertex i and vertex j. Furthermore, if i and j are in the same community, δ is 1; if they aren't, then δ is 0[1].

$$Q = \frac{1}{2m}\sum\left(A - \frac{K_i K_j}{2m}\right)\delta(C_i, C_j)$$

Modularity (Q) equation (Girvan and Newman, 2002).

Step iv. The modularity score with the optimal partition for each street neighbourhood subgraph is than assigned back to the root street. We then go back to step i. and repeat until the local modularity score of every street had been calculated. For interpretability, ones can take the inverse of the local modularity score to get a street neighbourhood connectivity measure.

3.1 Street neighbourhood subgraph

A key parameter to consider for the local modularity measure is in defining the street neighbourhood subgraph. Figure 2 shows an initial comparison of how the measure behaves, if we limit the number of nearest neighbours to K={100,200,300} for Central London in the UK. The result shows expectedly a more localised structure when K is lower and greater spatial coherency when K is larger. These initial observations show the City of London has a seemingly different local modularity pattern than its surrounding areas. In this study, we have selected the cut-off radii of K=300 nearest streets. We have also constraint the nearest streets to be within 40 topological steps away from the root street to ensure the neighbourhood subgraph diameter do not vary significantly. These parameters were selected qualitatively in order to capture spatial coherency. The street neighbour subgraph parameter would need to be validated empirically in future studies.

Figure 2: London Local modularity where we vary k=[100,200,300] nearest neighbours.

[1] This denotes a Kronecker delta function.

4 EXPERIMENTS

4.1 Visual description

The first experiment is a simple visual description of applying local modularity on two large metropolitan regions, Greater London in the UK and New York City in the US, to show how the measure behaves qualitatively for two large metropolitan regions. Specifically, this study will retrieved the street networks from Open Streets Maps. Below are the network statistics for the two metropolitan regions. The network retrieved for Greater London includes all 33 boroughs in London with ~184,000 street edges and ~228,000 street junctions. The network retrieved for New York City includes the five main boroughs of NYC (Manhattan, Brooklyn, Bronx, Queens and Staten Island) with ~55,000 street junctions and ~92,000 street edges. New York City does not include the adjacent areas such as Long Island and New Jersey which are often included in the larger metropolitan area of NYC.

	nodes	edges
Greater London	184,385	227,560
New York city	55,327	91,585

Table 1: street network statistics for case study areas

4.2 Street network stability experiment (edge removal simulation)

The second experiment is related to the concept of network robustness in the network science literature. Network robustness in network science can be defined as how vulnerable a network is when an error occurs or when a node/edge is removed[2] (Albert et al. 2000). In relation to percolation theory, such vulnerabilities are often characterised by its giant component size (Dorobritz et al 2009; Kitsak et al 2018) where a more robust network will be structurally more coherent when nodes or edges are removed when compared to a less robust network[3]. The street network stability experiment will follow a similar procedure but instead of measuring how fast the giant component collapses when streets are removed, we will be examining the stability of the giant component instead. More simply, instead of identifying vulnerable streets, we want to identify stable streets where when removed the network remains connected. The experiment aims to identify the streets that ensure stability of the network and as a validation to the inverse local modularity as a neighbourhood connectivity measure.

Our procedure for the simulation will measure the street network giant component size when each edge get removed sequentially. In the baseline scenario we will randomly remove a street edge and

[2] In the street network context, a more robust network will mean that removing a bridge or stations will not reduce your accessibility in reaching your destination.
[3] Giant component size gets smaller as you remove edges in a network. In the street network context, this can be interpreted as the largest island when bridges are removed.

track its giant component size until only one street remains. In the local modularity scenario, we will instead remove a street edge that has a higher inverse local modularity (street neighbourhood connectivity) sequentially until only one street remains. Network stability is then plotted using a line chart by tracking its giant component size. The area under the curve is then measured as an index of stability where higher is more stable. We conjecture in this experiment, the area under the curve for the inverse local modularity attack is higher than a random attack. The reason is that streets with more connected neighbours should realistically be edges that does not affect the stability of the network, in this case its giant component size. Specifically, we will run the street network stability experiment for four central areas namely; London in the UK, Toronto in Canada, Berlin and Munich in Germany. The street networks of these four areas were retrieved from Open Streets Map. We selected only the central areas of cities to ensure the areas are relatively homogenous within each case. London is the outlier here where we have retrieved a much larger region of the Central area. Below are the network statistics for the four case studies where London has ~19,300 nodes and ~24,800 edges, Munich has ~6,400 nodes and ~9,700 edges, Berlin has ~5,600 nodes and ~8,800 edges and Toronto has ~4,300 nodes and ~6,400 edges.

	nodes	edges
London	19,311	24,824
Munich	6,438	9,696
Berlin	5,609	8,827
Toronto	4,255	6,440

Table 2: street network statistics for case study areas

5 RESULTS

5.1 Visual Description

This section summarises the results for the visual description. Figure 3 shows the local modularity of Greater London where darker colour indicates lower local modularity and lighter colour indicates higher local modularity. We did not take the inverse here but ones can interpret lower local modularity to have higher neighbourhood connectivity and vice versa for higher local modularity.

