CASA0002 Urban Simulation Assessment

Part 1: London’s underground resilience

I. Topological network

I.1. Centrality measures

Centrality measure is used for investigating the most central nodes in a graph (Lorenzo *et al.* 2020). To characterize the nodes within the context of London's underground network, there are 3 centrality measure being selected: Degree Centrality, Betweenness Centrality and Closeness Centrality. The table below demonstrates their equations, definitions, characteristics for the underground network context.

Table 1 Summary of Degree Centrality, Betweenness Centrality and Closeness Centrality.

	Degree centrality	**Betweenness Centrality**	**Closeness Centrality**
Equation	$C_D(v) = deg(v)$ Where deg(v) is the degree of the vertex	$C_B(v) = \sum_{i \neq v \neq j \in V} \frac{\sigma_{ij}(v)}{\sigma_{ij}}$ Where i, j are different nodes, σ_{ij} is the number of shortest paths between i, j, $\sigma_{ij}(v)$ is the number of shortest paths between i, j containing the node v	$C_C(v) = \frac{n}{\sum_j d(i,j)}$ Where d(i,j) is the distance between the nodes i and j, n is the total number of nodes
Definition	It is determined by the number of neighbors (edges) connected to the node, the node with more edges is more central (Freeman, 1978).	It highlights that if the node is on the shortest path of many pairs of adjacent nodes, it is the most important one (Freeman, 1977).	It emphasizes that the shorter the distance between the node and all other nodes, the more important the node is (Freeman, 1980).
Meaning for underground and reason for finding the most crucial station	For the underground context, it is the number of stations connected to a station. When more stations are connected to the station, it is more possible that more commuters will transfer through this station. Therefore, the station with the most connections will be considered as the most crucial one for underground functioning.	For the underground context, a more central station is on more shortest paths between two any other stations and it determines the necessity of commuters transferring through this station. Therefore, the station with larger possibility to perform as a hub on the shortest path between other two stations, will be considered as the most crucial one for underground functioning.	For the underground context, a more central station travels shorter distance to all other stations and thus consumes less time for commuters to transfer. Therefore, the station with the shortest distance to other stations in total will be considered as the most crucial one.

The attribute for each node is calculated by python, and the script is attached in Appendix. The top 10 ranked nodes for the 3 measures are sorted out and listed below:

Table 2 First 10 ranked nodes with attributes for 3 measures

Degree Centrality		**Betweenness Centrality**		**Closeness Centrality**	
Node	**Attribute**	**Node**	**Attribute**	**Node**	**Attribute**
Stratford	0.0225	Stratford	23768.093434	Green Park	0.114778
Bank and Monument	0.0200	Bank and Monument	23181.058947	Bank and Monument	0.113572
King's Cross St. Pancras	0.0175	Liverpool Street	21610.387049	King's Cross St. Pancras	0.113443
Baker Street	0.0175	King's Cross St. Pancras	20373.521465	Westminster	0.112549
Earl's Court	0.0150	Waterloo	19464.882323	Waterloo	0.112265
Oxford Circus	0.0150	Green Park	17223.622114	Oxford Circus	0.111204
Liverpool Street	0.0150	Euston	16624.275469	Bond Street	0.110988
Waterloo	0.0150	Westminster	16226.155916	Farringdon	0.110742
Green Park	0.0150	Baker Street	15287.107612	Angel	0.110742
Canning Town	0.0150	Finchley Road	13173.758009	Moorgate	0.110314

I.2. Impact measures

There are two selected measures presenting for evaluating the impact of node removal on the network, which are clustering coefficient and the largest component. The table below lists the summary of the two measures

Table 3 Summary of impact measures

	Clustering coefficient	**The largest component**
Equation	$C = \frac{(\text{Number of triangles}) \text{ x } 3}{(\text{Number of connected triplets})}$ Where C is between 0 and 1	
Definition	It is a measure of the extent to which nodes in a graph tend to cluster together (Watts and Strogatz, 1998).	It is a connected component of a network that comprises the largest proportion of the overall vertices in the network (*FutureLearn*, 2017).
Meaning for London underground	For London underground graph, the clustering coefficient will greater than random network with the same number of nodes and edges, and be smaller than regular one. The station removal can lead to the decrease of clustering coefficient, but the decreasing rate will be different from different centrality measures.	Generally, the giant component contains increasing fraction of nodes with the expanding network, and vice versa. For London underground graph, station removal can result in the reduction of the largest component, if the removed node is important enough, the size of largest component will be significantly decreased.

