3D SPACE RESILIENCE ANALYSIS OF COMMERCIAL COMPLEX

Beijing APM as an Example

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Abstract. Commercial complexes have played an increasingly important role in contemporary cities. Due to the occurrence of crowded people or equipment overhauls, some paths in a commercial complex may become impassable, which can be seen as disruptions to its spatial system. This paper provides a practical method to quantify the spatial resilience of a commercial complex taking Beijing APM as an example. This study can be divided into the following three steps. First, transforming the realistic spatial path system to a directed network model. Second, using topological, metric, and angular distance as edge weight to calculate the centrality and present its distribution. Third, using two disruption processes, randomized and attractor-guided strategy, evaluates the spatial network's resilience. There are three conclusions from this study. The first one is the process of disruption is non-linear, and there is a phase transition process when it reaches the critical threshold. The second one is the most efficient disruption method is the topological BC attractor-guided strategy. The last one is the resilience of a commercial complex, whose 3D spatial network's resilience is lower than the 2D spatial network's resilience by comparison with Duan and Lu's (2013) study.

Keywords. Resilience; Robustness; Network Secience; Commercial Complex.

1. Introduction

Spatial resilience characterizes the ability of a building to maintain its essential functions when facing disruptions. In the field of network science, a robust network is more stable and harder to change. This paper uses the concept of robustness in network science to measure commercial complex's spatial resilience.

In recent years, commercial complexes have played an increasingly important role in cities worldwide and are considered as the prototype of the future vertical city. This paper aims to fill the research gap by proposing a method to quantify the spatial resilience of the commercial complex's 3D space structure.

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1.1. RESEARCH REVIEW

Most current research on spatial resilience within buildings has focused on their spatial forms and construction techniques (Phillips, Troup, Fannon, & Eckelman, 2017). However, few research has been done from the perspective of network science. This section analyses three streams of researches.

Network science studies network, which regards a complex system's main element as nodes and their relationships as edges that can be assigned weights. A holistic understanding of complex systems can be obtained by performing mathematical and statistical studies on the network. In the field of architecture, spatial syntax is a theory based on network science in which the connecting relationship between spaces of a building or a city, and was developed by Bill Hillier et al.(1989).

Robustness is the measure of resilience in network science. Albert, Jeong, and Barabási(2000) showed a method to calculate a network's robustness by using external disruptions. Based on the methods proposed by Barabási et al., the resilience of some complex systems has been investigated in power grid systems(Albert & Nakarado, 2004), metro systems(Angeloudis & Fisk, 2006), and urban water supply systems(Yazdani & Jeffrey, 2011). These works have also demonstrated the generalizability of Barabási's method.

Recently, researchers introduced the concept of robustness into the field of urban research. Duan and Lu (2013) studied the robustness of urban road networks in six cities, including Beijing, Paris, San Francisco, Toronto, Singapore, London, and find out that the variation of road networks' robustness is non-linearity in the process of disruption. Kermanshah and Derrible(2017) used the concept of robustness in their study to evaluate the effects of flooding on urban road networks. Casali and Heinimann(2020) studied the changes in Zurich's urban road network's robustness between 1955 and 2012 and concluded that Zurich's urban robustness increased because of the increasing road density during this period.

1.2. STUDY AREA

Our case study is Beijing APM, one of the most prosperous commercial complexes in Beijing, located in the Wangfujing business district in Beijing's central area. The total area of the building is 220,000 square meters, of which the commercial complex area is 140,000 square meters, and the daily passenger flow is about 150,000. The commercial complex is divided into seven floors (one underground and six above ground).

2. Methodology

The occurrence of crowded people or equipment overhauls can corrupt a building's spatial structure: an impassable path in a building might prevent users from reaching their destination. This phenomenon can be seen as disruptions to a building. Figure 1 illustrates the technology roadmap of this study. The first step is to decide how to build a network and the second one is to transform the spatial path system into a network model. The third step is to calculate the robustness of the network model by simulate disruptions. This study uses Rhino/Grasshopper as

the research platform, and the core analysis batteries are programmed on C Sharp.

