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Assessing Survivability of the Beijing Subway System

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To the Graduate Council:

I am submitting herewith a thesis written by Yan Li entitled "Assessing Survivability of the Beijing Subway System." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Geography.

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ABSTRACT

The assessment of survivability is a common topic in critical network infrastructure research. In order to examine the critical components whose disruptions can cause huge system degradation, many measures have been approached to depict the characteristics of network systems. Serving more than ten million passengers a day, the Beijing subway system, which ranks third in the world for its length and annual ridership, raises survivability issues in the face of potential disruptions of network components along with its constantly increasing complexity. In this research, we provide an accessibility-based survivability measure with which to explore how potential outages of network components might affect the overall functionality of the Beijing subway system. System survivability is measured from two perspectives: [1] connectivity under various simulated failures of stations and [2] variations in passenger flows in response to a disruptive influence. Plausible scenarios are constructed using local demographic data and daily ridership reports from subway management companies. To assess the possible range of influences, we develop a weighted rank-based simulation algorithm to approximate the extreme combinatorial disruption instances. The range of the potential effect highlights the best and worst-case scenarios so as to identify the critical components and help to prepare corresponding contingency plans. This research will enable the more legitimate allocation of limited emergency response resources and highlight the way of improving the survivability of the system.

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CHAPTER 1 INTRODUCTION

The assessment of survivability is a common topic in critical network infrastructure research. Much effort has been directed at developing approaches for exploring the potential outcomes of the unscheduled loss of network systems. Serving more than ten million passengers a day, the Beijing subway system is the third largest subway system in the world. However, as a fast-developing subway system serving one of the most rapidly expanding urban centers in the world, the Beijing subway system has not been explored from a survivability perspective. The goal of this research is to develop suitable measures and methods to assess the survivability of the Beijing subway system. Chapter 1 presents research background, research questions, and objectives. The organization of the thesis is outlined at the end of this chapter.

1.1 Research Background

This section demonstrates the background of the research. The importance of public transportation is discussed first, followed by the need for survivability assessment. The Beijing subway system and the City of Beijing are introduced last.

1.1.1 Public transportation

Transportation systems enable the movement of people and goods between origins and destinations across a network. Public transportation is a shared passenger transportation service that is available for use by the general public, including buses, trolleybuses, trams and trains, rapid transit, and ferries. It is a crucial part of the solution to the world's environmental, social, and economic challenges. First, mass transit is generally regarded as significantly more energy efficient than other forms of travel (Layton 2002). Second, public transportation can also increase urban population densities, thereby reducing travel distances and fossil fuel consumption (Newman 1999). In addition, public transportation ensures that all members of the society, not just those with a driving license and access to

automobiles, are able to travel (Litman 1999). Finally, it can ultimately reduce the total transportation cost for the public and frequently has a positive impact on real estate prices by reducing private vehicles and improving local accessibility (John 1996, Wang and Yan 2011). With the world's population soaring in recent decades, public transportation is getting increasing attention. In 2012, 10.5 billion trips on public transportation were made in the United States, and people in the U.S. boarded public transportation 35 million times each weekday (Publictransportation 2013). In particular, the importance of the public transport systems in China is quite stressed because the burden of the systems in China is even heavier than that in the US. In 2010, the average number of motor vehicles owned by one thousand people in the U.S. was 797, while in China it was 58 (The World Bank 2013). Under this circumstance, public transportation use in China is expected to be expanded to meet the increasingly urgent demand caused by the fast-growing population, especially in some urban areas such as Beijing, Shanghai, and Shenzhen.

1.1.2 The need of survivability assessment

Along with the growing importance of public transportation, its functionality of paths for movement can be severely hindered by disruptions (Matisziw et al. 2009). The devastating impact of the 2011 floods in southeastern Queensland (Lee et al. 2013), the 2004 Madrid train bombing, and the 2005 London Underground bombing display both the possibility of disruptions and the vulnerability of transportation systems confronted with such disruptions (CNN Library 2013a, 2013b). Since public transportation is embedded deeply into society, disruptions to system components can impair the functionality of the entire system, thereby causing huge socioeconomic costs, especially when the disruptions result from intended terrorist attacks (Angeloudis and Fisk 2006, Kim 2009).

Because of the growing importance of public transportation and its expensive recovery after being disrupted, management agencies tend to fortify the system beforehand to prevent potential disasters from the system. For example, the service of the

New York subway system is seasonally disrupted by flooding from rainstorms, and the cost for the system maintenance is huge, with $357 million being spent in improving 269 pump rooms since 1992 (Donohue 2007). This begs two questions: (1) how can disruptions be prevented from occurring, and what is the critical components in the system? And (2) how can the influence of disruptions be minimized? A preliminary approach to solve these questions is to identify the critical network components, and draw feasible scenarios to various situations on the system. Survivability is the capability of a system to fulfill its mission, in a timely manner, in the presence of threats such as attacks or large-scale natural disasters (Ellison et al. 1997, Mohammad et al. 2006). With limited resources to respond to an emergency, assessing survivability and exploring the potential scope of disruptive events are critical in network planning and risk management. Considering their socioeconomic importance, transportation systems, such as highway and road network, have been studied through hypothetical or empirical survivability analyses (Jenelius et al. 2006, O'Kelly and Kim 2007, Matisziw et al. 2009, Salmeron et al. 2004).

1.1.3 Case study

Beijing is the capital of the People's Republic of China and one of the most populous cities in the world with a population of more than twenty million in 2012 (BMBS and NSOB 2013a). It is the nation's political, cultural, and educational center. It is also home to the headquarters of most of China's largest state-owned companies, and is a major transportation hub where nine expressways, eleven national highways, ten conventional railways and three high-speed railways converge (Encyclopedia 2013). The Beijing Capital International Airport is the second busiest in the world by passenger traffic (PANYNJ 2013). In order to serve the local residents and transfer traffic flow from and to all over the country effectively, the local transportation system shoulders a heavy burden. Traffic jams become a major concern. Even outside of rush hours, several roads still remain clogged with traffic (Xinhua 2003). In the beginning of 2010, Beijing had about four million registered automobiles, which increased at a rate of 15,500 per week in 2010

(Gao 2010). Drastic measures, including limiting the number of new license plates issued and barring cars with non-Beijing plates from entering areas within the Fifth Ring Road during rush hours, are applied to mitigate traffic jams (ChinaAutoWeb 2010). Obviously, private vehicles are not the solution to the transportation problem of Beijing. Thus, the authorities have introduced several bus lanes, which only public buses can use during rush hours (CCTV 2009), but these lanes are still affected by traffic jams to some extent. Staying away from the influence of congestion on the ground is one of the largest advantages of the subway system. A flat fare of 2 RMB (about 0.30 USD) per ride with unlimited transfers on all lines except the Airport Express also makes it the most affordable rapid transit in Beijing (U.S. News 2013). Because of its cheap, timely and reliable service and operation, the subway has become the first choice among the transportation modes in Beijing (JSCHINA.com.cn 2014). In 2012 its annual ridership ranked third in the world with 2.46 billion trips highlighting that even a small survivability issue of the Beijing subway system will affect millions of its passengers (BMBS and NSOB 2013a, BMCT 2013a, Liu 2013a).

1.2 Research Objectives and Research Questions

A series of research challenges is involved in this study. In this section, three major objectives of this study are listed. To achieve these objectives, four research questions are further identified and discussed.

1.2.1 Research objectives

The proposed study aims to pursue three main research objectives: (1) to design an *accessibility-based survivability measure* (ASM) as a measure of survivability taking into consideration both topology and system flow aspects of disruptions' influences; (2) to develop a *weighted rank-based simulation algorithm* (WRSA) to make the ASM applicable for a large network; and (3) to assess the survivability of the Beijing subway system based on the designed measure through the algorithm.

1.2.2 Research questions

The following research questions are addressed to achieve the above objectives:

1. What is a suitable survivability measure? There are three types of survivability measures commonly-used in the survivability study of transportation networks: connectivity, characteristics as transportation paths, and system flow. They describe survivability from different perspectives. A measure including diverse perspectives may reveal a broad view of the facts.
2. Is there a way to approximate the survivability to all disruption scenarios within the current computation capability? The demand for computation soars with the increase of a network's complexity. The enumeration of all scenarios for the Beijing subway system is computationally not amenable, so a new algorithm is necessary.
3. What will be the performance of the Beijing subway system when confronted with single-station disruptions or combinatorial disruptions? The influence of a single disrupted station varies with the topological and geographic characters of the station. Different combinations of the disrupted stations complicate the question further.
4. Is the survivability of the system varying with time? Since the ridership of the system fluctuates with time in a week, the frequency of the stations being used and the distribution of the passengers' travel demand changes as well. Can this change be reflected in the survivability assessment?

1.3 Organization of the Thesis

This thesis is organized into six chapters. Besides the introduction in Chapter 1, Chapter 2 reviews the literature covering what has been done related to this study, including survivability measures, methods of exploring network disruption scenarios and other related topics. In Chapter 3, we detail the case study and the data utilized for analysis. In the fourth chapter, we provide the research framework coupled with the ASM and

WRSA. The fifth Chapter provides the research results followed by the conclusions in Chapter 6.

CHAPTER 2 LITERATURE REVIEW

The fundamental role of a network system is the paths of the interaction across the system. All too often, however, the paths are interdicted by unplanned events or targeted attacks (Murray and Grubesic 2007). Such disruptions can cause unscheduled loss of service capabilities within a network, resulting in costly repairs and widespread service outages. The fact that disruptions can take numerous forms complicates the study. For instance, targeted attacks seek to maximize system damage, while natural disasters, such as floods, hurricanes, and fires, also cause considerable damage to network systems over large geographic expanses. Therefore, the influence of disruptions, regardless of their origin, on a network system is often measured through the consequences. In survivability research, there is an implicit assumption that the direct result of disruptions on a system is limited. The worst direct influence is that a part of the system stops working. The scope of the affected network components is either a single node/link or a group of nodes/links. Even though the cascading reaction from a partial disruption may lead to the system's collapse, the fundamental characteristic of a network is the capability of maintaining its functionality confronted with partial network components' failure. Disruptions impair the functionality of a network system and modify the characteristics of it. Describing the influence of disruptions is the foundation for measuring the survivability of a network.

2.1 The Concept of Survivability

One of the foremost concerns in survivability research is exploring appropriate measures to evaluate system survivability. However, the concept of survivability itself does not have a commonly-accepted definition yet. The meaning of the term depends on the context (Jenelius et al. 2006). "Reliability" and "vulnerability" are two terms to define survivability. For example, Holmgren (2004) defines vulnerability as a collection of properties of an infrastructure system that may weaken or limit its ability to maintain its intended function when exposed to threats and hazards. Salmeron et al. (2004) compare vulnerability to the system's "cushion" against failed, destroyed, or otherwise unavailable system components, while Berdica (2002) focuses on the possibility of catastrophes by stating that vulnerability is the susceptibility to rare, though big risks. Even though the

definition varies with the context of study, vulnerability in the transportation network is commonly seen as the complement of reliability (Berdica 2002). According to Husdal (2004), vulnerability studies primarily focus on the impact or consequence of disruptions, and vulnerability is the non-operability of the network under certain circumstances. On the contrary, he states that reliability is an expression of the probability that a network will function. Thus, reliability may be regarded as the degree of stability of the quality of service that a system offers. In other words, vulnerability represents the extent to which the system loses its original functionality, while reliability measures the remaining functionality (Bagga, et al. 1993, Berdica 2002).

The relationship between vulnerability and reliability is more complicated, and it also matters how survivability is measured (Jenelius et al. 2006). As well introduced by Murray (2013), any network system can fail in various ways, and methods to examine its survivability have been developed based upon the type of systems and approaches. There are two types of measures describing the changes of a disrupted network: binary and fuzzy measures. Binary measures, which represent survivability within a range of values or through certain indices, follow all-or-nothing logic with system operation. Disrupted network components will be totally excluded from the system in this condition. On the contrary, fuzzy measures assume that network components function within a certain level of operation probability, such as the probability of a network disruption's occurring, the chance of network components' being disrupted, and the degree to which the disrupted components are able to maintain parts of their functionality. Reliability researchers generally prefer fuzzy measures, while binary measures are the first choice for vulnerability. In theory, applying a fuzzy measure is more realistic than a binary measure since the former takes into account the different malfunction possibility of network components. For example, Kim (2009) defines reliability as a network's capability to deliver flows or availability of paths between nodal pairs in the network, which depends on the probability of operation at the links or nodes. However, the prerequisite of applying fuzzy measures is that the empirical or hypothetical failure probability of a system or network components is known. Otherwise, the setting of the probability form could be arbitrary.

2.2 Survivability Measures

In both the traditional field of transportation and the newly emerging field of network science exist many measures for assessing the survivability of network-based systems (Matisziw et al. 2009). The four widely used network degradation measures are network connectivity, operational cost, capacity, and system flow, which can be classified into three types (Murray 2013, Kim 2012).

2.2.1 Measures based on connectivity

By definition, network connectivity concerns the existence of available or functional paths between origin-destination (O-D) pairs. The purpose of a network is to establish and maintain connectivity between a set of interacting elements to facilitate the movement of valuable goods and services across a system (Grubesic et al. 2008), thus the precondition of assessing the survivability of a transportation network is connectivity. Fundamental to all approaches for examining network survivability from the connectivity perspective is to represent complex networks as graphs. Introduced from the *graph theory*, regardless of diverse forms of transportation systems and disruptions, a network can be simplified as a collection of arcs or edges (e) that connects nodes or vertices (v). The arrangement of the elements (arcs and nodes) of a graph is typically referred to as network topology. Where a disruption is concerned, the removal or destruction of a node or arc in a system changes this arrangement, so graph theoretic measures are employed to evaluate network connectivity degradation.

Global graph theoretic measures provide a single index that summarizes network structures and hence can be used to compare different networks. These indices are largely based on three components: nodes, arcs, and segregated parts. Note that the Beijing subway system can be represented by a planar graph, Table 2.1 lists a set of the global indices for planar networks.

Table 2.1. Global graph theoretic measures

Name	*Equation*	*Notes*
Beta index	$\beta = e / v$	e = number of arcs in the graph
Cyclomatic number	$\mu = e - v + g$	v = number of nodes in the graph
Alpha index	$\alpha = \dfrac{e - v + g}{e_{\max} - (v-1)}$	g = number of separated parts in the graph
Gamma index	$\gamma = e / e_{\max}$	$e_{\max} = 3 \times (v-2)$

The first index is the beta index, where

$$\beta = \frac{e}{v} \tag{1}$$

β is a basic measurement of network complexity and is easy to interpret. The minimally connected network when all nodes are linked as a graph results in β equal to $(v-1)/v$, which indicates a treelike structure. $\beta = 1$ implies that there is one arc more than a tree, and $\beta > 1$ suggests a graph with circuits. The value of β for a maximally connected planar graph is $3(v-2)/v$. Given the number of separated parts (*g*), a second basic measure is the cyclomatic number, where

$$\mu = e - v + g \tag{2}$$

The cyclomatic number provides one with a basic idea of how many circuits there are in a graph. If the graph is a treelike structure, the cyclomatic number assumes a value of 0. If the graph has one circuit, μ assumes a value of 1. Derrible and Kennedy state that compared with “assortativity”, a modified cyclomatic number is a better network “robustness” indicator (Derrible and Kennedy 2010). Assortativity, which is proposed by Newman (2002, 2003), indicates the similarity of the adjacent nodes. It is often examined in terms of a node’s degree. A third global measure is the alpha index as defined in equation (3):

$$\alpha = \frac{e - v + g}{e_{\max} - (v - 1)} \tag{3}$$

α is a basic measure of connectivity that provides a ratio of the existing circuits to the maximum number of possible circuits in a graph. $e_{\max}$ represents the maximum number of arcs and is calculated as $3(v-2)$ in a planar network. Similar to the cyclomatic number, when α equals 0, the graph is a treelike structure. Thus, the removal of any arc would break the graph into disconnected parts. If $\alpha = 1$, no additional arcs can be added to the system without duplication. This represents a maximally connected graph. The value can be interpreted as the redundancy in the network. Finally, the gamma index, γ, is formulated as follows:

$$\gamma = \frac{e}{3(v-2)} \tag{4}$$

It is a measure that evaluates the ratio of the existing arcs to the maximum number of arcs possible in a network. In other words, γ represents the relative connectivity of a system. As γ approaches one, the network is more connected. If γ reaches 1, the graph is completely connected. All of these measures emphasize the relationship between the number of nodes and the number of arcs in order to reveal the existence of alternative connections in a graph. It is evident that the alternative connections can act as backup when the components along the original paths are disrupted. This redundancy improves the survivability of a network.