Meaning for Other networks	For other network application, for example, in social networks, nodes tend to form tight groups with potentially high density of ties, and it has higher possibility than randomly-built links between two nodes (Paul and Samuel, 1971); it also has been used for habitat network analysis, which can perform as an indicator to boost the robustness of the wild animal habitat network (Heer *et al.*, 2020); power grid network is another application, it can reflect network performance and enhance grid resilience (Mtawa and Haque, 2021).	For other network application, giant component is commonly applied instead of the largest component. Social network such as Facebook tends to form giant component for analyzing ego network structure (Arnaboldi *et al.*, 2015); it can also apply for power grids to support complex network analysis (Dong, Xiong and Hou, 2012); for genome-scale network, it justifies the application of dynamic complex networks (Huang, 2006).

I.3. Node removal

For non-sequential removal method, the largest component and average clustering coefficient are calculated by removing top 10 nodes one by one, the results are displayed below.

Table 4 Results of non-sequential removal method

	Degree Centrality		**Betweenness Centrality**		**Closeness Centrality**	
Removed Nodes	**Largest Component**	**Average clustering coefficient**	**Largest Component**	**Average clustering coefficient**	**Largest Component**	**Average clustering coefficient**
0	401	0.03038	401	0.03038	401	0.03038
1	379	0.03063	379	0.03063	400	0.02979
2	378	0.03003	378	0.03003	399	0.02928
3	377	0.02705	377	0.0301	398	0.02952
4	374	0.02729	371	0.03035	397	0.02808
5	371	0.02441	370	0.02933	396	0.02815
6	356	0.02447	369	0.02831	395	0.02991
7	355	0.02343	346	0.02499	394	0.03003
8	354	0.02197	345	0.02506	393	0.03011
9	352	0.02372	342	0.0216	392	0.03019
10	346	0.02379	339	0.02165	389	0.03026

In order to visualize the trend of variation among the node removing process, line chart is used for plotting as shown below.

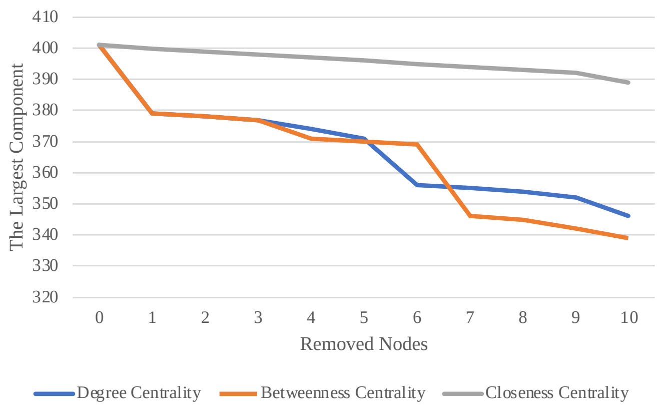

Figure 1 Largest component variation by using non-sequential removal method

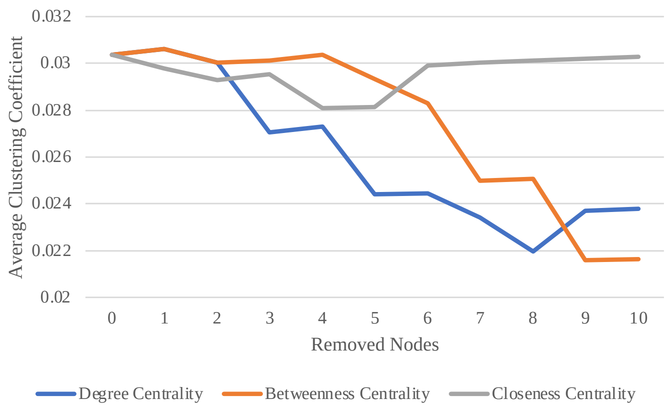

Figure 2 Average clustering coefficient variation by using non-sequential removal method

From Figure 1, it can be noticed that the trends are all declining for the three measures, which is reasonable as critical nodes removal can lead to isolation of several small-size community, the size of largest component will be subsequently reduced. However, closeness centrality is more stable than the others, the reason might be that the critical nodes of the centrality are on the shortest path to all the other nodes, if these nodes are removed, alternative path can be used, and the underground network is still able to normally work. The other two measures following relatively close trends: degree centrality highlights nodes with more edges, betweenness centrality highlights nodes on the shortest path of many pairs of adjacent nodes. The node removal might result in significant separation between nodes, hence the decrease trend is sharper. For Figure 2, it is obvious that the variation of closeness centrality is different from the other two measures, whose value is fluctuating around 0.03. The reason might be the removed nodes not only decrease the number of triangles but also decrease roughly the same number of connected triplets. While the other two measures impact greater on the number of triangles, which also indicate the importance of the nodes.