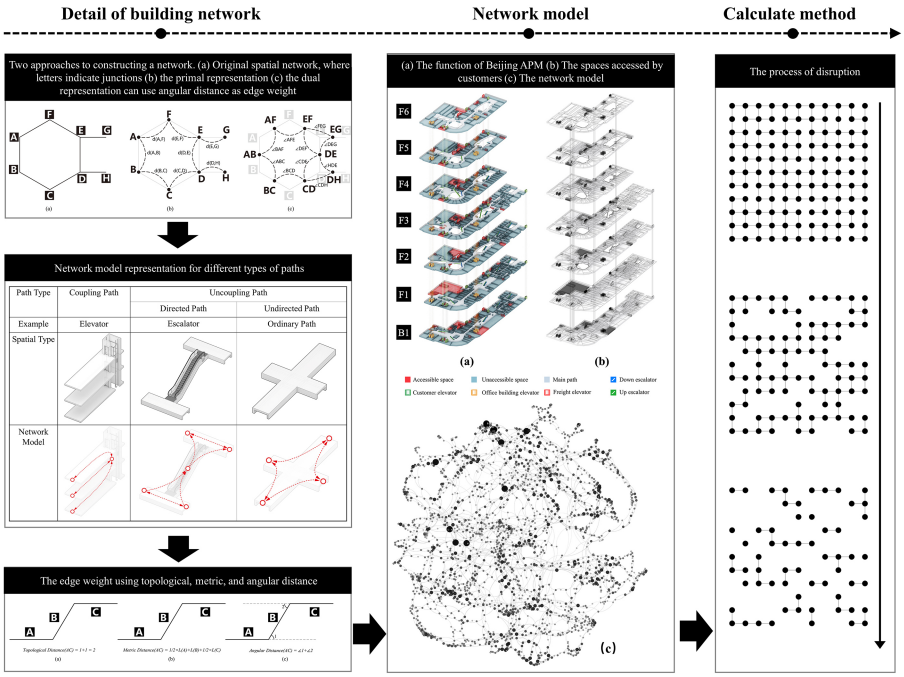


Figure 1. Technology Roadmap.

2.1. NETWORK MODELING

In a commercial complex, the path system connects all other systems, such as the sale system, service system, firefighting system, etc. All the pedestrians' movement depends on the path system, and other systems only provide space for people to stay. Therefore, the path system is chosen to be transformed into a network model.

There are two questions when using network models to represent the path system. The first one is although the undirected network has proven to be a useful way to describe the real world in previous studies. It could be errors when treating a directed path as an undirected path. As a result, we use directed networks to represent the path system of the building. The other is we have to decide which element in the path system as nodes and which as edges when constructing a network. There are two modeling ways: The first one is primal representation, which is the simplest. In this representation, we use junctions as nodes and the path between them as edges, which can use the topological distance and metric distance between two paths as edge weight. On the contrary, the other way is dual representation. This representation uses junctions as edges and the path between them as nodes, which can use the topological distance, metric distance, and the angular distance between two paths as edge weight. Because this study needs to

use the angular distance as edge weight to calculate the centrality, we choose the dual representation as the modeling method.

There are two main path types inside the commercial complex. The first type is the coupling path, which contains multiple paths, and if one of them impassable, other coupled paths cannot be used simultaneously, typically elevators. We use a node to represent the coupling path. The other is the uncoupling path, which can be subdivided into two types: one is the directed path, such as escalators, and the other is the undirected path.

2.2. NETWORK CHARACTERISTICS

Centrality is a concept to evaluate the importance of a node in a network, and there are several definitions of centrality in network science. In this paper, closeness centrality and betweenness centrality are used to measure the network.

The closeness centrality(CC) of a node measures its average farness (inverse distance) to all other nodes in a network. Nodes with a high closeness centrality have the shortest distances to all other nodes. Alex Bavelas(1950) introduced the method using the shortest path length to measure closeness centrality, which is formally defined as:

$$CC(s) = \frac{1}{\sum_t d(s,t)} \tag{1}$$

where both s and t are two nodes in the network, and $d(s,t)$ is the length of the shortest path between s and t.

Proposed by Freeman (1977), the betweenness centrality(BC) of a node in a network quantifies the number of times a node acts as a bridge along the shortest path between two other nodes, which is mathematically defined as follows:

$$BC(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{2}$$

where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(v)$ is the number of those paths that pass through v.

We used Dijkstra's algorithm to find the shortest path between two nodes in a network. Following the convention for analyzing segment models introduced by Hillier and Hanson (1989), we use three ways to assign weights to edges: topological distance, metric distance, and angular distance between two neighboring segments.

2.3. NETWORK RESILIENCE

In a commercial complex, path closures or breakdowns make it difficult for users to move between two places. With the increase of impassable paths, the commercial complex's space system will gradually become unusable, which is the idea behind the approach described in this section. We call this process disruption. There are two main issues in this section:

In this study, there are two approaches to disrupt an existing network: the first is to remove a node in the network each time, and the second is to remove an

edge in the network each time. Since we use dual representation to construct the network model, one path blocked corresponds to the network's one node deletion. Therefore, the first disruption method is chosen.