Local network measures, on the other hand, are computed for individual arcs or nodes within a network, emphasizing their relative topological characteristics. The simplest local measure of nodal connectivity is the degree of the node. The connectivity matrix (*C*-Matrix) serves to represent the topological connectivity of network systems (*G*). Let us define the 1st level C-Matrix (C^1) as the adjacent connection matrix of a network. If a node *i* is connected to another node *j*, then its connectivity (c_{ij}^1) is defined with 1, otherwise 0 in C^1. The degree of each node can be determined by summing the

total number of direct (one-step) connections between node i and all other nodes in the system:

$$\delta_i = \sum_{j=1}^{v} c_{ij}^1 \tag{5}$$

where

v: the number of nodes in the graph;

$$c_{ij} = \begin{cases} 1, & \text{if nodes } i \text{ and } j \text{ are directly connected} \\ 0, & \text{otherwise.} \end{cases}.$$

In many cases, higher-degree nodes are assumed to be more critical to network operation, given their greater direct association with other nodes (Grubesic et al. 2003). Computing the average degree of all nodes results in β discussed earlier (see Table 2.1. Global graph theoretic measures).

Unfortunately, the degree of a node does not address how a node is integrated with non-adjacent nodes. By powering C^1, the connectivity matrices describing the non-adjacent connections are determined. The *k*th power of C^1 represents the number of nodal sequences of length *k* linking nodal pairs. The largest *k* is equal to the diameter of the network (*d*) to ensure that at least one nodal sequence connecting the two most distant nodes in the network is counted. The sequences computed do not necessarily represent valid paths of movement because nodes may be visited repeatedly (Harary et al. 1965). However, the number of internodal sequences tabulated through powering is indicative of how proximate a node is to other nodes within a system, and summing the powers of *C* produces a matrix of total connectivity, *T*:

$$T = \sum_{k=1}^{d} C^k \tag{6}$$

Row sums of *T* (e.g., $T_i = \sum_{j \neq i} t_{ij}$, where t_{ij} are the items in *T*) indicate the importance of each node. Higher nodal values (T_i) suggest a more connected node. All nodal

connectivity values can be further summed into a total connectivity value for the network (e.g., $T_{all} = \sum_{i} \sum_{j \neq i} t_{ij}$).

2.2.2 Measures based on characteristics as transportation paths

Besides connectivity measures, there is another type of measures that takes into account how the components in a transportation system are linked, including operational costs and system capacity. Rather than focusing on the existence of paths between the origins and destinations, operational costs concern the impedance between them (Jenelius et al. 2006, Nicholson 2003). Time, cost, distance and tariff are often used to measure the cost. In common cases, operational costs are decided by absolute locations, transportation methods, the market, etc. Operational costs may be increased due to network disruptions as alternative more expensive routes may become necessary. Thus, the influence of disruptions on a network system can be represented by the increase of the operational costs. As an example, Corley and Sha (1982) are the pioneers in viewing shortest path performance in the context of network survivability. The notion of “shortest” indicates the minimum of the operational cost of paths. Corley and Sha (1982) attempt to explore the maximal influence of removing one network component. Israeli and Wood (2002) and Lim and Smith (2007) extend the algorithm proposed by Corley and Sha (1982) to handle the problem of maximizing the impact of disruptions with limited disruption budget on different network systems.

Topological distance is a good example of operational costs. A group of local graph theoretic measures describing nodal accessibility based on topological distance can also be used to evaluate the survivability of a network. As listed in Table 2.2, these measures are all derived from the *D* matrix or the Shimbel matrix, whose elements d_{ij} indicate the topological shortest-distance between any nodal pairs (Shimbel 1953). Among them, the Shimbel index measures the sum of the shortest paths between node *i* to any other nodes (d_{ij}, $j = [1, v]$). A smaller Shimber index is indicative of a node that is

more accessible or that has efficient connections to other network nodes, while a larger index indicates a greater level of effort is needed by a node to traverse the network. The dispersion index measures the total accessibility of a whole network by summing up the Shimber indices of all nodes. In order to compare the accessibility of nodes and networks, these two indices can be normalized with the size of the network to get the average version of the indices. By replacing the topological shortest distance between nodal pairs (d_{ij}) with other cost measures, these indices will indicate the characteristics of a network from other aspects. However, in scenarios where disruptions disconnect a network into separated parts, the shortest paths need to be specifically defined. For example, the network shown in Figure 2.1 contains 10 nodes in total. The disruption on node *4* will increase the shortest topological distance between nodes 0 and 9 from 2 steps to 3 steps. Disruptions on nodes 4 and 5 simultaneously will separate the network into two disconnected parts, where the path between nodes 0 and 9 will be excluded from the shortest path calculation or represented mostly by infinity. Thus, the interpretation of the indices concerning the operational costs needs to be done accordingly.

Table 2.2. Local graph theoretic accessibility measures

Name	*Equation*	*Notes*
Shimbel index	$S_i = \sum_{j=1}^{v} d_{ij}$	
Average Shimbel index	$AS_i = \frac{\sum_{j=1}^{v} d_{ij}}{v-1}$	v = number of nodes in the graph d_{ij} = the shortest path distance between nodes *i* and *j* $i \neq j$
Dispersion index	$D = \sum_{i=1}^{v}\sum_{j=1}^{v} d_{ij}$	
Average dispersion index	$AD = \frac{\sum_{i=1}^{v}\sum_{j=1}^{v} d_{ij}}{(v-1)\times v}$	

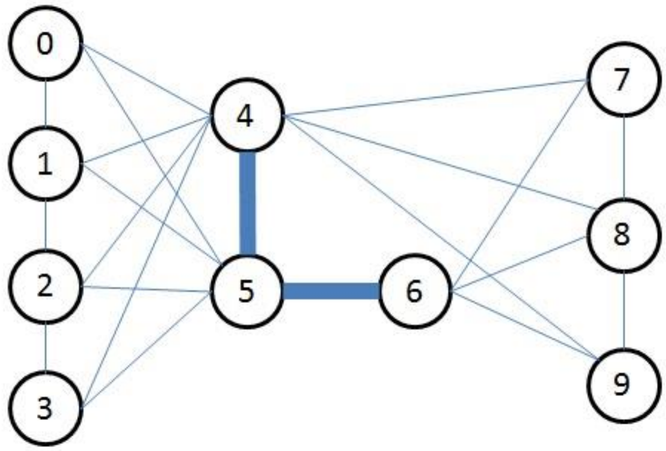


Figure 2.1. A network system

Besides operational costs, system capacity, which refers to the maximum flow between nodes (O-D pairs) at any given time, is often used as well (Ratliff et al. 1975, Wood 1993). Obviously, the disruptions of network components reduce the capacity and limit the maximum O-D flow possible. The maximum flow between any nodal pairs in a network obviously depends on the capacity of individual node and arc components. Nodes can be described in terms of the activity they can process. As an example, if a node represents a station in a subway system, the capacity is the maximal number of passengers it can handle at any given time. Arcs can also be capacitated. In terms of a subway system, the arc represents subway lines between stations, and it has a capacity relative to the capacity and the frequency of the subway train. Returning to the network in Figure 2.1, let us suppose that the capacity of the wider arcs is 2 units while that of the thinner arc is 1 unit. In status quo, the capacity between nodes 0 and 9 is 3 units, including three 1-unit node paths along 0-4-9, 0-5-6-9, and 0-1-5-6-8-9. If the arc between nodes 5 and 6 is disrupted, the maximum flow between nodes 0 and 9 remains only 1 unit. Additionally, other measures are also used according to the specific study context. For example, the direct connection index is used to indicate the level of a node connected directly to other nodes in a network, which is helpful when examining the change of airlines hub-and-spoke structures (Shaw and Ivy 1994, Shaw et al. 2009).

2.2.3 Measures based on system flow

System flow refers to the existing levels of interaction between O-D pairs and measures the actual function of the network; therefore, the effect of a potential disruption can be gauged by the magnitude of the flow affected. System flow is simply the total interaction/flow between all nodal pairs in the network. In the special case where there is only one unit of flow along each arc and no intra-node flow, the system flow is equal to the connectivity. Regarding system flow in a network in the context of survivability, Myung and Kim (2004) present an integer program to identify those arcs whose removal results in an upper bound on network failure and discuss an algorithm for finding a lower bound. Their formulation relies on identifying feasible paths for each O-D pair and tracking the availability of facilities involved in each path. A preprocessing technique is employed to focus only on O-D pairs that can be disrupted given the removal of a specified number of edges. Murray et al. (2007) present a general model that can be solved to give maximum and minimum system flow impacts when components are interdicted. However, to estimate the amount of traffic flow accurately, many preconditions have been set before the modeling. Some examples of the preconditions are as follows: (1) the public is not aware of the disruptions (Murray-Tuite and Mahmassani 2004); (2) the public is aware of the disruptions and makes a detour, but the total travel demand is constant (Jenelius et al. 2006); and (3) the public is aware of the disruptions and makes a detour, and, at the same time, the travel demand decreases with time (Nicholson 2003). It is obvious that all of the above-mentioned preconditions are possible after disruptions, and that public awareness of disruptions gradually evolves from one condition to another. A proper assumption of public awareness of disruptions is helpful for accurate estimation. In this study, with the help of modern operation and broadcast systems of the subway, passengers are assumed to be aware of disruptions immediately, and the flow within the system will change according to the spatial interaction model.

2.3 Methods of Exploring the Scenarios

Central to the assessment of network disruptions and the associated survivability to such disruptions is the identification of potentially important disruption scenarios, which delineates the range of disruptive influence. Lots of approaches exist for indicating these scenarios. These approaches differ primarily in how disruption scenarios are assessed and understood. A scenario in this context refers to a set of nodes and/or links impacted by disruptions. The impact on the system functionality can be drawn using any survivability measure. In some cases, an affected facility may be rendered completely inoperable by a disruption (e.g., the closure of a subway station). In other instances, a disruption may impact network activity to a lesser degree given that only some of the functionality of a facility may be lost, for example, an accident may block a single lane of an interstate highway segment only. Impacts can range from those directly associated with network operation, such as connectivity, flow, or capacity reduction, to more complex associations, such as the economic impacts affecting the production and consumption of flows. The following part introduces the four types of approaches and methodologies which are commonly considered to tackle the problem.

2.3.1 Scenario-based approaches

Scenario-based approaches evaluate the potential consequences of a specific disruption scenario or a small set of scenarios, which is perceived to be important. To explore a particular disruption and to compare the influence of different scenarios are the main goals of the approaches. For example, special attention might be drawn to transportation hubs located at metropolises in highway networks. With a limited number of scenarios considered, relatively detailed analyses of each scenario, such as applying more refined models of impacts on flow and considering detailed information on the costs involved, are feasible through these approaches. Other parameters unique to each scenario can also be easily integrated in the analysis. The above-mentioned survivability measures, including network connectivity, operational costs, system capacity, and system flow, are involved in analyses to evaluate the impact of disruptions on network performance.

Scenario-based approaches have been applied in a range of survivability assessing contexts. For instance, Kim et al. (2002) and Ham et al. (2005) examine the influence of a natural disaster, which can compromise specific portions of the U.S. transportation network, on both the average shipment length and the cost of transporting commodities. In another case, Suarez et al. (2005) consider the resulting impacts of sea rise to transportation performance in a coastal area. Specific disruption scenarios are defined by the levels of sea rise anticipated in various planning periods.

The major benefits of this type of analysis are that professional knowledge can be used to identify important scenarios and that relatively complex analytical approaches can be used to evaluate each potential scenario. The focus on a limited number of scenarios also allows for many intricacies unique to each scenario to be addressed. The final results of such analyses can provide a very detailed understanding about the ramifications of the particular scenarios assessed. The insights gained from this process can be of use in determining the value of a component, or a set of components, to network activity and related processes. However, the potential drawback to scenario-based approaches is that relatively few scenarios are typically evaluated. First, many transportation networks have been assembled incrementally over time by a variety of institutions and agencies and in some cases eventually merged. Therefore, a focus on a single component or portion of a network of local interest can produce misleading insights into survivability at larger scales. Second, potential exists for important scenarios to be overlooked, resulting in inaccurate characterizations of network survivability. This drawback is frequently exacerbated since scenario-based approaches are often conducted by a variety of agencies emphasizing different aspects of transportation networks. Thus, the comparison of the results of different approaches is different.

2.3.2 Strategy-based approaches

To evaluate the consequences of disruptions following a specific strategy on networks attracts the main attention of the strategy-based approaches. Unlike in scenario-based approaches where a set of potential disruption scenarios is selected based on professional

background knowledge, in strategy-based approaches, the scenarios of interest are those following a hypothesized sequence or strategy of disruption. For example, it might be assumed that the attackers who design a targeted attack would try to maximize the influence of the attack and at the same time minimize the probability of being detected (Yates and Casas 2012).

The basic assumption behind these approaches is that the negative impact on the network would vary with the different topological structures and the types of attacks (i.e. random or targeted disruption). Thus, many statistical physics measures focused on the analyses of specially constructed types of networks are employed. One common methodology is to rank network components (arcs/nodes) in the order of their importance (usually based on their topological characteristics), and successively remove them, assessing the impact on network operation at each stage (Albert et al. 2000). This basic approach is also improved by updating components' importance and ranking them after each removal of arcs/nodes (Albert et al. 2004, Holme et al. 2002). In this context, three network structures have been explored in detail to provide insight into the statistical complexities of network connectivity of systems: exponential, small-world, and scale-free networks.

Not surprisingly, levels of survivability in these network structures vary. Because both exponential graphs and small-world networks are topologically homogeneous, random and targeted attacks on nodes in these systems have basically the same effect. Nevertheless, because scale-free networks are inhomogeneous, they are exceedingly tolerant of random attacks, but the survivability of them confronted with targeted attacks depends a lot on the survivability of the hubs.

The limitation of strategy-based approaches is that the survivability assessment of networks is biased and limited by the assumed attack strategy. While one network configuration might appear more survivable faced with a random loss of nodes, it might be less survivable if faced with other types of losses that are not considered. Second, this type of approaches often needs to make assumptions related to the way in which network losses will be coordinated. Such assumptions can produce misleading results as many

networked systems entail a complex mesh of interrelations between network components that are difficult to assimilate by evaluating the characteristics of individual facilities (Doyle et al. 2005). Furthermore, in some approaches, network components are required to be ranked according to their importance at first. But the importance of components and the hidden influence of simultaneous disruptions on a set of components are exactly what are needed to be revealed in survivability study. Therefore, similar to scenario-based approaches, the accuracy of strategy-based approaches is determined by the initial understanding of the network and disruptions.

2.3.3 Mathematical programming approaches

Mathematical programming approaches are well-known for their ability to provide insight into solution bounds (minima/maxima) for a wide range of spatial planning problems so that administrators and managers can be more capable of reducing a network's vulnerability to these events (Salmeron et al. 2004, Matisziw et al. 2009). Compared with the above-mentioned scenario-based and strategy-based approaches, mathematical programming approaches are useful in the search for potentially important scenarios. In other words, those scenarios with the greatest potential to impact network operation may not always involve the most obvious facilities and are instead related to the function of the system as a whole.

Various mathematical programming approaches to assessing network survivability have been proposed. For example, Murray et al. (2007) evaluate scenarios of router loss in a telecommunications network. A flow interdiction model is proposed to identify interdiction bounds according to connectivity and/or flow associated with a system of origins and destinations. Another example is that Church et al. (2004) seek to indicate the r most important supply nodes whose disruptions will result in the largest influence on the original p-median problems and maximal covering problems according to the change of weighted distance. Other adaptations of this basic approach have also been proposed. If q disrupted supply nodes indicated by Church et al. (2004) are able to be fortified to be prevented from interdictions, Church et al. (2007a) maximize the

influence of the fortification. Church et al. (2007b) expand the application of the *r*-interdiction models (Church et al. 2004) by taking into account probabilistic network conditions and disruptions.