Next, for sequential removal method, after each removal of the top node, the centrality measures are recomputed, then the largest component and average clustering coefficient are calculated, until 10 nodes are removed.

Table 5 Results of sequential removal method

	Degree Centrality			Betweenness Centrality			Closeness Centrality		
Removed Nodes	**Top Node**	**Largest Component**	**Average Clustering Coefficient**	**Top Node**	**Largest Component**	**Average Clustering Coefficient**	**Top Node**	**Largest Component**	**Average Clustering Coefficient**
0	Stratford	401	0.03038	Stratford	401	0.03038	Green Park	401	0.03038
1	Bank and Monument	379	0.03063	King's Cross St. Pancras	379	0.03063	King's Cross St. Pancras	400	0.02979
2	Baker Street	378	0.03003	Waterloo	378	0.03087	Waterloo	399	0.03003
3	King's Cross St. Pancras	377	0.02705	Bank and Monument	377	0.02997	Bank and Monument	398	0.02872
4	Canning Town	374	0.02729	Canada Water	376	0.02926	West Hampstead	397	0.02808
5	Green Park	360	0.02441	West Hampstead	375	0.02933	Canada Water	396	0.02815
6	Earl's Court	359	0.02338	Earl's Court	227	0.0294	Stratford	226	0.02822
7	Waterloo	358	0.01658	Shepherd's Bush	226	0.02263	Earl's Court	226	0.02838
8	Oxford Circus	357	0.0151	Euston	196	0.02268	Shepherd's Bush	225	0.02158
9	Willesden Junction	355	0.01684	Baker Street	173	0.01934	Oxford Circus	195	0.02164
10	Turnham Green	341	0.01688	Acton Town	170	0.01628	Paddington	194	0.0234

Line chart below exhibits the variation among the node removal of sequential method.

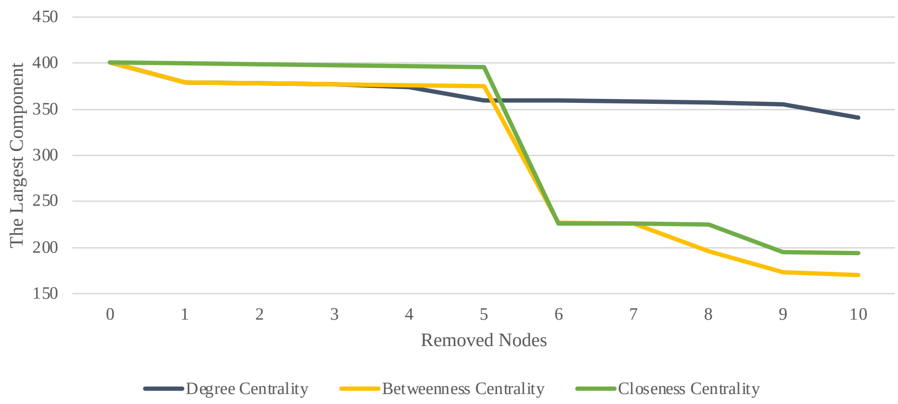

Figure 3 Largest component variation by using sequential removal method

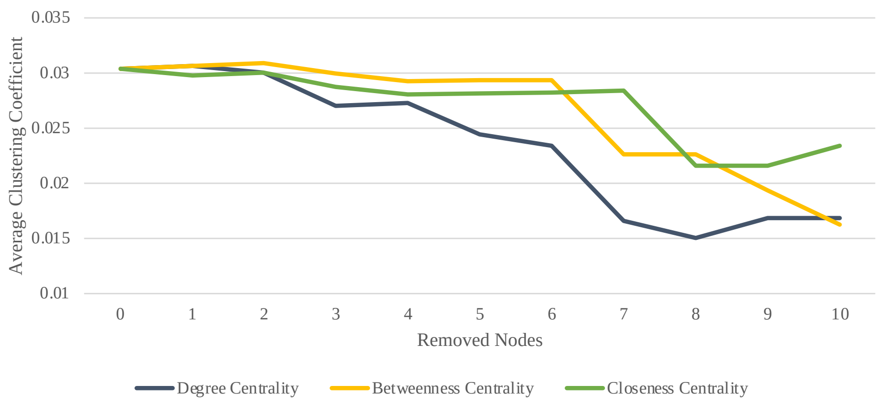

Figure 4 Average clustering coefficient variation by using sequential removal method