Another issue is what rules are used to remove nodes, called disruption strategies. There are two disruption strategies in this paper. One is the randomized strategy (i.e., randomly deleting a node each time in the process). The other is the attacker-guided strategy (i.e., deleting nodes in order of their centrality in the process). After each disruption frame, we use the giant component scale, which is the largest part that any two nodes are connected after disruption, to evaluate its impact. The calculated data are used to draw a plot to visualize the commercial complex's spatial network's resilience. After calculating the size of the giant component $S(f,q)$, there is a indicator: the ratio $R(f)$ of $S(f,q)$ to the number of nodes N. Barabási(2016) proposes that the Molloy-Reed criterion can determine when a network loses its giant component and calculates the critical threshold. The Molloy-Reed criterion is based on an observation that if there is a giant component in a network, then each node should have at least two neighboring nodes on average, which is calculated as follows.

$$\kappa = \frac{\langle k^2 \rangle}{\langle k \rangle} > 2 \tag{3}$$

where $\langle k \rangle$ is the average degree of the network, and the degree of a node is the number of edges it connects.The $R(f)$ measures are defined in the randomized strategy as:

$$R(f) = \frac{1}{Q}\sum_{q=1}^{Q}\frac{S(f,q)}{N} \tag{4}$$

where Q is the total number of iterations, which is 500 in this study, and N is the original number of nodes. When using attacker-guided strategy, the value of $R(f)$ only need to be calculated once.

3. Analysis and result

Figure 2 shows the analysis process in Grasshopper. After transforming its path system into a network model, the closeness centrality(CC) and betweenness centrality(BC) distributions are firstly calculated at three edge weight: topological, metric, and angular distance. The network is then disrupted using randomized and attacker-guided strategies when calculating the giant component's size after each disruption. The third step compares the similarities and differences of the network's resilience under the two disruption strategies.

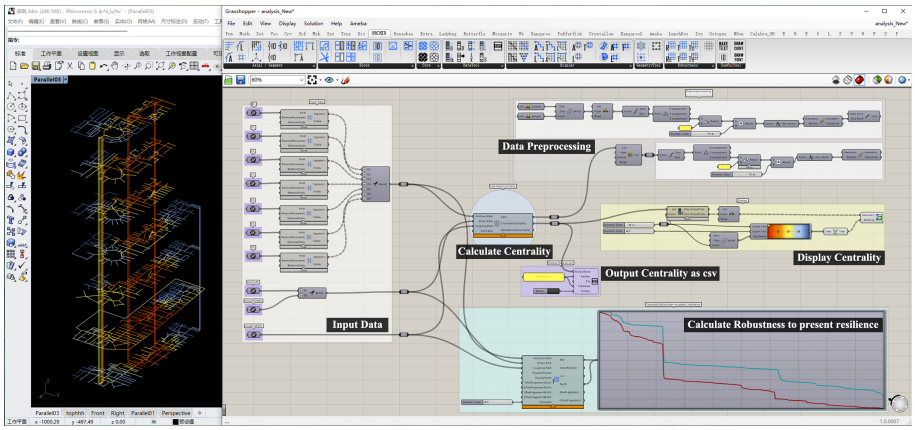


Figure 2. The analysis process in Grasshopper.

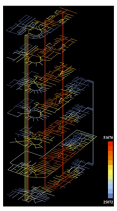
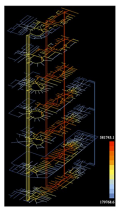
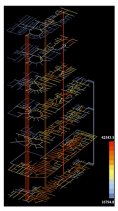
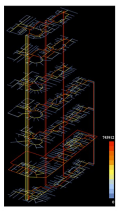
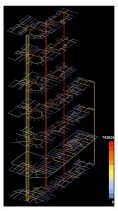
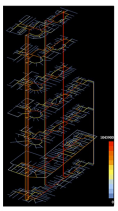
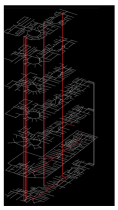
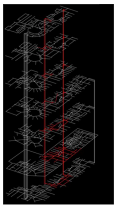
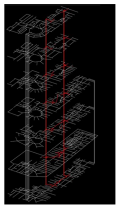
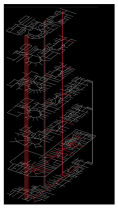
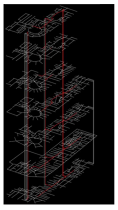
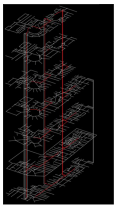
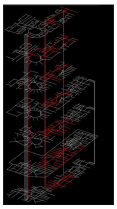
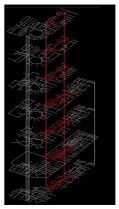
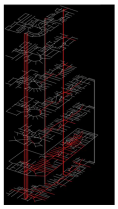
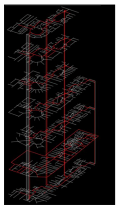
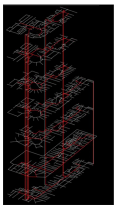
3.1. SPATIAL NETWORK CHARACTERISTICS