There are limitations to mathematical modeling methods as well. First, networks can be very structurally and operationally complex. Hence, there may be many variables and relationships that need to be accounted for in the mathematical model specification, which is challenging. The mathematical programming models simplify the problem by adapting fixed shortest distance or fixed interaction of O-D pairs. More complex models are also proposed, such as travel time which is monotonically increasing and differentiable everywhere (Erath et al. 2009, Luathep et al. 2011). Travel time dynamically decided by the volume through certain paths is also employed to deal with traffic congestion's influence (Murray-Tuite and Mahmassani 2004). However, disruptions' consequences that cannot be simplified as a mathematical model are still beyond the ability of this kind of approaches. Second, a focus on the worst-case scenario(s) may omit little disruptions in alternative scenarios, which may not be as damaging as those in the worst-case, but still create problems for the operational continuity of network systems. Finally, limitations often exist on feasible model size and the ability to effectively obtain a model solution.

2.2.4 Simulation-based approaches

Simulation approaches to survivability assessment can be insightful if there are no prior assumptions concerning how network components will be disrupted. In other words, unlike scenarios-based and strategy-based approaches which only take into account the specific set of scenarios selected based on prior knowledge and strategies, simulation approaches do not depend on the priori knowledge but seek to handle all combinations of network components. Simulation analysis acknowledges that for any network there are many possible planning scenarios to be considered. Even for moderately sized networks, uncovering potential survivability and associated scenarios can be challenging, given the complex spatial relationships between origins and destinations. Compared with

mathematical programming approaches, simulation approaches are more flexible in adapting other measures and taking into account more aspects of network characteristics simultaneously. Note that both binary and fuzzy measures can be used in a simulation approach. For example, Jenelius et al. (2006) remove individual nodes from a highway network and measure the change in O-D flow cost in each scenario. In a recent study, Kim (2009) computes the range of remaining functionality of subway systems when faced with disruption to nodes in combinatorial disruption scenarios based on the failure probability of network components. Furthermore, simulation assessment of scenarios can also involve the specification of many other parameters, such as the performance metric used to evaluate disruption, characterizations specific to the temporal and spatial scale of analyses, and the property of network systems varying because of disruptions. This is important since network activity and other operating conditions can exhibit a large degree of temporal and spatial variability, so can the mitigation and the repair strategies following a disruptive event. Given the information on the dynamic nature of network conditions, simulation can also be used to explore important shifts and changes in network survivability in relation to such variability.

While simulation certainly has its benefits, it also has the potential to overlook important scenarios. Although simulation of relatively simplistic cases where a single network component is impacted is logically simple when enumeration of all scenarios is tractable, it is generally required to develop special algorithms to deal with large amount of computation for simulation of complex scenarios involving multiple network components (Kim 2009). In simulation approaches, therefore, the goal is to evaluate a suitable number of scenarios to obtain an effective characterization of the range of possible impacts (Murray et al. 2008). For instance, if a network is composed of *n* nodes and the complete loss of *m* network node is a major planning concern, then ${}_nC_m = n!/[(n-m)!m!]$ potential scenarios exist. The situation becomes more complex when larger network systems are tackled and more network components are disrupted simultaneously.

In conclusion, this chapter explores topics relevant to this study that have been amassed from previous research. The concept of network survivability is clarified first by

comparing two commonly-used definitions and the context in which they are employed. In order to describe the ramifications in disruption scenarios, three kinds of survivability measures are reviewed, followed by the methods of exploring the important scenarios at the end of this chapter.

CHAPTER 3 A CASE STUDY

The case study of this thesis is located in Beijing, the capital of the People's Republic of China and one of the most populous cities in the world (BMBS and NSOB 2013a). In this chapter, the transportation and the urban morphology of Beijing are briefly introduced to describe the context in which the Beijing subway system is operating. By comparing it with other public transportation systems, we highlight the uniqueness of the subway system, which is followed by the introduction of each subway line and some examples of the typical disruptions occurring in the subway system. Finally, the fluctuation of the passenger flow is presented to show the fact that the survivability of the system, which is not constant, may vary in a week.

3.1 Beijing

Beijing is China's political, cultural, educational center (Encyclopedia 2013). Most of China's largest state-owned companies set their headquarters in Beijing, which makes Beijing a special economic center in China. Thus, the transportation of Beijing is expected to meet the heavy travel demand of both the local residents and the travelers.

Owing to its superior political status, Beijing serves as one of the largest rail hubs in China's railway network. Even passenger trains in China are numbered according to their direction in relation to Beijing. For example, if a train from Beijing to Shanghai is Z13, the same train returning from Shanghai will be numbered Z14. Ten conventional rail lines radiate from the city. In addition, the Datong–Qinhuangdao Railway, which is an electrified rail line serving as a major conduit for coal exportation, passes through the municipality to the north of the city center. Three high-speed rail lines also serve the city: the Beijing-Tianjin Intercity Railway; the Beijing-Shanghai High-Speed Railway; and the Beijing–Guangzhou High-Speed Railway, whose destinations are the most critical cities in North China, East China and South China respectively. From Beijing, direct passenger train service is available to most metropolises in China. International train service is available to Mongolia, Russia, Vietnam and North Korea. In 2012 the annual ridership of

the rail system from Beijing was more than 100 million, and it is still increasing (BMBS and NSOB 2013b).

Beijing's primary airport is the Beijing Capital International Airport, which is the second busiest airport in the world after Hartsfield-Jackson Atlanta International Airport (PANYNJ 2013). After renovations for the 2008 Olympics, the airport now contains three terminals, with Terminal 3 being the second largest in the world. The airport links Beijing with almost every other city in China with regular air passenger service. The civil aviation passenger volume in 2012 was about sixty million, which was nearly three million more than that in 2011 (BMBS and NSOB 2013b). In order to facilitate the transportation between the airport, which is approximately 20 kilometers northeast from the city, and the city center, a special light rail "Airport Express" connecting it to the Beijing subway system was constructed in 2008.

Beijing is also connected by roads to all parts of China as a critical part of the National Trunk Road Network. Nine expressways of China as well as eleven China National Highways serve Beijing. The local transportation and urban morphology are also shaped by road networks. Five "ring roads" concentrically surrounding the geographical center of the city, the Forbidden City, support Beijing's urban transportation (Students' Academy 2010). Figure 3.1 shows the administrative districts the Beijing subway system serves. In 2005 according to the development and functions of each administrative district, Beijing was segregated into four areas. Xicheng and Dongcheng, which are located within the range of the 2nd Ring Road, are determined as the Core Districts of Capital Function (shown in orange). In ancient China, these districts were within the city wall of Beijing as the capital for over six hundred years, thus many government headquarters are located in these districts, following the tradition. The goal of these districts is to serve as the center of national politics, culture, financial administration and international communication. Many subway lines serve these districts, so passengers are able to access the system through several accessible stations within a short distance.

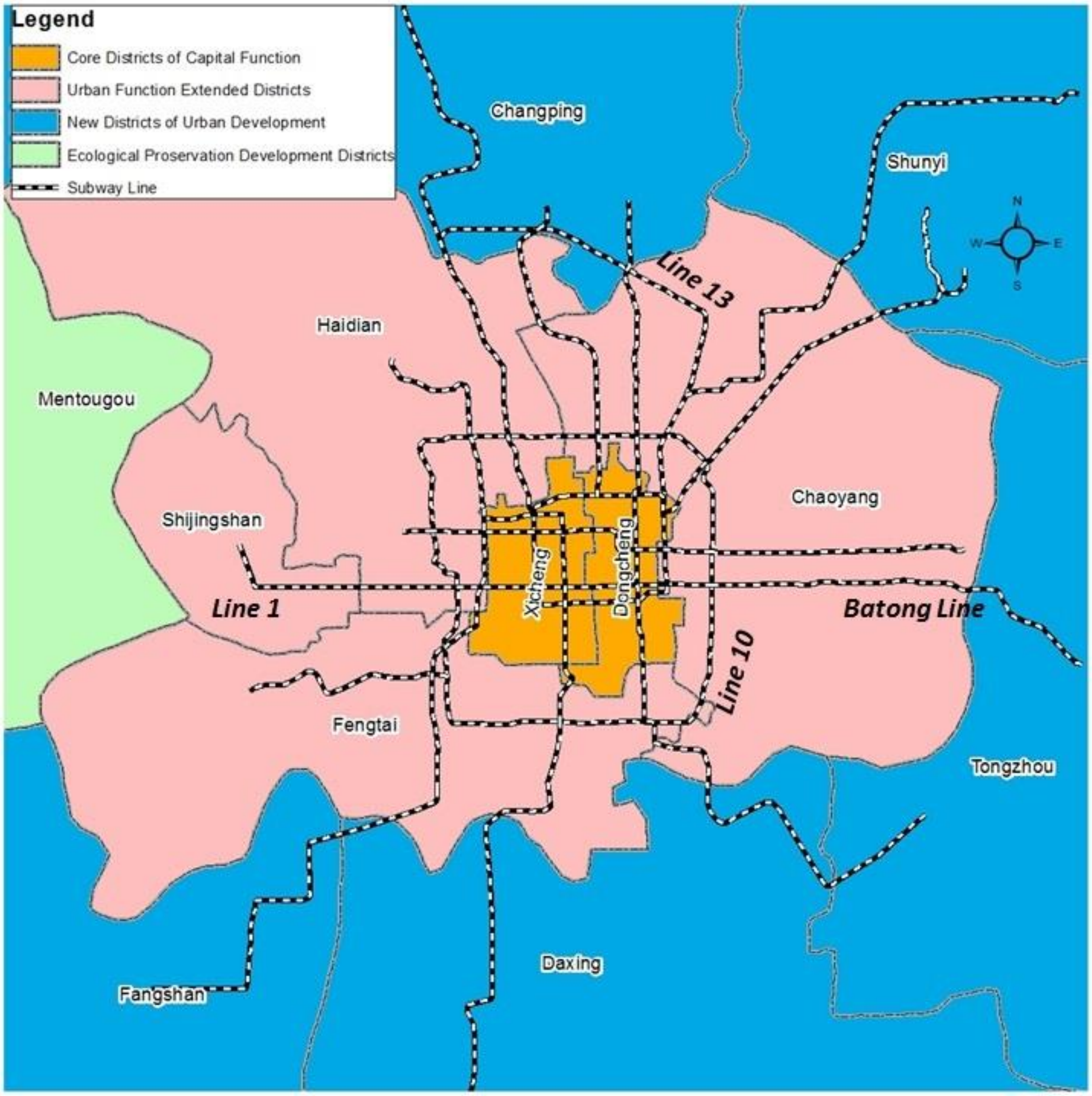


Figure 3.1. Beijing

As shown in Figure 3.1 in pink, the Urban Function Extended Districts contain Chaoyang, Haidian, Shijingshan and Fengtai, which surround the core districts and are within the range of the 5th Ring Road. These districts are intended to support the core districts and to become the center for financial services, education, and high-technology. The number of subway lines here is less than that in the first area just mentioned above. Outside the range of Beijing subway Line 10, which is close to the boundary between this area and the first area, most of the subway lines are branch lines linked with only one *bridge* to the rest of the system. The bridge here is defined as the stations with the degree

larger than two and acting as the only connection for a subway line to the rest of the system. The blue area in the Figure 3.1 is the New Districts of Urban Development, most of which are still suburban and rural areas. The goal of these areas is to develop manufacturing and modern agriculture. Through the rapid evolution for more than ten years, the Beijing subway system has extended its service area to part of the districts with several peripheral branch lines. As the only way to access the subway system, the branch lines may have special criticality when faced with disruptions. The Ecological Preservation Development Districts are preserved for water resources, tourism, and environmental protection, which have not been served by the Beijing subway system.

The population density for the four areas is 23407, 7488, 958, and 213 per square kilometers respectively, which indicates that most of the population and services are in the first two areas. Even though the structure of the city is delineated by several concentric rings, Beijing suffers from imbalanced development. In ancient China, the northern part of the Core Districts of Capital Function (the inner city) was the residence of royalties, aristocrats, wealthy merchants and the middle-class, while ordinary folks were only allowed to dwell in the southern part (the outer city). This imbalance is exacerbated by the development following the residence pattern. After the economy of China started to boom in the 1980s, the reconstruction in the southern part of the city was obstructed by the high population density. The areas to the east and north of the city center, which were previously mostly rural areas, became the first choice for new companies and institutes. In the Urban Function Extended Districts, Chaoyang is home to the majority of Beijing’s many foreign embassies. Sanlitun, which is well-known for many popular bars and international stores, as well as the Olympic Green built for the 2008 Summer Olympics are also located in Chaoyang. Beijing’s CBD, centered on the Guomao area in Chaoyang, is home to a variety of corporate regional headquarters, shopping precincts, and high-end housing. The second-largest district in urban Beijing (after Chaoyang) with 431 square kilometers in area is Haidian District. Haidian is famous for its science and education with a large concentration of universities, research institutes, libraries, and scientific instruments and equipment. The concentration of well-educated residents in this district attracts many high-tech companies. Zhongguancun (an area in Haidian), dubbed "China's Silicon Valley", is a major center in electronics and

computer-related industries, as well as pharmaceuticals-related research (BMBS and NSOB 2013a). However, the southern districts attract much less attention. In 2008, the sum of the GDP in the five southern districts (former Chongwen, former Xuanwu, Fengtai, Fangshan, and Daxing) was less than one fifth of that in the five northern districts (Haidian, former Xicheng, former Dongcheng, Changping, and Chaoyang) (Li 2009). Xishan or the Western Hills dominates the western part of Beijing. Most parts of Mentougou, as well as the western parts of Haidian, Shijingshan, Fengtai and Fangshan are mountainous, which limits the expansion of the urban area of Beijing westward. The imbalance is also reflected in the distribution of the subway lines. Line 1 and Batong Line are almost along the boundary of northern and southern Beijing. The density of subway lines is much higher in the northern part. Besides more branch lines there is also an arc line, Line 13, constructed in the north. This imbalance is expected to result in different survivability.

3.2 The Beijing Subway System

Even though Beijing has long been well known for the number of bicycles on its streets, its motor traffic has been rising rapidly and has created a great deal of congestion (Meimeili 2014). At the end of 2012, the number of the registered automobiles in Beijing was 5.2 million, while it was only 1.6 million in 2000 (BTMB 2013). This rise in automobile ownership brings about traffic jams as a major concern. The worst traffic jam in history happened along the Beijing-Tibet expressway to the north of Beijing in 2010. The 62-mile long traffic jam lasted for twelve days (Gorzelany 2013). Traffic in the city center is also often gridlocked and is only predicted to get worse as the number of vehicles on Beijing’s roads increases. It is predicted that Beijing will have over 6 million cars on its roads by 2016 (Mu 2012). Besides the increase in the number of automobiles, Beijing's urban layout also has the potential to worsen the situation. Due to the original city planning, many government offices, shopping centers and large enterprises are located in the downtown area of Beijing, while most of their employees live far away. It has become a major burden on the local transportation system to carry them in and out of the city during rush hours. Drastic approaches have been taken to mitigate traffic jams

(ChinaAutoWeb 2010). Large amounts of money has been spent in dealing with congestion, including 180 billion RMB (about 30 billion USD) spent between 2004 and 2008 (Du 2003). However, the approaches have not prevented the condition from worsening. The average time wasted on congestion per vehicle was 1 hour and 55 minutes on weekdays in 2013, increasing by 25 minutes from that in 2012 (BMCT 2014). This result shows that limiting the number of registered vehicles cannot completely tackle congestion when confronted with the soaring population and the growing travel demand in Beijing. In addition to the restrictions on the number of cars on the roads and the construction of new roads, the fares of public transportation have been decreased to encourage more people to use it.