From Figure 3, the declining trends are the same as Figure 1, which is due to the similar reason. However, there is a drastic decrease occurring after removing the 5th node among the lines of betweenness and closeness measures. Checking the removed stations from the Table 5, it could be noticed that the previously removed nodes are the same except the first node, hence the reason might be that these nodes are significantly important and connecting a large number of nodes under each measure condition, the removal can lead to considerable separations between nodes. As for degree measure, the recalculation does not affect the node ranking since it is depending on the number of edges, and multiple nodes have the same number of edges, hence the variation for both strategies are almost identical. For Figure 4, all the measures are showing apparent decrease among the removal, which is better for resilience analysis comparing to largest component measure. The rates of betweenness and closeness are close, which might because most of the removed 10 stations are the same within both measures, the calculated results tend to be close. And degree centrality has the most remarkable variation, since the removed nodes contain a large number of edges, the removal can lead to the triangles drastically reduction.

Subsequently, in order to compare the difference between the non-sequential and sequential strategies, Figure 1 and 3, Figure 2 and 4 are combined respectively.

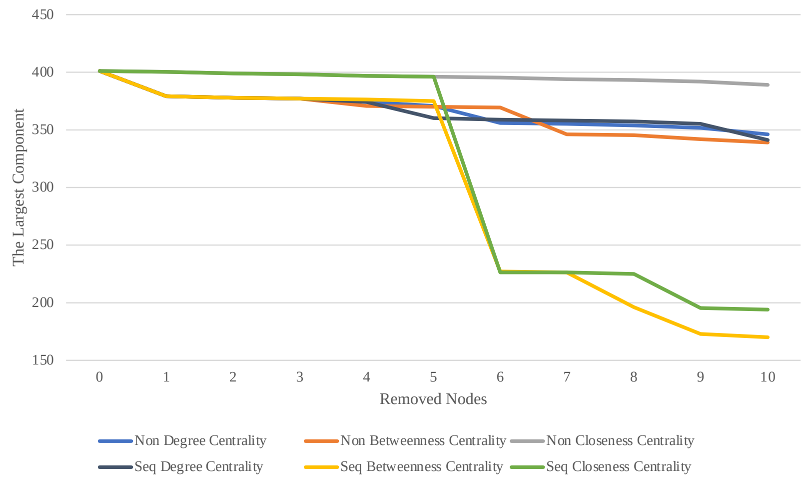

Figure 5 Largest component variation of both methods

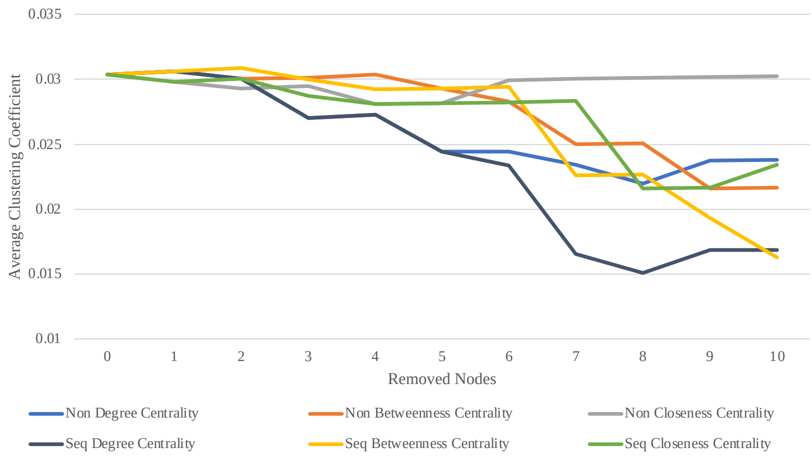

Figure 6 Average clustering coefficient variation of both methods

Combining the previous analysis and the figures above, for centrality measures: degree centrality is easily interpreted and generally well response to the node removal process. However, this measure can only collect the local information of a node, multiple nodes contain the same amount of degree, resulting in distinguishing difficulty (Kang *et al.*, 2011). In addition, this measure only depends on the topology of the graph, weights cannot be involved for measure. Therefore, it cannot reflect the complexity of the underground network. Betweenness centrality also responds well to the removal process, since the communication between two indirectly connected nodes relies on the third-party nodes between them, in other words, the nodes in-between control the most paths of information delivery (Sci.unich.it., 2022). For the underground network, the removal of the higher betweenness nodes might considerably affect the functioning between other nodes, which emphasizes the significance of this measure in the underground context. Closeness centrality can present the close relationships as well as the average shortest path between stations. However, the high closeness station is not robust as the most critical one within underground network, alternative communication might exist, and the factor of distance is not considered for the topology network, therefore, it is not sensitive to underground node removal. Overall, betweenness centrality can reflect better the importance of a station for the function of the underground.

For node-removal strategies: both strategies can reflect the importance of the removed nodes, although the non-sequential method is easy for operating, the sequential one is more practical, since the network is dynamic, once a station is closed (removed), the rest should be regarded as a new network for normal functioning and this is the reason for resilience analysis, hence the centrality need to be recalculated.

For impact measures: from Figure 5 and 6, the variations for both impact measures are decreasing. The largest component measure is relatively understandable for the changes, while clustering coefficient can generate significant variations among different centrality measures, which would be more valuable for evaluating damage after node removal.