Some places in Beijing APM are inaccessible to customers, such as the staff area, firefighting stairway, office building service facilities, etc. This study building a network model base on the spaces accessed and used by customers. The volume of the Beijing APM is L-shaped, and its horizontal customer path consists of one main street connecting four atriums, which are numbered sequentially in one to four. And the vertical paths are composed of escalators and elevators located around the four atriums. This section characterizes spatial networks by using closeness centrality(CC) and betweenness centrality(BC)(Table 1). The top 5%, top 10%, and the top 25% values of CC and BC are selected as quantiles to visualize the spatially distributed features.

Horizontally, three CC are distributed unevenly in Beijing APM. The topological CC and metric CC show a decreasing radial distribution around Atrium No.3. The angular CC is centered on the north-south main street, connecting Atrium No.2 and Atrium No.4, which is different from the topological CC and metric CC. Vertically, the closer a floor is to the ground, the more possibility of paths with the high CC value the floor has. The angular CC distribution showed the most significant vertical variation, and the distribution of topological CC also had this trend. The metric CC shows almost no such tendency.

The segments with high BC coincide with the main public paths, such as elevators, paths around the atriums, the main street in the building, etc. Among the three BC distributions, topological BC has the best ability to identify paths because it can accurately identify both indoor and outdoor public paths. Metric BC has the second strongest ability to identify pathways, and it has difficulty identifying outdoor public pathways. Angular BC is the worst one.

Table 1. The distribution of centrality.

	Topological CC	Metric CC	Angular CC	Topological BC	Metric BC	Angular BC
Centrality						
Top 5% Segment						
Top 10% Segment						
Top 25% Segment						

3.2. DISRUPTION ANALYSIS

3.2.1. Randomized strategy

The first disruption process, randomized strategy, set all network nodes to have equal importance. And during the process, we delete the nodes of the network randomly one by one. Figure 3(a) illustrate the average $R(f)$ after 500 times random disruptions.

The figure shows the $R(f)$ decreased non-linearly by following three phases. Firstly, $R(f)$ almost unchangeable when from 0 to 10% of nodes are removed, and it means that the whole network remained mostly connected. Then, between 10% and 30% of nodes are removed, $R(f)$ declines rapidly, and the network's intactness is disrupted. The phase transition occurs when 16% of the nodes are removed. In the third stage, $R(f)$ is extremely small when more than 30% of the nodes are removed.

3.2.2. Attractor-guided strategy

Attractor-guided disruptions on the network based on CC can simulate that important destinations in a commercial complex, such as essential stores, cannot be reached. And based on BC can simulate that essential paths in a commercial complex cannot be passed. Firstly, we calculate CC and BC of Beijing APM's spatial network with three edge weights: the topological, metric, and angular distance. Then, nodes are deleted based on each node's centrality from largest to smallest (i.e., the more important the node is, the more chances it will be deleted). Figure 3(b-c) shows the result.

There are three phases with the decrease of $R(f)$ using attractor-guided strategy. $R(f)$ keeps stable when 22%(topological CC), 38%(metric CC), 5%(angular CC), 2%(topological BC), 4%(metric BC) and 6%(angular BC) of nodes are removed. Then a dramatic fall of $R(f)$ occurs in these critical thresholds, and it means the size of the giant component decreases rapidly at this point. After the phase transition process, the network is destroyed to pieces, and the spatial system became unusable.

3.3. COMPARISON

Figures 3(d) provide an intuitive illustration of the $R(f)$ of all seven processes. Based on it, we compare the similarities and differences between them.