The major forms of public transportation in Beijing include the public bus service (including trolleybus), the Beijing subway system and the Beijing suburban railway. Public bus service in Beijing is the most extensive, widely-used, and affordable form of public transportation in the urban and suburban districts of the city. In 2012, there were 996 bus routes and 21839 buses operating, which delivered 5 billion rides (BPTG 2013). However, when confronted with congestion, the public buses are also trapped. Without proper designation and operation, bus stops can be a possible cause to impede normal traffic flow as well. Lots of new concepts have been introduced and applied to improve the bus service. Nowadays, there are four Bus Rapid Transit (BRT) lines in Beijing, including specific stations and lanes reserved only for buses. This system can effectively increase the average speed of buses in rush hours. However, there are still issues remaining that need to be tackled. For example, the specifically reserved lanes for buses actually reduce the available roads for private vehicles, which may worsen the traffic condition to some extent. The lack of BRT at crossroads may clog the whole system. The fact that the separated BRTs have not been joined to become a network also reduces the functionality of the BRTs (Bao 2013). In order to handle the problems, the Beijing Transportation Authorities are experimenting with a new type of public transport vehicle called the 3D Express Coach, also known as the straddling bus. The bus runs along a fixed route, and its passenger compartment spans the width of two traffic lanes. It straddles the roads at an overall height of 4 to 4.5 m (13.1 to 14.8 ft.), thus vehicles lower than 2 m (6.6 ft.) high will be able to pass underneath the bus, reducing the number of

traffic jams caused by ordinary buses loading and unloading at bus stops (Lee 2010). Even though this invention may improve the public bus service, it is still in the experiment phase. The Beijing suburban railway, which is a commuter rail service that connects urban Beijing with outlying districts and counties beyond the reach of the city's Beijing Subway network, is still under construction. Thus, the Beijing subway system, as a service totally beyond the influence of the congestion on the ground, is the most timely and reliable public transportation service especially during rush hours in downtown, and it has become one of the first choices among transportation modes in Beijing with annual ridership ranking third in the world at 2.46 billion trips in 2012 (BMBS and NSOB 2013a, BMCT 2013a, Liu 2013a).

The Beijing Subway is a rapid transit rail network that serves the urban and suburban districts of Beijing. After its initial line was completed in 1969, it has grown to 17 lines, 227 stations and 465 km (289 mi) of track in operation (shown in Figure 3.2), making it the third longest subway system in the world after Seoul and Shanghai (Tang 2012). The subway lines generally follow the checkerboard layout of the city. Most lines run parallel or perpendicular to each other and intersect at right angles. According to the areas they serve, the lines can be classified into 2 groups.

Lines serving the urban core:

- Line 1 is a straight east-west line underneath Chang'an Avenue, which bisects the city into north-south segments. It connects major commercial centers, Xidan, Wangfujing, Dongdan and Beijing’s CBD.
- Line 2 is a rectangular loop line following the Ming-era city wall that once surrounded the inner city. It stops at 11 of the wall's former gates (whose names end in “men”), which have become busy intersections now, as well as the Beijing Railway Station. The traditional financial center, Beijing Financial Street in the Fuxingmen and Fuchengmen area, is also along this line. It was the first loop line of the system.

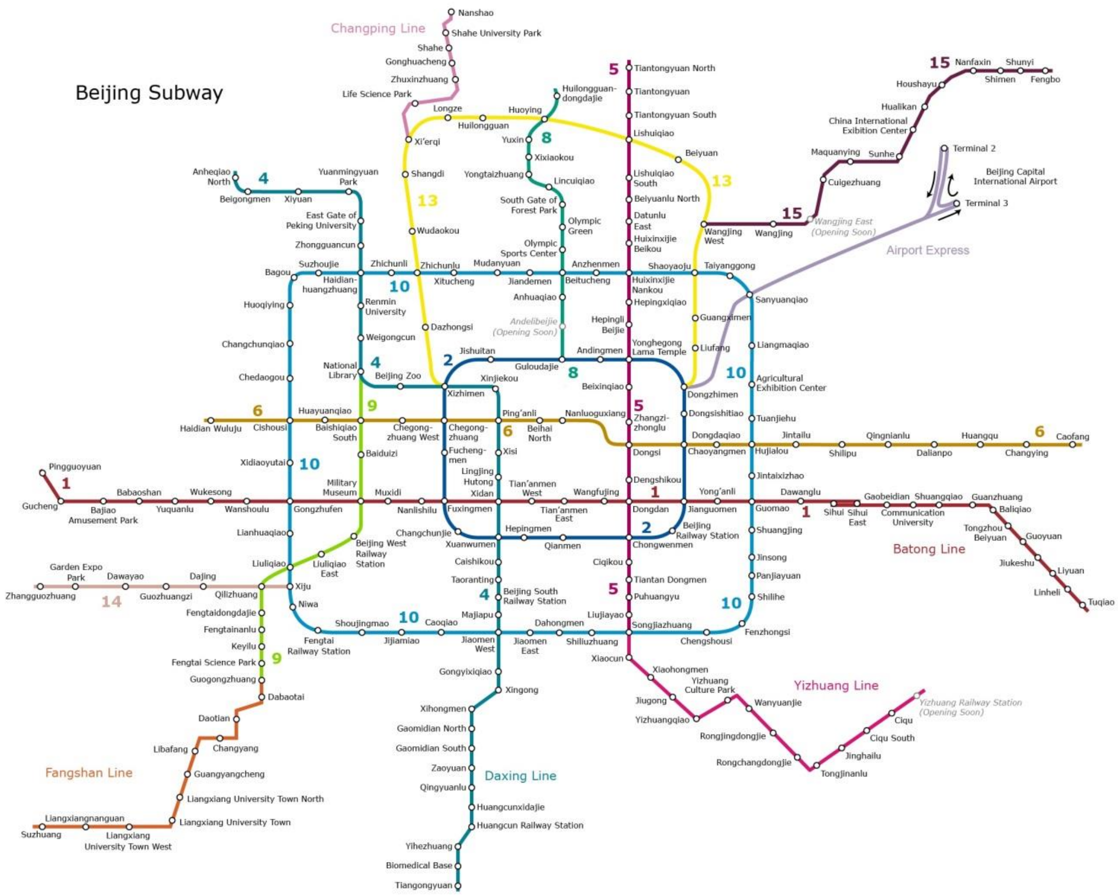


Figure 3.2. Schematic map of the lines of the Beijing subway system in operation (Not to scale) (Beijing Subway 2013)

- Line 4 is a mainly north-south line running west of the city center with stops at the Summer Palace, Old Summer Palace, Peking and Renmin Universities, Zhongguancun Technology Park, National Library, Beijing Zoo, Xidan and Beijing South Railway Station. It extends southward to Daxing district as Daxing Line.
- Line 5 is a straight north-south line just to the east of the city center. It connects several large apartment complexes, like Tiantongyuan, Beiyuan and Songjiazhuang, with the city center. It also passes by the tourist attractions of Temple of Earth, Lama Temple and the Temple of Heaven.
- Line 6 is a nearly straight east-west line running parallel to the north of Line 1. It links the large apartment complexes to the east of the city center, namely

Chaoqing, Changyin and Dingfuzhuang, with Beijing Financial Street and other shopping centers.

- Line 8 is a north-south line following the city’s central axis from Changping District through Huilongguan and the Olympic Green to Guloudajie, which is a transfer station to Line 2.
- Line 9 is a north-south line running west of Line 4 from the National Library through the Military Museum and Beijing West Railway Station to Guogongzhuang, southwest of the city center. It extends southwest to Fangshan District as Fangshan Line.
- Line 10 is a larger loop line outside Line 2 that connects every other line passing the city center. It is also the busiest line in the system and the longest loop subway line in the world (Xinhua 2013).

Lines to outlying suburbs:

- Batong Line extends Line 1 eastward from Sihui to suburban Tongzhou District as a surface level rapid transit rail line. Because it passes many large apartment complexes and promotes the construction of the residential areas in Tongzhou District, Batong Line is one of the most crowded lines in the system (Xu 2011). Even though the parallel Line 6 opened in 2012 shares parts of its traffic flow and causes a 12.14% decrease of its daily ridership and a 10-20% reduction in flow during rush hours, during peak hour the line still operates above 100% capacity (BMCT 2013b).
- Airport Express connects the Beijing Capital International Airport with Line 10 at Sanyuanqiao and Lines 2 and 13 at Dongzhimen.
- Line 13 arcs across the north of the city. It extends Line 2 north by connecting Xizhimen and Dongzhimen, at the northwest and northeast corners of Line 2.
- Line 15 branches off Line 13 at Wangjing West and runs northeast to suburban Shunyi District.
- Changping Line branches off Line 13 at Xi'erqi and runs north to Changping District.

- Line 14 runs west from Xiju on Line 10, across the Yongding River, to Zhangguozhuang in Fengtai District. It connects the China (Beijing) International Garden Expo with the city center.
- Fangshan Line extends Line 9 south from Guogongzhuang to Fangshan District in the southwestern suburbs.
- Daxing Line extends Line 4 south to Daxing District.
- Yizhuang Line extends from Line 5's southern terminus to Yizhuang District.

The last decade has been a transition period for the Beijing subway system, as its operation mode has changed from single line operation to network operation and experienced the largest effective growth in the world cities (Niedzielski and Malecki 2012, Wang et al. 2012). Before Beijing won the bid to host the 2008 Summer Olympics, the Beijing subway system only had its first two lines (Line 1 and Line 2) built in the 1970s. The rapid evolution exposes the problem that the system may suffer from malfunctions and disruptions. The following are some examples:

- The worst accident of the Beijing subway system happened on July 5, 2011, when an escalator malfunction at the Beijing Zoo station killed one person and injured 28 others (Zhan and Lea 2011).
- Due to the heavy load and malfunctions of the signaling system, Line 10 of the Beijing subway system used to stop working six times in a month (Xi 2013).
- Because Line 1, Line 2, Line 13 and Batong Line of the Beijing subway system were designed and constructed early, there is no platform screen door which separating the platforms and the tracks along these lines. Accidents, such as accidental falls off the platform, suicide attempts and homicides by pushing, happen occasionally (Shen and Sun 2013, He 2014, Yin and Xiao 2014).

All the accidents remind us that the disruptions of the Beijing subway system, whether accidental or intentional, can occur randomly and may affect different stations simultaneously.

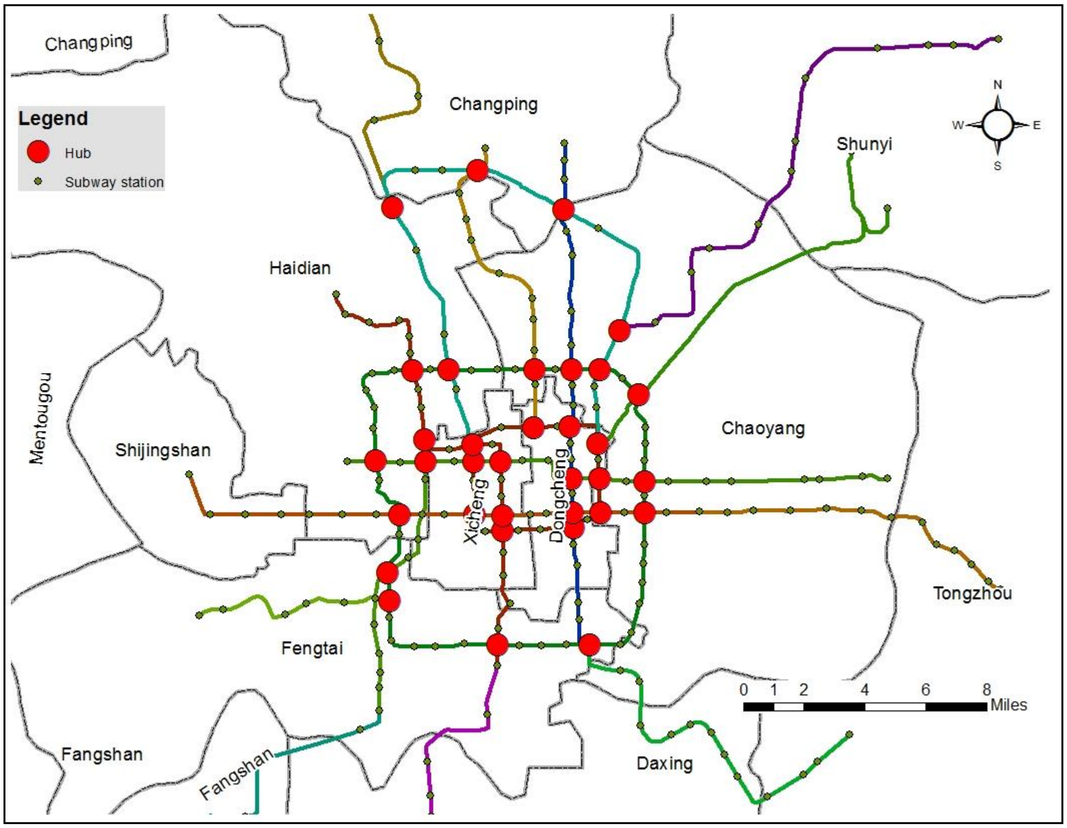


Figure 3.3. Hubs in the Beijing subway system

Subway stations are often classified into two types based on their roles in the network: non-transfer and transfer stations. Note that unlike a non-transfer station, a transfer station connects different lines to collect traffic flows and to reallocate them, resulting in more frequent use and a heavy concentration of passenger flow. In theory, selected multiple disruptions of transfer stations may easily disconnect the system to an extent, while a single and random disruption rarely causes a critical situation of operation (Kim 2009). Shown in Figure 3.3 with red points are the *hubs* in the Beijing subway system, which are the stations whose degrees are greater than two. The hubs are a special subset of the transfer stations in the system because some of the transfer stations only connect the terminus of two subway lines, and their degrees are equal to two. These transfer terminus do not serve to collect traffic flow and redirect it, which makes their function similar to the non-transfer stations. Therefore, these special cases are excluded from the candidate set in the analysis. Under this definition, in the Beijing subway

system, 34 hub stations are identified and are used as a candidate set for disruptions in our analysis.

3.3 The Passenger Flow of the Beijing Subway System

In the analysis, to measure survivability, the passenger flow of a station is estimated using the population distribution and the distance to any other station. A challenge for estimation is how to define the served area of the subway system, which is delineated based on the walking distance. Different values have been applied in the previous research. Shaw (1991) consider 2,000ft as a reasonable distance to estimate of the maximal walking distance for the Miami Tri-Rail system. Kuby et al. (2004) select a round distance of one-half mile for the walking distance. Considering the land use in Beijing, we assume that places within one-hour walk (5 km) are the subway system's served area (Browning et al. 2006, Mohler et al. 2007). As illustrated in Figure 3.4, we generate a five-kilometer buffer zone of the network. Thiessen polygons are applied to divide the served areas into separate service zones of stations. Then we estimate the potential passengers of each station within its service zone using the Sixth National Population Census taken in November, 2011. With more subway stations concentrating, the city center is separated into more tiny areas. The service areas tend to expand progressively as they approach the suburbs. The population within each service area is shown in Figure 3.4 with different shades. From the city center to the suburbs, the sizes of the service areas generally increase, while the population density decrease. Thus, the number of each station's potential passengers decreases at first, followed by an increase, and then decreases again.