The result shows that the more regularly gridded and highly connected areas such as Soho in Central London, Kensington and Chelsea in West London and Walhamstow in East London have lower local modularity (or higher inverse local modularity). The result also shows that less regularly gridded areas such as the City of London and less connected areas such as Thamesmead and the Isles of Dogs in the east have higher local modularity (or lower inverse local modularity).

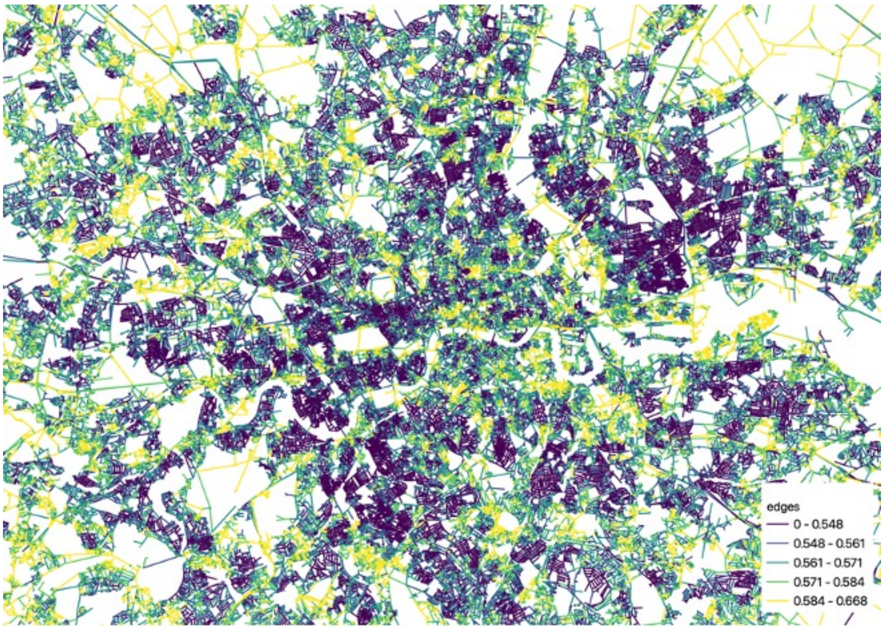

Figure 3: Greater London Local Modularity

Figure 4 shows the local modularity of New York City with the same colour spectrum. The result shows the more regularly gridded and highly connected areas such as midtown and uptown in Manhattan and the areas across Brooklyn have lower local modularity (or higher inverse local modularity) while the less regularly gridded areas such as Greenwich Village and Wall Street in Downtown New York have medium levels of local modularity and the less connected areas near the motorways of the city have higher local modularity (or lower inverse local modularity).

Figure 4: New York City local modularity

5.2 Street network stability experiment

This section summarises the results for the network stability experiment. We visualise the local modularity for the four case studies of Central Berlin, Central Toronto, Central London and Central Munich in figure 5. The visual summary uses the same colour spectrum where darker colour has lower local modularity (higher connectivity) and areas with lighter colour indicates higher local modularity (lower connectivity). The patterns are similar to the previous case studies.

Figure 5: Visual summary for the four case study cities in the robustness experiment. Top left: Berlin,Germany; Bottom Left: Munich, Germany; Top right: Toronto Canada; Bottom Right: London, UK;

Next, we show the network stability plots for the four case studies. For each network stability plot, the x-axis denotes the number of edges remaining and the y-axis denotes the giant component size by the number of nodes (the simulation can be read from left to right). The orange line denotes the size of the largest component as each edge is removed from a random edge removal attack while the blue line denotes the size of the largest component as each edge is removed from the inverse local modularity edge removal attack.