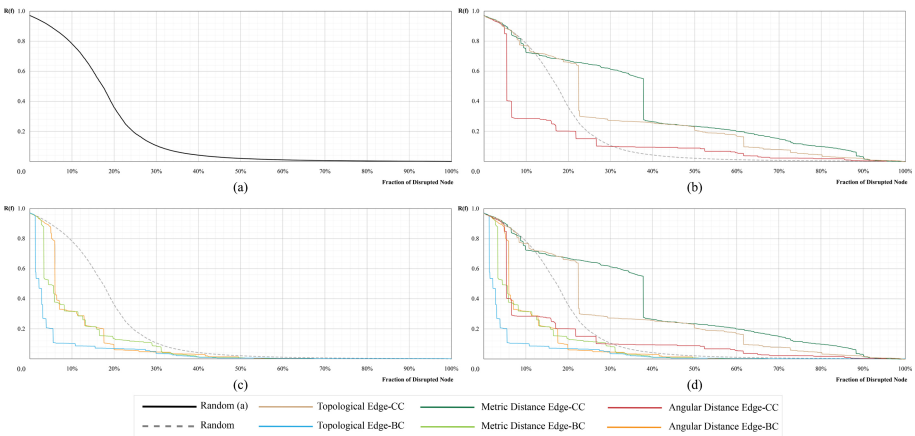


Figure 3. (a) R(f) of randomized strategy (b) R(f) of CC attractor-guided strategy (c) R(f) of BC attractor-guided strategy (d) R(f) of all seven processes.

The line chart of the robustness distribution function $R(f)$ with randomized strategy showed a steady decline during the whole disruption process. And the value of $R(f)$ do not change drastically around the critical threshold as well. It is different from all six other processes using attractor-guided strategy.

There are two common points between the three attractor-guided strategy distribution functions using closeness centrality(CC) as edge weight. One is more nodes than randomized strategy's function need to be removed to reach the critical

threshold. And the other is that the size of the giant component is larger after the phase transition. There are also significant differences between the three process. The node number that needs to be removed to reach the critical threshold is different, which is 22%(topological CC),38%(metric CC), and 5%(angular CC). The first two number is larger than 16%, the critical threshold of randomized strategy. The size of the three giant components after phase transition is also different. After the phase transition, the giant component's size with metric CC and topological CC are similar, and two of them are larger than the size with angular CC. The comparison shows that the topological CC and metric CC attractor-guided strategy delayed the network's collapse. In contrast, the angular CC attractor-guided strategy accelerated the process.

There are also two common points between the distribution function's strategy distribution function using the betweenness centrality(BC) as edge weight. Not only do the fewer nodes need to be deleted to reach the critical threshold, but the giant component size is also smaller after the phase transition. The difference between the three is the number of nodes that need to be deleted to reach the critical threshold, which is 2%(topological BC), 4%(metric BC), and 6%(angular BC). The result of the comparison shows that all three processes accelerate the collapse of the network.

Duan and Lu (2013) show a two-dimensional spatial network would malfunctions when more than 50% of the nodes are randomly removed, or 20% of the nodes are removed by order of topological or metric BC. Comparing their findings with this study, we found that the commercial complex path network's resilience is worse than a two-dimensional road spatial network's resilience, which means three-dimensional spatial networks are less resistant to disruption.

4. Discussion

Resilience analysis from network science perspective can effectively quantify the impact of disruption in commercial complexes. However, there are three factors that might affect the analysis, and we hope to overcome these issues in future research.

First, in this paper, we assumed that each node deletion is an independent event. In fact, in a network of a commercial complex's path system, a node's error might cause the error of its neighboring nodes, and we call it cascading failures. This may cause this paper's simulation results to deviate from the actual situation and affect the results' accuracy.

Second, This study building a three-dimensional spatial network model without including the Beijing APM's surrounding paths. However, the surrounding space also affects people's understanding of its inside space.

Third, This study only experiments on one commercial complex, Beijing APM. Therefore we can not verify the generalizability of the conclusions. In the future, we hope to use the same approach to study more spatial network to draw more generalizable conclusions.

5. Conclusions

This paper proposes a method to quantify the resilience of a 3D spatial structure and provide a perspective for architects to understand it. This study has three findings as follows.

First, the spatial resilience of 3D spatial networks under disruption is non-linear. Specifically, it can be divided into three phases: the first stage is that the giant component's size remains basically unchanged. Then, the phase transition happened, and the giant component vanishes. Many tiny components exist after the critical threshold during the third stage.

Second, among the strategies used in this study, The most efficient one is the topological BC attractor-guided strategy, where the spatial network undergoes a phase transition when 2% of the nodes are removed. While the least efficient way is the metric CC attractor-guided strategy, and its critical threshold is 38%.

Third, by comparison with the discussion of Duan and Lu (2013), we can conclude that the resilience of 3D spatial networks in the commercial complex, such as Beijing APM, is lower than the 2D road network's resilience. As the vertical city moves from theory to reality, architects should understand that while the 3D spatial path network is highly efficient, it is also has a low spatial resilience when facing disruptions.

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