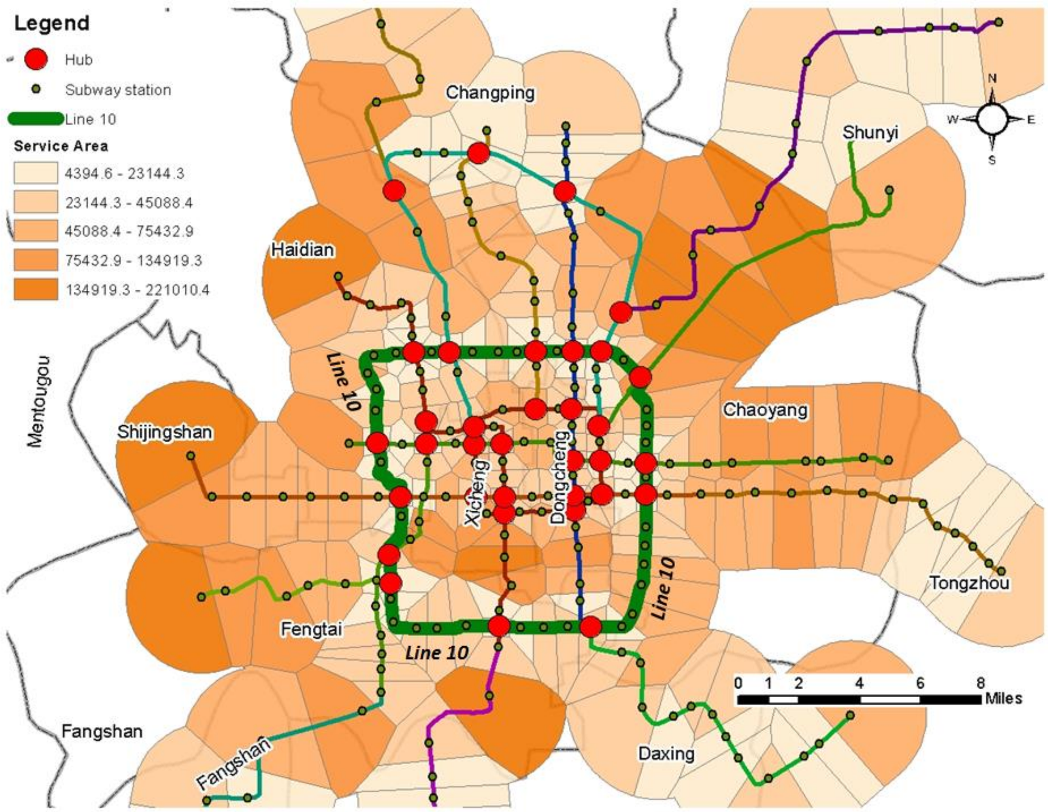


Figure 3.4. The population served by the Beijing subway system (Note: 5 km buffer applied and delineated based on Thiessen polygons)

The shortest paths between every two stations based on the network distance are generated at all disruption scenarios including status quo, because we assume that passengers will be informed of disruptions immediately so that they can adjust their trips accordingly. By calculating the shortest paths at each scenario, passenger flow across the system can be estimated more accurately. Considering that even though the distances between every two adjacent stations are not completely identical, the time taken to travel between adjacent stations is similar (for example, 2-3 minutes for the Beijing subway system), we use the topological distance to simplify the computation (Beijing Subway 2014).

The estimated passenger flow should be adjusted based on the days of the week, considering that daily ridership and travel demand to each line fluctuate. For example, the number of passengers using the subway system on Friday is 3 million more than that on Sunday (Beijing Subway 2013). To reflect this fact, the estimated flows are adjusted

based on the empirical daily ridership of each subway line for two weeks (5/20/2013-6/2/2013). The ridership date are from the official weibo account of the Beijing subway system. We adjust the estimated passenger flow of a station by multiplying the ratio between the actual daily ridership and the estimated passenger flow along the line at status quo. In this study, we select the actual ridership of Friday and Sunday to represent the passenger flow of weekdays and weekends, respectively. As illustrated in Figure 3.5, the ratios between the ridership on Friday and Sunday of each subway line are not constant. For example, even though the ridership of Lines 1, 2, and 4 are almost identical on Friday, the difference between the ridership on Friday and Sunday is much smaller on Line 4 than the differences on the other lines. As introduced above, Line 4 is a major north-south line running west of the city center, and its extension to the south, Daxing District, is Daxing Line, which shares a similar ratio of daily ridership on Friday and Sunday. Meanwhile, the ridership fluctuation of the lines serving the southwest of the system, like Line 9, Daxing Line, Fangshan Line, and Line 14, is smaller than that of other lines. It is reasonable to speculate that this imbalance may result in the differences in the characteristics of the Beijing subway system. Thus, we explore its survivability results for weekdays and weekends.

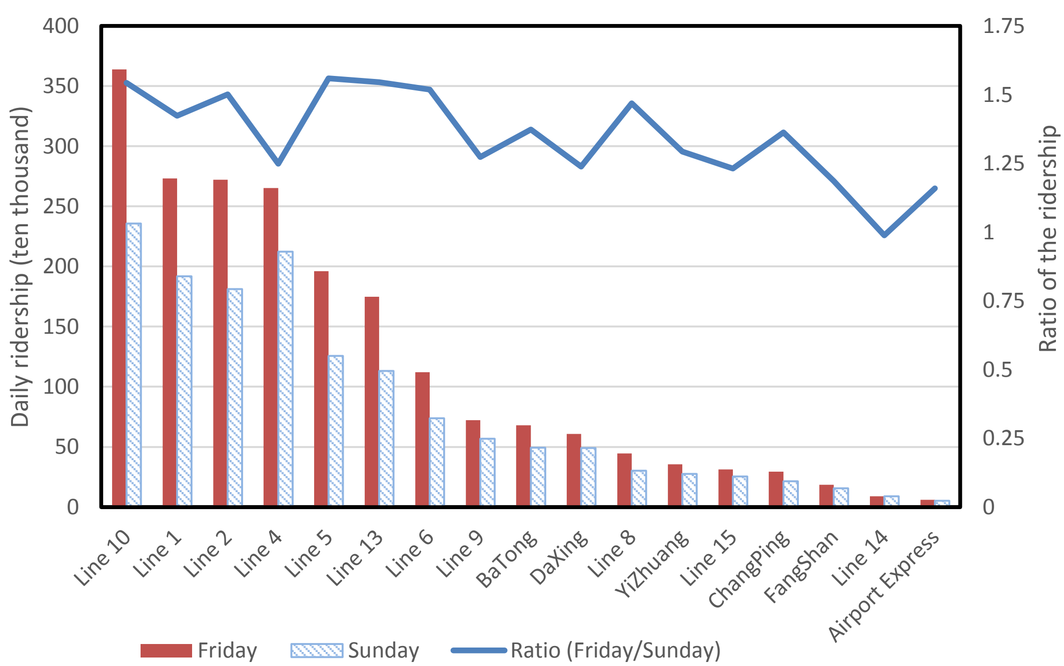


Figure 3.5. Daily ridership of subway lines

CHAPTER 4 METHODOLOGY

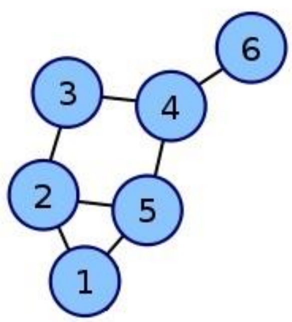
In this paper, we define the term *survivability* as the ability of a network system to maintain its topological and functional state when a certain level of disruptions on stations occurs simultaneously. Note that disruptions affecting the same number of stations are considered as being on the same disruption level. For example, at the m^{th} disruption level, where the number of disrupted stations is m out of the 34 hubs, the number of possible scenarios at the level is ${}_{34}C_m$. Accordingly, the total number of potential incidences for two-hub disruptions is ${}_{34}C_2 = 561$. The accessibility-based simulation measure (ASM) examines the network survivability of the Beijing subway system from no disruption (status quo) to the level in which all of the 34 hubs are disrupted from two perspectives: [1] system connectivity loss (T_m^{loss}) and [2] system flow loss (F_m^{loss}).

4.1 Data Preparation

According to the survivability measures reviewed in Chapter 2, several empirical data are necessary for survivability assessment. Now that a subway system is evaluated as a network system, the network itself is the foundation for any analysis. A network can be represented by its topology which indicates the arrangement of arcs and nodes, while a map recording the geographic locations of the network components will offer more information. Other data needed are determined by the survivability measures applied. A measure considering the influence of congestions may require empirical data, such as the traffic volume and the speed of vehicles, to build a model.

There are many data models for transportation networks. For instance, almost all commercial GIS packages connect or represent a network as a set of nodes interconnected by a set of links with their coordinates. Because the absolute geographic locations of the subway stations and lines are not applied in the calculation directly, the Beijing subway network is also represented as a matrix between the origins and destinations. The matrix of a network system (G) on n nodes is a $n \times n$ matrix where the

entry a_{ij} are the property of the links between node i and j. Because there is no loop directly from any node i to itself in the Beijing subway network, the diagonal entries are always equal to 0. The entries represent different network properties. For example, the entries can indicate the length of the shortest path between nodal pairs, which results in a *D* matrix or Shimbel matrix. The connectivity matrix (hereafter *C*-Matrix) is used to represent the topological connectivity of network systems. The entries in the 1st level *C*-Matrix (C^1) is defined to represent the adjacent connections between every two nodes. If a node is connected to another node, then we define their connectivity as 1, otherwise 0 in C^1 (as shown in Figure 4.1).



Spatial Representation of a Network

i i	1	2	3	4	5	6
1	0	1	0	0	1	0
2	1	0	1	0	1	0
3	0	1	0	1	0	0
4	0	0	1	0	1	1
5	1	1	0	1	0	0
6	0	0	0	1	0	0

1st level C-Matrix

i = [1, n], j = [1, n],

n: the number of the nodes in the graph.

Figure 4.1. 1st level *C*-Matrix

C^1 is required to be generated as the starting point of the following processes. The raw data record the sequences of the subway stations along each line. It is reasonable to assign that the stations, except the termini, are connected with their two adjacent stations, because the subway lines do not bifurcate. Every terminus is only linked to one adjacent station. In this case, transfer stations, which exist on different lines, will be represented repeatedly in the matrix. For example, the station "Xizhimen", which is on Line 2, Line 4 and Line 13 has three columns/rows related to it to represent its adjacent relationships on the three lines respectively. In order to connect separated lines through the transfer stations, a virtual connection is applied to link the transfer stations on different lines. For instance, the connectivity between the station "Xizhimen" on Line 2 and that on Line 4 is

assigned as 1, which indicates that transferring from Line 2 to Line 4 through Xizhimen will take the same amount of time as moving between the adjacent stations along a line, approximately 2-3 minutes (Figure 4.2). Because the repeated transfer stations on different lines share similar properties, after evaluating the survivability, only the results of the first cases are included in the analyses. For example, in the case of Xizhimen, Xizhimen on Line 2 is chosen to represent this station in the final analyses.

	...	Xizhimen (Line 2)	...	Xizhimen (Line 4)	...	Xizhimen (Line 13)	...
...				...			
Xizhimen (Line 2)		0		1		1	
...		...		...		...	
Xizhimen (Line 4)	...	1	...	0	...	1	...
...		...		...		...	
Xizhimen (Line 13)		1		1		0	
...		...		...		...	

Figure 4.2. Virtual connections for transfer stations in C^1

The simulation is adjusted to represent the real world more accurately by applying the transferring penalty. Now that the transfer stations exist repeatedly in the matrix, a dictionary, which records the indices of the transfer stations in the matrix, is generated to accelerate the positioning of the transfer stations when changing their connectivity. In a disruption scenario, the connections between the disrupted stations and their adjacent stations are destroyed, which is processed as the following steps:

- Step 1: Find the indices of the disrupted stations ([$i_1, i_2, i_3, j_1, j_2, ...$]) according to the dictionary.
- Step 2: Position the corresponding columns and rows in C^1 based on the indices from the first step, and assign all the entries in them as 0.

4.2 System Connectivity Loss

Now that C^1 at status quo is generated from the raw data, and will be modified in disruption scenarios because of different stations disrupted. Let us define the *k*th level C-Matrix (C^k) as the *k*-step connection matrix of a network, which results from $C^{k-1} \times C^1$ $(k \geq 2)$ and $C^{k-1} = C^{k-2} \times C^1$ $(k \geq 3)$, and so forth. Each entry (c_{ij}^k) in C^k represents the number of possible paths with length *k* between nodal pairs (nodes *i* and *j*). Thus, not only the adjacent connections but also connections with certain steps can be recorded in a series of *C*-Matrices. Then the sum of the entries in all the C^k indicates the topological connection of a network ($k = [1, d]$, d = the diameter of the network, which is the length of the longest shortest path between the nodal pairs in a network), where all the possible paths with *k* steps ($k = [1, d]$) are recorded. Note that the number of meaningless paths visiting nodes repeatedly increases with *k*, α^k is employed to mitigate the attenuation effect ($\alpha = 0.5$). We define this measure as the system connectivity (T^{sys}), as expressed below:

$$T^{sys} = \sum_{k=1}^{d} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha^k c_{ij}^k \quad (7)$$

,

where

k: the number of steps;

α : the constant to mitigate the attenuation;

d: the diameter of the network *G*;

n: the number of nodes in the network G;

c_{ij}^k : the entry at the i^{th} column and the j^{th} row in C^k ($i = [1, n]$, $j = [1, n]$).

A larger value of T^{sys} indicates a more complex and more highly connected network. Note that disruptions occurring at subway stations affect the topological relationship in the network by removing all links to the disrupted station, resulting in a decrease in the total connectivity of the network, T^{sys}. The system connectivity loss to the number of m nodal disruptions (T_m^{loss}) is calculated by the disparity between the total connectivity index in this scenario (T_m^{sys}) and the original T^{sys} at status quo (T_0^{sys}):

$$T_m^{loss} = T_0^{sys} - T_m^{sys} \tag{8}$$

A larger T_m^{loss} value represents a smaller survivability after a disruption due to its reduced path availability. T_m^{loss} varies with the combinatorial effect of the stations based on different sets of stations disrupted. By comparing all T_m^{loss} values at the m^{th} disruption level, the critical scenarios when m stations are disrupted are revealed.

4.3 System Flow Loss

Besides connectivity, the magnitude of the system flow loss ($F_{m,day}^{loss}$) is also selected to reflect the impact of disruptions. We assume that after disruptions the original passenger flow is redirected to alternative subway paths rapidly, and the system flow therefore reaches a new balance, although the volume of passengers decreases due to the increasing travel distance after rerouting. In this research, the flow loss is assessed based on the spatial interaction model, which means the number of passengers between two stations will decrease with increasing travel distance caused by disruptions. The shortest distances between the nodal pairs are calculated simultaneously when generating *C*-Matrix series to reduce extra computational burden. To estimate the loss of passenger flows in the m^{th} disruption scenario and compare the difference in ridership between weekdays and weekends, we use four steps. First, suppose that there are two stations where the number

of the potential passengers are P_i and P_j, respectively, in the network, and that their distance is (d_{ij}); then the volume of passenger flows V_{ij} is calculated using

$$V_{ij} = \frac{(P_i \times P_j)}{d_{ij}} \tag{9}$$

Then, the total volume of the passenger flow at station i ($V^S{}_i$) is equal to the sum V_{ij} from station i to all other stations:

$$V^S{}_i = \sum_{j \in S} V_{ij} \tag{10}$$

where

S: the set of all stations in the Beijing subway system except the station i itself.

Second, the total inbound and outbound of a subway line a ($V^L{}_a$) is calculated by summing $V^S{}_i$ of the stations along this line:

$$V^L{}_a = \sum_{i \in A} V^S{}_i \tag{11}$$

where

$V^S{}_i$: the estimated volume of passenger flow of station i;

a: a subway line of the Beijing subway system;

A: the set of subway stations along subway line a.

Third, $V^S{}_i$ should be calibrated by the ratio between the actual ridership ($r_{a,day}$) and the estimated total inbound and outbound of line a at status quo ($V^L{}_a$). Because the actual ridership is recorded according to the number of tickets used in stations, it reflects the actual inbound and outbound along subway lines. Line a represents the line passing station i, which can be two or more lines. Because of different $r_{a,day}$ used, the adjusted system flow reflects the remaining functionality of stations after disruptions on Friday and Sunday. For the m^{th} disruption scenarios, the adjusted system flows at station i (noted $V'_{m,day,i}$) are calculated using

$$V'_{m,day,i} = V^S_{m,i} \times \sum_{a \in U^L} \frac{r_{a,day}}{V^L_{a,0}} \tag{12}$$

where

m: the index of the disruption level;

$r_{a,day}$: the actual ridership along subway line *a* on a certain day (*day*: Friday or Sunday);

V^L_a: the estimated volume of the passenger flow along subway line *a* under status quo;

$V^S_{m,i}$: the estimated volume of the passenger flow of station *i* at the m^{th} disruption level;

U^L : the set of subway lines passing station *i* because more than one line passes transfer stations.

The fourth step is to sum the adjusted volume of passenger flow of all the stations to calculate the total volume of passenger flow in the whole system for the m^{th} disruption scenario ($F_{m,day}$):

$$F_{m,day} = \sum_{i \in S} V'_{m,day,i} \tag{13}$$

In the final step, the system flow loss ($F^{loss}_{m,day}$) is simply the difference between F_{day} at status quo and $F_{m,day}$ for the m^{th} disruption scenario.