II. Flows: weighted network

II.1.

According to the topological analysis, betweenness centrality indicates that Stratford station is considered as the most relevant stations for assessing the vulnerability of the underground. Regarding weighted network, the measure should add a factor of weight, which is the inverted flows, the reason is because the flow weights represent the distances, the higher the flow value is, the closer the two nodes are. Table 6 shows the calculated results of betweenness centrality for a weighted network. It is not the same as the one derived in I.1, although most of nodes are still in the top 10, the order is totally different since the flows of the stations are varied from each other.

Table 6 First 10 ranked nodes with weighted attributes for betweenness centrality

Node	**Weighted Attribute**
Green Park	44892.50
Bank and Monument	39758.50

Waterloo	31904.25
Westminster	29664.50
Liverpool Street	26530.00
Stratford	26125.00
Bond Street	22996.50
Euston	22314.00
Oxford Circus	21207.00
Warren Street	19916.00

II.2.

For the weighted network, the largest component is excluded as it only considers the number of nodes in the biggest sub-network. While the clustering coefficient can still be applied to weighted network, since it represents a statistically significant level of cohesiveness that measures the global density of network triplets (Barrat *et al.*, 2004), additionally, the measure is adjusted to add flow weights and calculate the weighted clustering coefficient.

A new measure for assessing node removal is average degree, which is the average number of edges for a node, the value is associated with the correlations between the degree of connected nodes (Barrat *et al.*, 2004).

II.3.

Table 7 exhibits the average clustering coefficient and average degree results for non-removal and removing highest ranked node in topological network. Under the condition of betweenness centrality, the results of topological network indicate that the clustering coefficient result is slightly increased, while the average degree is decreased. Hence for average degree performs better outcome of node removal.

Table 8 displays the results with the same process within weighted network. Since the considerable flow weights are involved in the calculation, the average clustering coefficient results are much smaller than the topological results, and average degree results are significantly larger than the topological one. In addition, since the highest ranked node is not the same as topological one, the top node is removed, and the results indicate that both the clustering coefficient and average degree are decreased, which indicate better performance than topological network. Since in real world, each station has different commuter flows, even if one station is not quite important in topological network, it might contain a large number of flows, which should also pay attention and be considered for studying resilience. However, such factor cannot be detected based on the amount of topological information alone. In weighted network, the flow factor is involved in the degree of each node, and the ranking results therefore is more robust than topological one. Consequently, the closure of Green Park station within weighted network will make the greatest impact on the commuters.

Table 7 Node removal results of topological network

	Average clustering coefficient	**Average degree**
Non-removal	0.03038	2.3292
Top node removed	0.03063	2.29

Table 8 Node removal results of weighted network

	Average clustering coefficient	**Average degree**
Non-removal	0.001579	49530.4090
Top node removed	0.001318	46511.025

Part 2: Spatial Interaction models

III. Models and calibration

III.1.