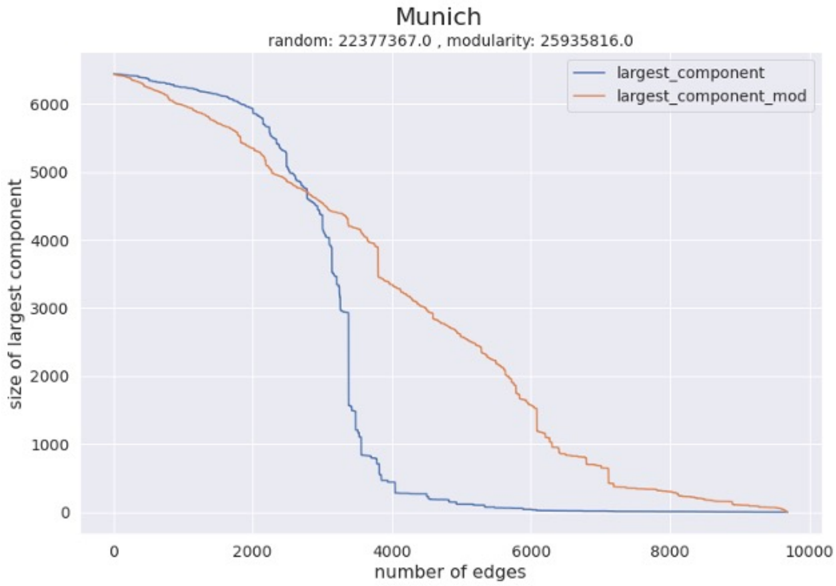

Figure 6: Munich network stability plot

Figure 6 shows the network stability plot for Munich. The result shows the random attack has a transition at approximate ~3000 edges where the size of the largest components breaks down from having over 5000 nodes to less than 500 nodes. The result also shows the inverse local modularity attack is flatter where there isn't a sudden shift in component size. The area under the curve for the inverse modularity removal is ~16% larger than the random removal. Thus removing streets with higher neighbourhood connectivity is more stable than at random in Munich expectedly.

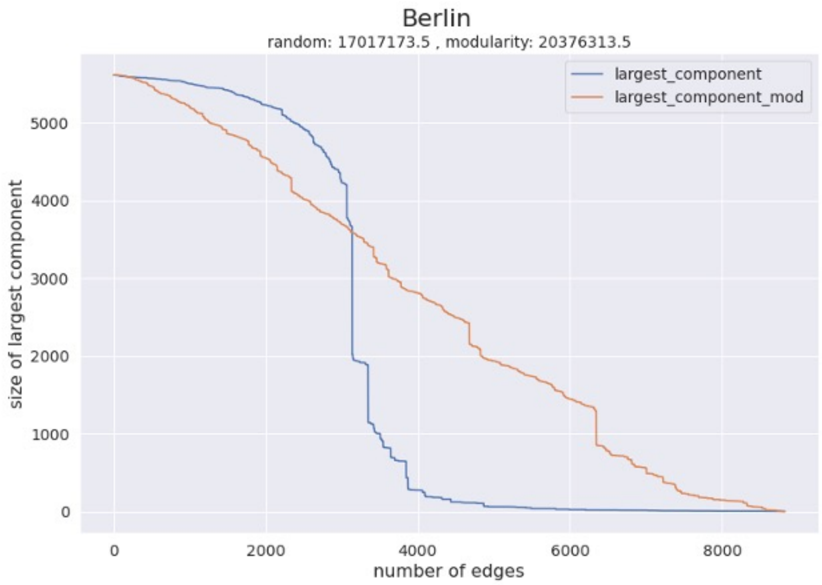

Figure 7: Berlin network stability plot

Figure 7 shows the network stability plot for Berlin. The result shows a very similar pattern to the Munich case study where the random attack in this case has a transition starting at around ~2000 edges while the inverse local modularity attack stays pretty flat throughout. The area under the curve for the inverse modularity removal is ~20% larger than the random removal. Thus removing streets with higher neighbourhood connectivity is more stable than at random for Berlin as well.