4.4 The Method of Exploring Network Resilience

When the number of disrupted stations is fixed, the extent to which a network system will degenerate varies with the disrupted stations' topological importance and the scale of passengers served. Now that both topological attributes and service functions of the stations are different, a range, which is defined by the best and worst scenarios, can be drawn for any given number of disruptive stations, is an efficient way of identifying a group of critical stations and examining the resilience of the network system. Prior attempts have been made to identify the simulation results using the concept of an

envelope (Kim 2009). As illustrated in Figure 4.3, named *survivability envelope*, the y-axis represents the level of network survivability and the x-axis represents the m^{th} $(m = 0, \ldots, n)$ disruption levels. The range of the disruptions' impact is drawn from status quo (*0*th level) to the level where all transfer stations are disruptive (*n*th level). At each level, the gap between the best and worst scenarios (minimum and maximum negative impacts, respectively) is the *survivability performance.* For example, if the best and worst scenarios are 50% and 1.8% at the 100th level, then the survivability performance is 48.2%. The range will be narrowed with the levels.

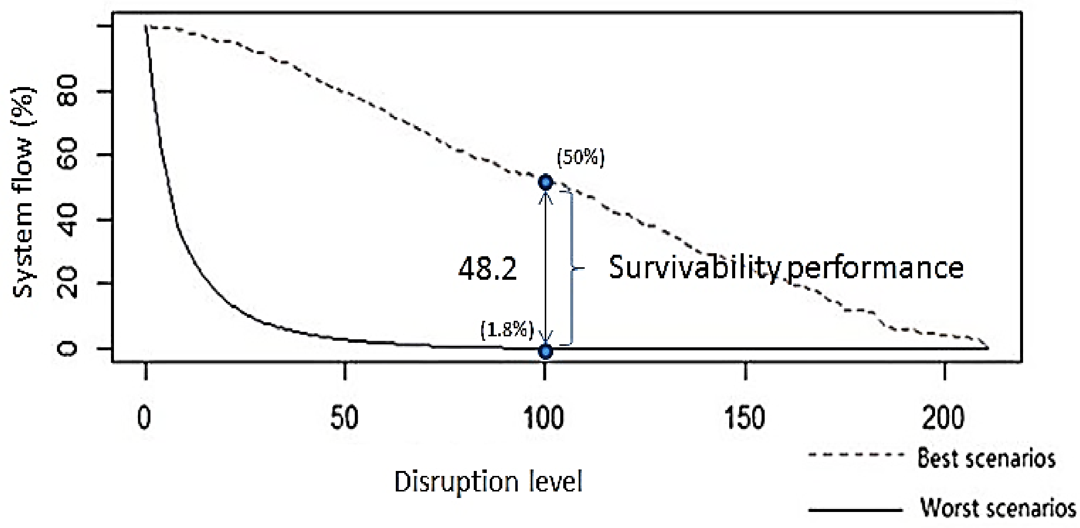


Figure 4.3. Survivability envelope

A significant challenge in drawing the envelopes is the complexity of the computation to complete the simulation, which heavily depends upon the network size and disruption levels. Although we only consider 34 hubs in generating scenarios, it is computationally burdensome for some range of disruption scenarios. For instance, the computation of the 1st level disruption for the enumerated 34 scenarios ($_{34}C_1$ = 34) takes nearly 85 seconds using the Windows 7 32-bit OS platform with Intel® Core™ i5-2.60GHz. Given this condition, simulating all the scenarios at the 5th level will cost $_{34}C_5 \times 85 \div 34$ seconds (more than 8 days). Before the 17th level, the computation complexity increases with the number of disrupted stations. At the 17th level, the explicit

enumeration will cost about 184 years. Thus, simulating scenarios between the 5th and 29th levels is not well applicable. To tackle this problem, *Weighted Rank-based Simulation Algorithm* (WRSA) is developed to traverse the potential disruption scenarios. The process of the WRSA consists of two parts. At lower complexity levels, where the explicit enumeration is tractable (i.e., 0 to 4th, and 30 to 34th), all the possible scenarios are enumerated, and the best and worst scenarios are identified. However, for other levels, the algorithm searches the scope of potential disruption scenarios by constructing the set of candidate hubs, which is a subset of all hubs, using the global rank index ($GRI_{m,i}$) of each hub at each level. This index evaluates the criticality of the hubs based on their local rank index ($LRI_{m,i}$) at all levels that have already been explored. The steps to calculate $GRI_{m,i}$ ($1 \leq m \leq 34$) are as follows. Suppose that the best and worst scenarios are identified at the mth level. The algorithm sorts all scenarios at the mth level from best to worst in terms of the criteria, T_m^{loss} and $F_{m,day}^{loss}$. The best scenario in each criterion represents the most survivable, while the worst scenario represents the least survivable case. The next step is to construct the most and least critical hub sets from the selected scenarios. In the selected scenario, the WRSA evaluates the criticality of the hubs according to the influence of the scenarios they contribute to, which means that each hub has two different ranks, named $rt_{m,i}$ and $rf_{m,i}$, corresponding to each criteria T_m^{loss} and F_m^{loss}, respectively. Using these two ranks, the indices $LRI_{m,i}$ and $GRI_{m,i}$ are calculated for each hub i at the mth level using (14) and (15), respectively:

$$LRI_{m,i} = w \times rt_{m,i} + (1-w) \times rf_{m,i} \quad (0 \leq w \leq 1, m \geq 1) \tag{14}$$

$$\begin{cases} GRI_{1,i} = LRI_{1,i} \\ GRI_{m,i} = LRI_{m,i} + 0.5 \times GRI_{m-1,i} \quad (m \geq 2) \end{cases} \tag{15}$$

where

w: the weight to calibrate the importance of the two survivability measures (in this research, 0.5 is applied to treat both measures being equal).

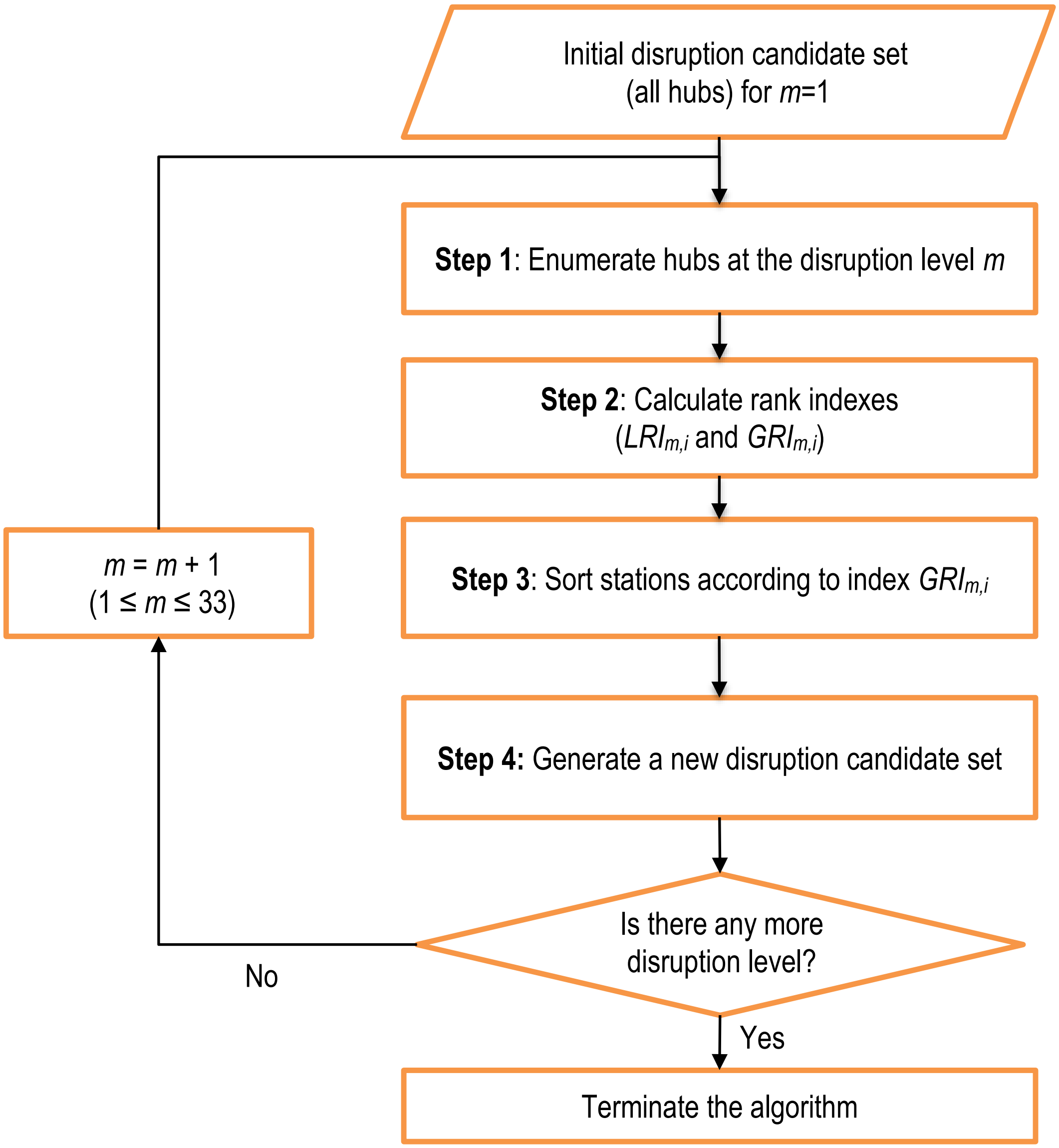


Figure 4.4. Weighted rank-based simulation algorithm

As shown in Figure 4.4, the algorithm includes all hubs in the candidate set for the 1st to the 4th levels and 30th to the 34th levels, which are applicable for explicit enumeration, and generate a disruption candidate set for the m^{th} level according to $GRI_{m-1,i}$ when $5 \leq m \leq 29$. Specifically, the WRSA requires four steps.

- Step 1: Explicitly enumerate the potential combinatorial disruption scenarios of the disruption candidates at this level. Calculate T_m^{loss} and $F_{m,day}^{loss}$ for each scenario.

- Step 2: Calculate the criticality for the selected stations using $LRI_{m,i}$ and $GRI_{m,i}$.
- Step 3: Sort the stations based on $GRI_{m,i}$ from the most critical to least critical stations. These candidate sets are used to complete the scenario.
- Step 4: Select *n* top stations and *n* bottom ones in the set of candidate stations for the next level scenario.

When *m* equals the number of the hubs in the system, the algorithm is terminated with all potential disruption levels explored.

In order to validate the algorithm, 1000 potential disruptions are generated randomly in each disruption level. The quality of the algorithm is determined by the percentage of random scenarios whose reaction to disruptions can be predicted in the range set by the algorithm.

CHAPTER 5 RESULTS

By applying the WRSA, the simulation of the potential disruption scenarios in the Beijing subway system becomes applicable. In each simulated disruption scenario, the ASM measures the influence of the corresponding disruption from both the connectivity and system flow perspectives so that the criticality of the set of hubs can be revealed. Before the results of the assessment can be used to explain the ramifications of disruptions, we discuss first how effectively the WRSA is able to approximate the range of the disruptions' influence. Because the disruptions happening at a single station are most common, the second part of this chapter discusses the criticality of every hub based on the different consequences caused by excluding one of the hubs each time from the system. The last part of this chapter presents the impact of the disruptions occurring at a group of stations simultaneously.

5.1 Validation of the WRSA

For the Beijing subway system, the explicit enumeration of the potential disruption scenarios cannot be completed within a reasonable time when the number of disrupted stations is between 5 and 29. For example, the largest number of the potential scenarios is in the 17th level with ${}_{34}C_{17} = 2.33 \times 10^{9}$. Following the ASM and the WRSA, the number of the potential scenarios in each level is limited to 20 thousand to accelerate the computation and to, in turn, make more in-depth exploration of the combinatorial disruption scenarios possible.

As a heuristic method to speed up the process of finding a satisfactory solution where the exhaustive search is impractical, the WRSA is required to be validated before its results can be considered reasonable. In this study, 1000 disruptions are randomly generated at every disruption level from the 5th to the 29th levels, which results in 25,000 samples in total. These samples are used to check how well the algorithm can perform in determining the range of the impact of disruptions.

Figure 5.1. The comparison of the survivability envelops according to (a) the normalized system connectivity; (b) the normalized system flow on weekdays (Friday); (c) the normalized system flow on weekends (Sunday)