Table 9 briefly demonstrates four types of spatial interaction models and their features.

Table 9 The Family of Spatial Interaction Models

<table>
<tr><th rowspan="2"></th><th rowspan="2">The Unconstrained Model</th><th colspan="2">The Singly Constrained Models</th><th rowspan="2">The Doubly Constrained Model</th></tr>
<tr><th>The Origin–Constrained Model</th><th>The Destination–Constrained Model</th></tr>
<tr><td>Equation</td><td>$T_{ij} = KO_iD_j\exp(-\beta c_{ij})$ subject to $\sum_{i=1}^{n}\sum_{j=1}^{m} T_{ij} = T$</td><td>$T_{ij} = A_iO_iD_j\exp(-\beta c_{ij})$ subject to $\sum_{j=1}^{m} T_{ij} = O_i$</td><td>$T_{ij} = O_iB_jD_j\exp(-\beta c_{ij})$ subject to $\sum_{i=1}^{n} T_{ij} = D_j$</td><td>$T_{ij} = A_iO_iB_jD_j\exp(-\beta c_{ij})$ subject to $\sum_{j=1}^{m} T_{ij} = O_i$ & $\sum_{i=1}^{n} T_{ij} = D_j$</td></tr>
<tr><td>Parameters</td><td colspan="4">Where i denotes origins; j denotes destinations; T_{ij} denotes the flow from i to j; O_i and D_j denotes origin and destination activities;K denotes scaling constant, which adjusts the trips to ensure the sum of them reaches the total number of trips T; c_{ij} denotes generalized travel cost; β denotes friction of distance parameter, which controls the impact of generalized travel costs</td></tr>
<tr><td>Constraint</td><td>There is an overall constraint for the model that is the trips add up to T</td><td>The constraint is the trips attracted to the origin</td><td>The constraint is the trips attracted to the destination</td><td>The constraint is the trips attracted to both origin and destination</td></tr>
</table>

III.2.

In order to utilizing all of the population, jobs and flows, unconstrained model is selected, as each parameter can be considered during the calculation. The model is built and calibrated in the Python script attached in Appendix. Table 10 shows that the fitting effect is significantly improved after calibration.

Table 10 Goodness-of-fit

	R^2	**RMSE**	**Beta**
Initial model	0.03464	485.365	0.0001
Calibrated model	0.3212	108.334	0.6228

IV. **Scenarios**

IV.1. Scenario A

The flows with adjusted jobs are calculated by Python, the results are shown in Table 11.

Table 11 Flow results for Scenario A

station_destination station_origin	Abbey Road	Acton Central	Acton Town	Aldgate	Aldgate East	All Saints	Alperton	Amersham	Anerley	Angel	...	Woodgrange Park	Woodside Park	Woolwich Arsenal	All
Abbey Road	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	17.0	600.0
Acton Central	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	3.0	NaN	NaN	1225.0
Acton Town	NaN	NaN	NaN	24.0	24.0	NaN	4.0	2.0	NaN	25.0	...	NaN	4.0	NaN	3743.0
Aldgate	NaN	NaN	7.0	NaN	19.0	NaN	NaN	1.0	NaN	19.0	...	NaN	3.0	NaN	2884.0
Aldgate East	NaN	NaN	8.0	20.0	NaN	NaN	3.0	1.0	NaN	20.0	...	NaN	3.0	NaN	3172.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Woodford	NaN	NaN	12.0	32.0	32.0	NaN	NaN	NaN	NaN	33.0	...	NaN	NaN	NaN	4864.0
Woodgrange Park	NaN	9.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	530.0
Woodside Park	NaN	NaN	8.0	21.0	21.0	NaN	4.0	NaN	NaN	22.0	...	NaN	NaN	NaN	3092.0
Woolwich Arsenal	30.0	NaN	NaN	NaN	NaN	37.0	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	7894.0
All	275.0	550.0	3055.0	7729.0	8268.0	385.0	1081.0	462.0	140.0	8639.0	...	133.0	1159.0	1802.0	1542402.0

IV.2. Scenario B

To increase the cost of transport, 2 values are selected. for the power model, and the results are displayed in Table 12 and 13.