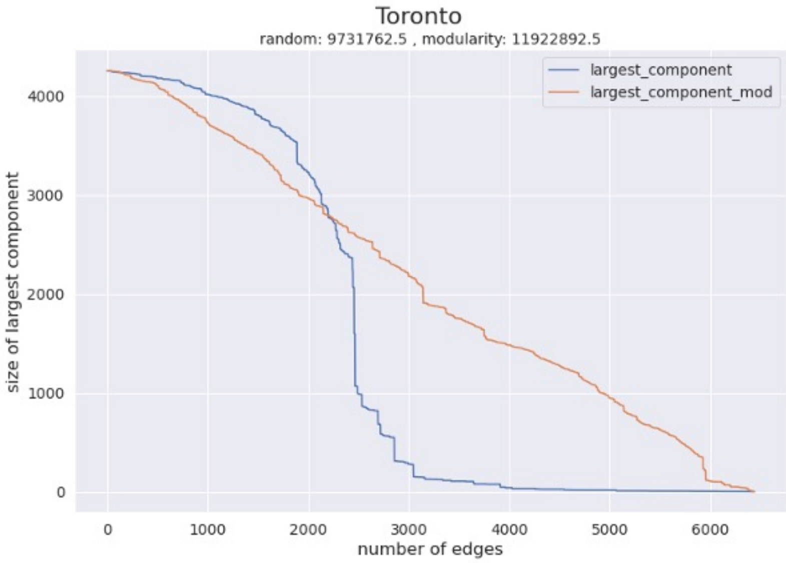

Figure 8: Toronto network stability plot

Figure 8 shows the network stability plot for Toronto. The result shows a very similar pattern to both the Munich and Berlin case study. However the transition for the random attack starts earlier due to the size of the graph being smaller. The area under the curve for the inverse modularity attack is ~22% larger than the random attack. Thus removing streets with higher neighbourhood connectivity is more stable than at random for Toronto.

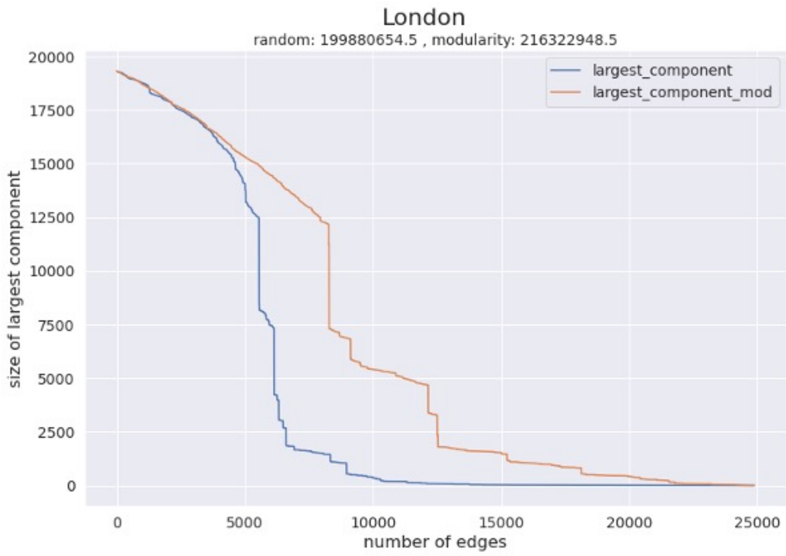

Figure 9: London network stability plot

And finally figure 9 shows the network stability plot for London. The result shows a distinctively different pattern to the previous three cities. Both the random attack and the inverse local modularity attack has a more similar profile with clear transitions. The random attack in this case has an earlier transition when compare to the inverse modularity attack. The inverse local modularity attack on the other hand have two step transitions, one after ~7500 edges and one after ~12500 edges. The line plot also shows the inverse local modularity attack has a fatter tail near the end of the removal process. The area under the curve for the inverse modularity attack is ~10% larger than the random attack which is significantly less than the other cities. The differences in the results might be caused by the larger graph retrieved for Central London that consists of more diverse urban areas than the other cases.

6 CONCLUSIONS

To summarise, we proposed a new measure called local modularity that leverages on concepts from space syntax, urban planning and network science, in capturing street neighbourhood connectedness. The measure is able to delineate and characterise areas visually in both Greater London and New York City. For example, the measure is able to identify more connected and gridded areas such as Soho in London and Midtown in New York. We then validated the measure by running a street network stability experiment where we sequentially remove either a random edge or a targeted edge with higher inverse local modularity (street neighbourhood connectivity). In all four cases, the targeted attack with higher inverse local modularity achieves a higher level of stability than a random attack. These results suggests that disconnecting streets with higher neighbourhood connectivity is less likely to fail and is harder to severe. The implication here is that the measure can potentially identify areas with high connectedness but also measuring street network severances at a neighbourhood level.

A number of limitations remain. As this is a proof of concept study, we have selected a particular street neighbourhood method (K^{th} nearest neighbours) and a particular nearest neighbour parameter through observations. Sensitivity analysis is necessary to exhaustively test how the measures react to different street neighbourhood definition (eg. network distance radii) with different parameters (eg. Rad={400m,800m,1200m}). Secondly, there were also a lack of case studies for the network stability experiments. The main reason is attributed to computation. As the graph increase in size, the duration of the stability experiment increases substantially. In future studies, we intend to run the network stability experiment for more cities, over a set of hyper-parameters, comparing different edge removal/attack methods to ensure the simulation results are consistent, stable and robust.

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