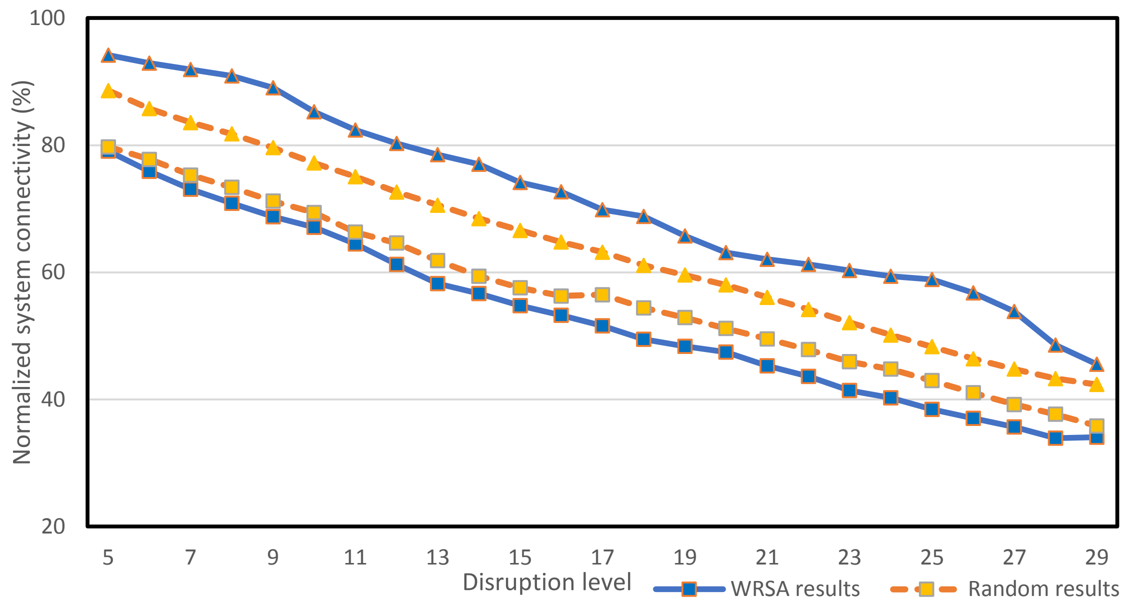


Figure 5.1.a

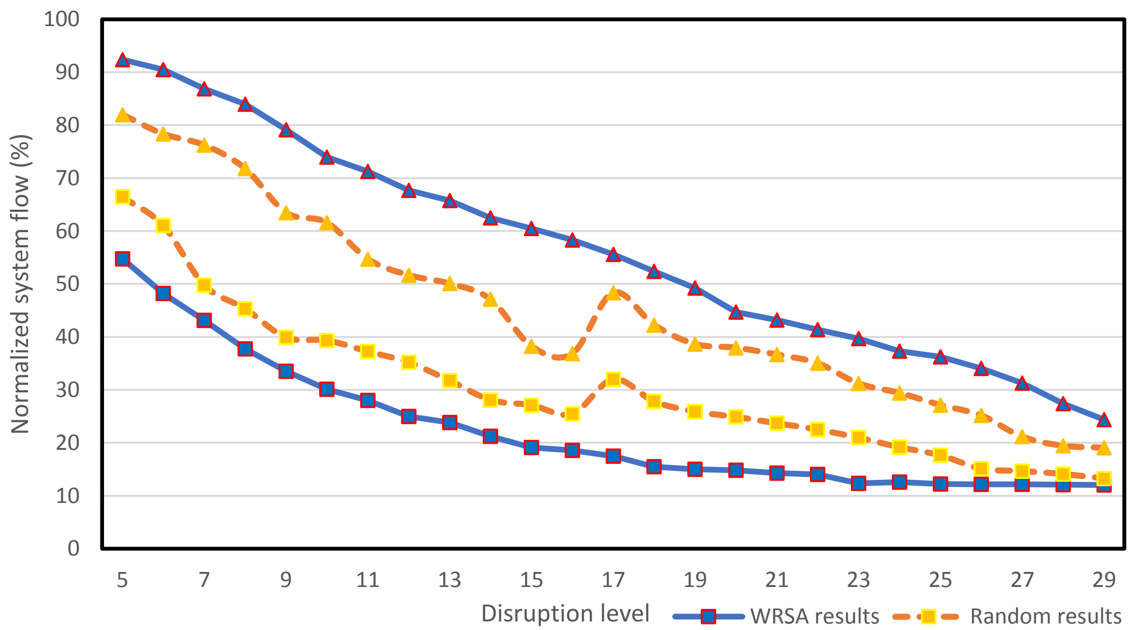


Figure 5.1.b
Figure 5.1 continued

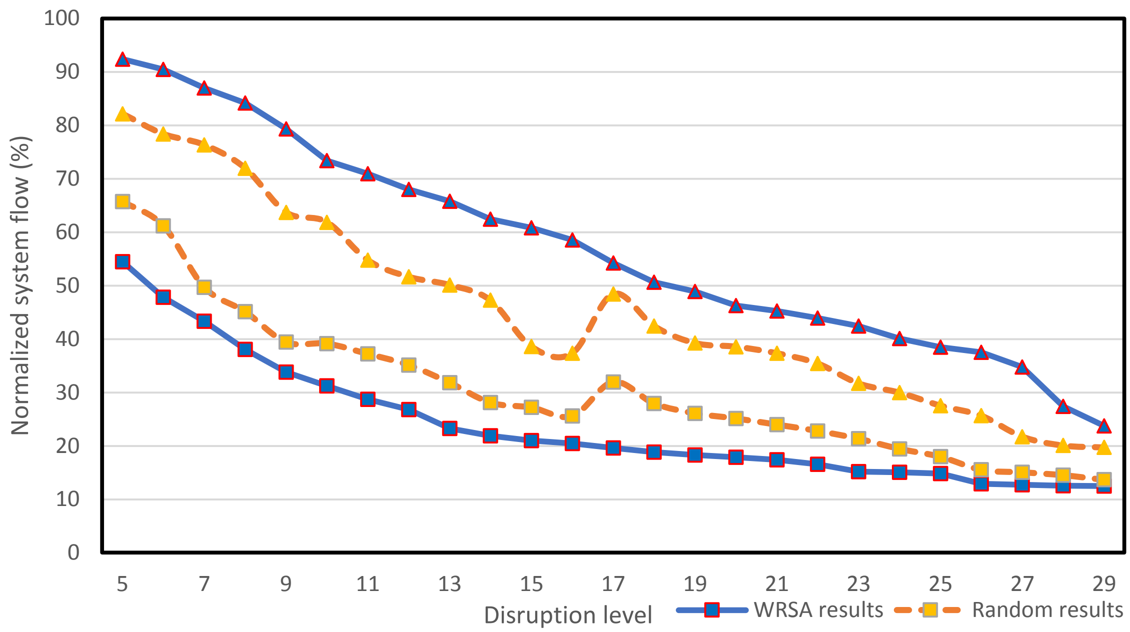


Figure 5.1.c
Figure 5.1 continued

Figure 5.1 shows the comparison between the survivability envelops of the WRSA's results and the random ones according to the ASM. The ranges of the impact of the random disruptions, which are delineated with yellow dash lines, are within the area defined by the results of the WRSA. Even though this random examination does not guarantee that the boundary determined by the WRSA is perfect, it is reasonable to believe the algorithm is effective to approximate the extremes among the potential scenarios. Based on the exploration of all disruption levels, two items are worth noting in the following sections.

5.2 Hub Criticality

The first analysis is focused on evaluating the network survivability at an individual hub in terms of the ASM. Based on the computation, the criticality of the hubs is ranked according to their T_1^{loss}, $F_{1,Friday}^{loss}$ and $F_{1,Sunday}^{loss}$. A higher rank indicates the hub is more critical.

Table 5.1. Part of the survivability results of the first level disruptions

Rank	T_1^{loss}		$F_{1,Friday}^{loss}$		$F_{1,Sunday}^{loss}$	
	Hubs	Value	Hubs	Value (thousand)	Hubs	Value (thousand)
1	Xizhimen	143.76	Gongzhufen	1052.14	Gongzhufen	737.21
2	Dongzhimen	117.57	Guomao	922.18	Guomao	644.54
3	Chegongzhuang	100.98	Wangjingxi	815.70	Wangjingxi	569.54
4	Gongzhufen	93.31	Xierqi	772.61	Xierqi	533.20
5	Chaoyangmen	89.13	Jiaomenxi	709.50	Liuliqiao	526.58
6	Songjiazhuang	87.49	Liuliqiao	708.38	Jiaomenxi	516.10
7	Jianguomen	86.81	Haidianhuangzhuang	667.74	Hujialou	498.14
8	Yonghegong	85.30	Hujialou	655.62	Haidianhuangzhuang	445.91
9	Dongdan	83.20	Songjiazhuang	602.77	Songjiazhuang	425.20
10	Shaoyaoju	81.32	Xizhimen	580.40	Xizhimen	406.48

Table 5.1 summarizes the ranks of the top ten critical hubs and the values of their survivability measures, and Figure 5.2 shows the distribution of the normalized ASM.

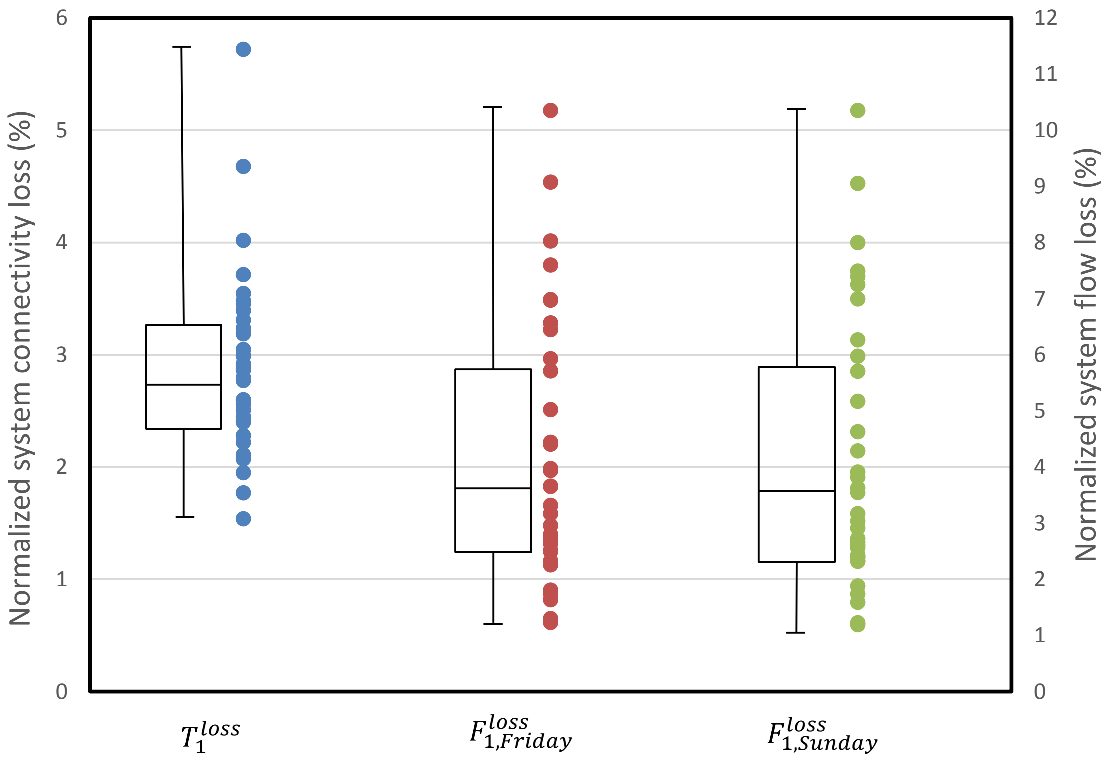


Figure 5.2. Survivability results of the first level disruptions

In Figure 5.2, T_1^{loss} represents the loss of possible paths caused by one-hub disruptions. In order to highlight the extent to which the disruptions affect the connectivity, T_1^{loss} normalized with the system connectivity at status quo is used. The T_1^{loss} of the three most critical hubs, Xizhimen, Dongzhimen, and Chegongzhuang, is much higher than the rest hubs. Both of Xizhimen and Dongzhimen are the hubs connecting Line 2 and Line 13. As introduced in the Chapter 2, Line 2 is the only loop line serving the city center, which is the traditional "inner city", while Line 13 is a special line solely serving the northern part of the city and intersecting with four branch lines in the north. In particular, the degree of Xizhimen is five, which is the largest in the system, followed by Dongzhimen whose degree is four. Chegongzhuang is the hub next to Xizhimen on Line 2, and its property of connectivity is similar to Xizhimen. The geographic locations of the rest of the top ten critical hubs based on T_1^{loss} are also shown in Figure 5.3 with green circles. Notably, similar to the above-mentioned three hubs, most of the critical hubs are clustered within

Line 2, which indicates the hubs in the center of the system have a large influence upon the system connectivity than the peripheral hubs. The result is consistent with the common assumption that the stations at the center not only affect the connections from/to them, which is similar to the peripheral stations, but also the connections that pass the center of the system.

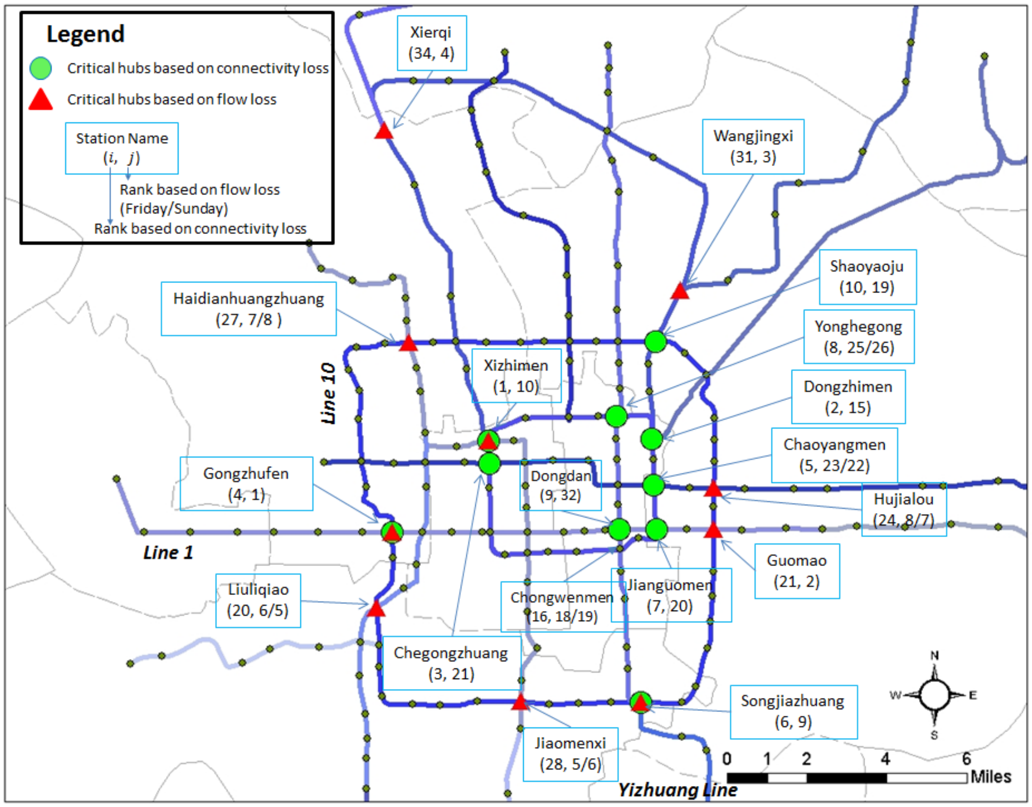


Figure 5.3. The locations of the top 10 critical hubs based on topological loss and flow loss

Meanwhile, the three exceptions along Line 10 display an important fact that Line 10 is effective to redirect connections which would pass Line 2 instead. One good example is Songjiazhuang, which ranks 6th and connects Line 10 and Yizhuang Line. Without Line 10, Chongwenmen, which is the adjacent hub of Songjiazhuang on Line 2, would be the bridge of Yizhuang Line and would have the criticality similar to Songjiazhuang. However, Chongwenmen ranks 16th in reality, because when it is disrupted, there are remaining connections to Yizhuang Line through Line 10. Finally, most of the normalized T_1^{loss} are about 2%-3%, and their average is 2.9%. The small standard

deviation of T_1^{loss} also points out the influence of targeted and random disruptions at a single hub is similar according to the system connectivity.

However, through T_1^{loss}, it is difficult to reveal other attributes of subway systems, including geographic features such as distance, time, and actual passenger demand. In that sense, the results of critical hubs based on $F_{1,Friday}^{loss}$ and $F_{1,Sunday}^{loss}$ more clearly reveal the criticality of hubs with different interpretations. First, as observed in Figure 5.2, similar to the normalized T_1^{loss}, the values of the $F_{1,Friday}^{loss}$ and $F_{1,Sunday}^{loss}$ normalized with the corresponding daily ridership at status quo also concentrate at 3%-4%. However, they reveal more outliers than T_1^{loss} does. For example, if the most critical hub, Gongzhufen, which is the bridge connecting Line 1 and Line 10 (labeled in Figure 5.3), is disrupted, the west part of Line 1 would be completely excluded from the system, and the estimated passenger flow would decrease by nearly 11% on both Friday and Sunday. This is consistent with the fact that Line 1 and Line 10 are the two busiest lines in the Beijing subway system. There are seven hubs the disruptions at which will cause more than 6% system flow loss, while the worst connectivity loss is less than 6%. Compared with T_1^{loss}, which weighs all the stations the same, $F_{1,Friday}^{loss}$ and $F_{1,Sunday}^{loss}$ reveal more serious potential influences of the one-hub disruptions. Second, notice that all the critical hubs based on $F_{1,Friday}^{loss}$ and $F_{1,Sunday}^{loss}$, except Xizhimen, are bridges. This fact is very significant in terms of network survivability because excluding one of the bridges can result in losing the entire passenger flow from or to an entire branch line. Third, in our analysis, 11 out of 34 (33%) hubs will cause a system flow loss of more than 5%, and the average system flow loss would be 4.2% on both days. In other words, given the daily ridership of the system, the expected value of the number of the affected passengers confronted with a one-hub disruption is nearly 427,000 on Friday and 300,000 on Sunday, highlighting that even a minor disruption in a large subway system such as Beijing's can trouble a large number of customers. Fourth, the distribution of the top ten critical hubs also reflects a special pattern of the system. Gongzhufen and Guomao, which are the top two critical hubs, are both the hubs connecting Line 1 and Line 10. Line 1 had always been the busiest line in

the system until its ridership was outnumbered by that of Line 10 in 2013 (Liu 2013b). The extension of Line 1 to the eastern part of the city, Batong Line, is also well-known for its high ridership (Xu 2011). Wangjingxi, Xierqi, Jiaomenxi, and Liuliqiao are similar, which are all the bridges to the branch lines that do not share service areas with other lines. However, the locations of the first two hubs determine that they are more critical than the latter two, because the southern and the southwestern parts of Beijing served by the latter two are the less developed areas within the city. Finally, the members of the top ten critical hubs indicated by $F_{1,Friday}^{loss}$ and $F_{1,Sunday}^{loss}$ are identical, although there are some changes in the lower ranking among them. The fluctuation of the passenger flow across a week does not affect the criticality for the top five hubs. However, the changes of the rank of the remainder of the stations also imply that some stations play more important roles on weekends or vice versa.

5.3 Network Resilience

The network resilience to combinatorial disruptions is also important. According to the scenarios, disruptions that involve multiple hubs will decrease the system's functionality dramatically based upon what particular set of hubs are disrupted simultaneously.

Figure 5.4 shows the survivability envelope of the normalized system connectivity and the disruption levels. The bar represents the survivability performance of the system connectivity. From the 8^{th} to the 26^{th} level, the survivability performance is almost constant and less than 20%. The decreasing rates of the system connectivity in the best and the worst scenarios are similar as well. When the total 34 hubs are disrupted, 30% system connectivity remains.