Table 12 Flow results for Scenario B 1

station_destination station_origin	Abbey Road	Acton Central	Acton Town	Aldgate	Aldgate East	All Saints	Alperton	Amersham	Anerley	Angel	...	Woodgrange Park	Woodside Park	Woolwich Arsenal	All
Abbey Road	0	0	0	0	0	0	0	0	0	0	...	0	0	1	598.0
Acton Central	0	0	0	0	0	0	0	0	0	0	...	2	0	0	1223.0
Acton Town	0	0	0	71	67	0	0	0	0	67	...	0	0	0	3744.0
Aldgate	0	0	24	0	0	0	0	1	0	0	...	0	3	0	2880.0
Aldgate East	0	0	24	0	0	0	6	1	0	0	...	0	3	0	3168.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Woodford	0	0	0	3	1	0	0	0	0	18	...	0	0	0	4863.0
Woodgrange Park	0	15	0	0	0	0	0	0	0	0	...	0	0	0	531.0
Woodside Park	0	0	0	29	27	0	0	0	0	9	...	0	0	0	3090.0
Woolwich Arsenal	1	0	0	0	0	68	0	0	0	0	...	0	0	0	7893.0
All	345	748	2193	7787	7929	444	738	253	174	8100	...	241	738	4430	1541089.0

Table 13 Flow results for Scenario B 2

station_destination	Abbey Road	Acton Central	Acton Town	Aldgate	Aldgate East	All Saints	Alperton	Amersham	Anerley	Angel	...	Woodgrange Park	Woodside Park	Woolwich Arsenal	All
station_origin															
Abbey Road	0	0	0	0	0	0	0	0	0	0	...	0	0	33	598.0
Acton Central	0	0	0	0	0	0	0	0	0	0	...	7	0	0	1218.0
Acton Town	0	0	0	32	31	0	0	0	0	29	...	0	2	0	3734.0
Aldgate	0	0	8	0	5	0	0	1	0	13	...	0	3	0	2886.0
Aldgate East	0	0	9	6	0	0	3	1	0	15	...	0	3	0	3170.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Woodford	0	0	8	29	26	0	0	0	0	33	...	0	0	0	4866.0
Woodgrange Park	0	13	0	0	0	0	0	0	0	0	...	0	0	0	531.0
Woodside Park	0	0	5	23	23	0	2	0	0	19	...	0	0	0	3093.0
Woolwich Arsenal	31	0	0	0	0	52	0	0	0	0	...	0	0	0	7892.0
All	345	750	2213	7773	7927	444	730	251	171	8103	...	244	741	4429	1541966.0

IV.3. Comparison

For the results of the three scenarios, 50% decrease of jobs can result in more impact on flow redistribution. Since the prediction of this situation is more far from the data flows (as shown in Table 14), which results in more significant variation, while other two are exhibited relatively robust results.

Table 14 Data flow distribution

station_destination	Abbey Road	Acton Central	Acton Town	Aldgate	Aldgate East	All Saints	Alperton	Amersham	Anerley	Angel	...	Woodgrange Park	Woodside Park	Woolwich Arsenal	All
station_origin															
Abbey Road	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	32.0	599
Acton Central	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	0.0	NaN	NaN	1224
Acton Town	NaN	NaN	NaN	3.0	17.0	NaN	35.0	0.0	NaN	11.0	...	NaN	0.0	NaN	3745
Aldgate	NaN	NaN	0.0	NaN	0.0	NaN	NaN	0.0	NaN	17.0	...	NaN	0.0	NaN	2886
Aldgate East	NaN	NaN	2.0	0.0	NaN	NaN	0.0	0.0	NaN	20.0	...	NaN	1.0	NaN	3172
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Woodford	NaN	NaN	2.0	5.0	47.0	NaN	NaN	NaN	NaN	22.0	...	NaN	NaN	NaN	4868
Woodgrange Park	NaN	0.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	530
Woodside Park	NaN	NaN	1.0	26.0	11.0	NaN	0.0	NaN	NaN	59.0	...	NaN	NaN	NaN	3093
Woolwich Arsenal	20.0	NaN	NaN	NaN	NaN	7.0	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	7892
All	345.0	750.0	2202.0	7782.0	7932.0	444.0	741.0	256.0	173.0	8103.0	...	242.0	745.0	4428.0	1542283

(word count: 1670)

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Appendix

Github link of Python script:

https://github.com/joeylizh/Urban_sim_assessment/blob/main/Assessment/Assessment.ipynb