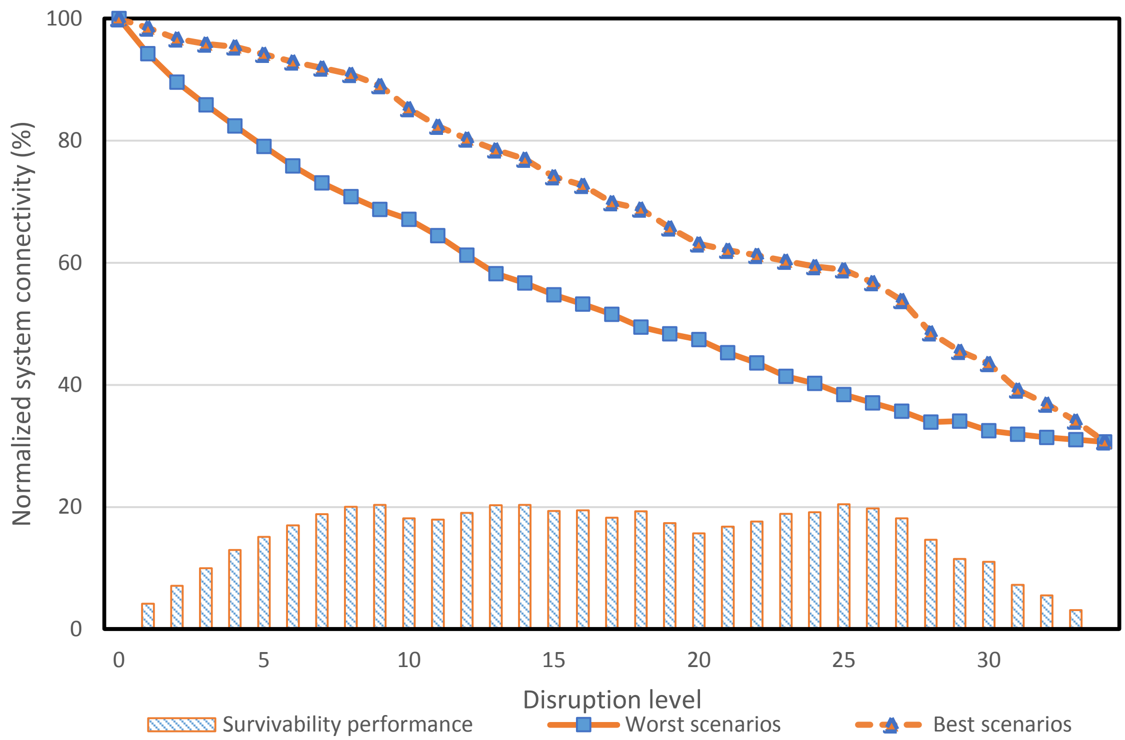


Figure 5.4. Survivability envelopes of system connectivity

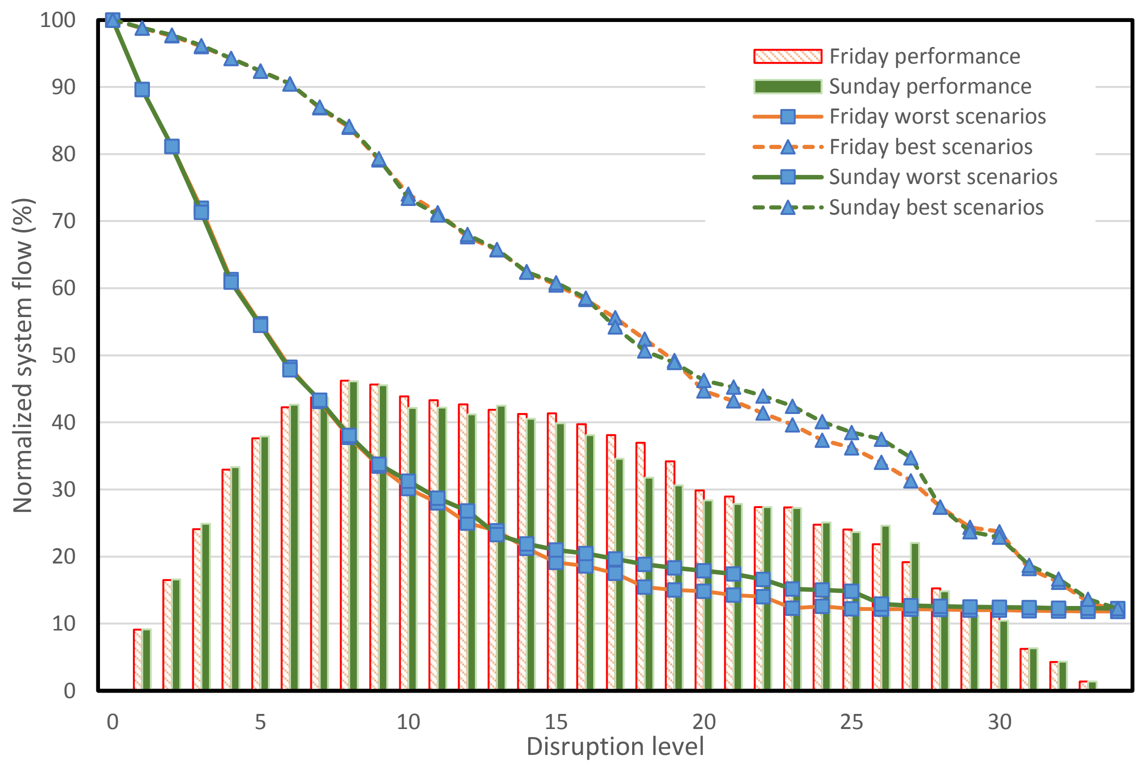


Figure 5.5. Survivability envelopes of system flow for Weekdays (Friday) and Weekends (Sunday)

Recall that the system connectivity only handles the topological characteristics of the network, so that it is less efficient to reveal the potential survivability issues hidden by other geographic factors. Figure 5.5 shows the survivability envelopes of the normalized estimated system flow and the disruption levels for Friday and Sunday. Compared with the survivability envelope of system connectivity in Figure 5.4, the envelopes in Figure 5.5 clearly show that the system flow is more sensitive to the disruptions than the system connectivity. Furthermore, the following several points draw special attention. First, in terms of the worst scenarios drawn in solid lines, the influence of one additional disrupted hub decreases with more hubs disrupted. Before six hubs are disrupted, the additional disrupted hub will cost a 7-10% system flow loss on average, and the system only maintains half of its original flow, while the final 17 hubs only cause less than 10% normalized system flow loss. However, in terms of the best scenarios, the influence of one additional disrupted hub is small at first. The decreasing rate raises and almost reaches a constant after the 6^{th} level, and the system can maintain half of its passenger flows until 18 hubs are disrupted. The discrepancy between the decreasing rate of the normalized system flow in the best and worst scenarios results in the changing survivability performance. The gap between the normalized system flow in the best and worst scenarios ranges from a few percent to as high as 46% at the 8^{th} disruption level. As the disruption level increases, the gap first increases rapidly, reaches its peak at the 8^{th} level and then decreases slowly. In other words, the potential difference between the consequences of a targeted attack and a random disruption reaches its peak at the 8^{th} level. This wide gap also clearly indicates that the subway system is vulnerable to targeted disruptions rather than random accidents.

Comparing the survivability envelopes of Friday and Sunday, the differences between their boundaries, delineated by the best and worst scenarios, are not obvious by the 15^{th} disruption level, which is consistent with our finding in the stations' criticality that the fluctuation of the system flow is not strong enough to affect the criticality of some stations. After disruptions affect more stations, the remaining system flow on Friday tends to be less than that on Sunday in both the best and worst scenarios. Thus, on Friday, hubs shoulder relatively more work than on Sunday. Finally, when all the hubs

are disrupted, only nearly 10% system flow remains, which means the 34 hubs determine the main functionality of the system with 227 stations.

Now that the effect of the fluctuation of the system flow is apparent after the disruption involves more than 15 stations, we take the worst scenarios in the 20th level as an example to explore how they affect the system from a geographic perspective. Figure 5.6 shows the worst scenarios and marks the locations of the hubs on Friday (triangles) and Sunday (squares). There are five stations that are different between the two days, and these stations are labeled with frames. If a city axis is drawn from north to south, it is apparent that the four different stations on Friday are all located in the northern and eastern part of the system, while there are two stations on Sunday, "Cishousi" and "Jiaomenxi", which are located on the southwest corner of the system with no match on Friday.

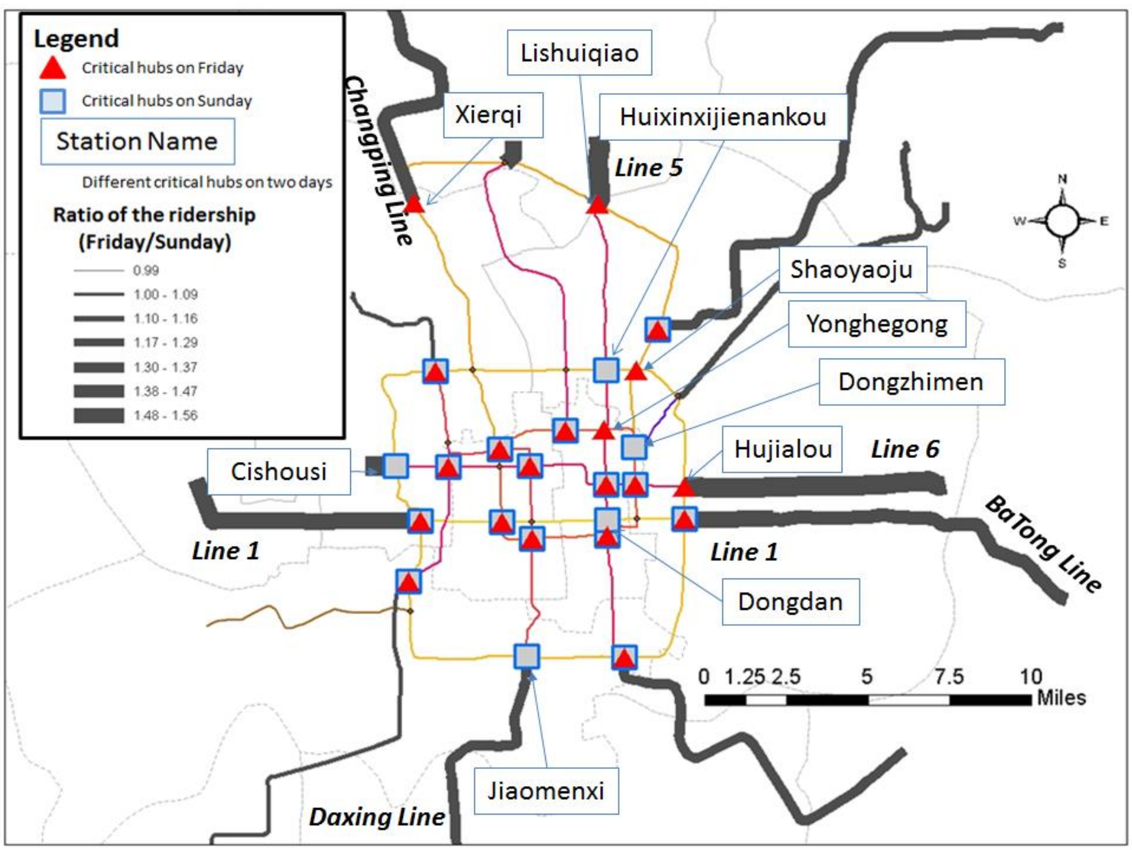


Figure 5.6. The worst scenario where 20 stations are disrupted

Consistent with the finding in the previous section, 5 out of the 10 different hubs are bridges, namely “Lishuiqiao”, “Hujialou”, “Jiaomenxi”, “Cishousi”, and “Xierqi”. These hubs have a large effect on the system’s survivability. The degree of the fluctuation of the system flow is highlighted with the width of the branch lines in Figure 5.6 representing the ratio between the flow on Friday and Sunday. The ratios of the “Line 5”, “Line 6”, “Line 1”, “Batong Line” and “Changping Line” are obviously much larger than the other lines. On Friday, the percentage of passengers using the branch lines in the east part of the system is larger than on Sunday. In other words, the imbalance of the ridership on branch lines between the eastern and the western parts of Beijing is more apparent on Friday than on Sunday. The change of this imbalance influences the relative criticality of the hubs and results in a difference in the distribution of the hubs.

CHAPTER 6 CONCLUSIONS

This chapter summarizes the achievements and contributions of this study. We identify several methods of improving the results of the study that are likely to be handled in the future. Clearly, this study is the starting point of a more accurate assessment compared with the previous research.

6.1 Summary of the Study

Transportation systems facilitate the movement of people and goods between origins and destinations across a network. With the world population soaring in recent decades, public transportation, as a shared passenger transport service available for use by the general public, is attracting more attention. The common modes of public transportation include buses, trolleybuses, trams and trains, rapid transit, and ferries.

Along with the growing importance of public transportation, its functionality of paths for the movement can be hindered by both accidental and intentional disruptions (Matisziw et al. 2009). Much effort has been directed at developing methods and approaches of exploring the potential outcomes of the unscheduled losses of public transportation. In this thesis, two major definitions about survivability (vulnerability and reliability) are provided to clarify the concept. According to the literature reviewed, *vulnerability* represents the extent to which the system loses its original functionality. In vulnerability assessment, binary measures is the simple but first choice. Binary measures represent survivability within a range of values or through certain indices to evaluate the given network system, and follow the logic of all-or-nothing of a system operation. On the other hand, *reliability* is an expression of the probability that components within the network will function, which often utilize fuzzy measures with certain specific probability form. Fuzzy measures assume that network components operate within a certain level of operation probability. The probability of a network disruption's occurring, the chance of network components' being disrupted, the degree to which the disrupted components are able to maintain parts of their functionality, and so forth are applied to improve the estimation of survivability. Three commonly-used survivability

measures are explored to highlight the criteria of the survivability assessment. Based on the review, the term *survivability* in this study is defined as the ability of a network system to maintain its topological and functional state when facing a certain level of disruptions. In order to assess the impact of network disruptions and the associated survivability to such disruptions, the identification of potentially important disruption scenarios, including the best and worst scenarios which delineate the range of disruptive influence, is required. Lots of approaches, which differ from each other primarily in how disruption scenarios are assessed and understood, exist for indicating those scenarios. After comparing the characteristics of the four major approaches, including scenario-based approaches, strategy-based approaches, mathematical programming approaches, and simulation-based approaches, this study takes a simulation-based approach because it is more applicable to the case study, the Beijing subway system.

The Beijing subway system, which ranks third in the world for its length and annual ridership, serves Beijing, the capital of the People's Republic of China and one of the most populous cities in the world with more than 20 million residents in 2012 (BMBS and NSOB 2013a). Because of the rapidly increasing number of vehicles and the city's original layout designation, the traffic conditions of Beijing are quickly degrading, which attracts increasingly more attention to the public transportation. As a public transportation mode completely beyond the impact of traffic jams on the ground, the Beijing subway system serves as a crucial means of transportation for a mass of people. Its growing importance, as well as geographic and functional features, requires specifically designed research on its survivability because this research provides valuable information for better preparation in terms of network protection. Furthermore, the fluctuation of the passenger flow of the Beijing subway system in a week displays the potential of different survivability varying with time.

In particular, based on reviewing the former network survivability research, an accessibility-based survivability measure has been developed in this study. This measure captures the differences of the consequence from two perspectives. The system connectivity loss is used to measure the impact from the topological aspect while the system flow loss is employed to measure the impact from the functional aspect. Because

the system flow loss admits the differences existing between subway lines and stations by taking into account the distances and the daily ridership, it is expected to reveal more detail about the system. In order to tackle the computational issues of the simulation-based approaches, a weighted rank-based simulation algorithm (WRSA) is developed to reduce the computational requirement. Even though it is a heuristic method, its effectiveness is well verified by 25,000 random samples, which prove the algorithm is sufficient to be utilized.

As an empirical study, we highlight several important findings as follows. First, the differences between the survivability based on the system connectivity and the system flow are obvious. The system flow is more sensitive to the disruptions and estimates the criticality of the stations differently to the system connectivity. This difference indicates the limitation of the system connectivity as a survivability measure because the system connectivity does not consider the differences among the geographic characteristics of the stations. Second, when facing single station disruptions, the Beijing subway system shows a strong survivability. Only 33% of disruptions on one hub will cost more than an estimated 5% passenger loss for the entire system. Meanwhile, the roles of several critical stations are prominent. For example, the disruption on Gongzhufen will cause more than 10% passenger loss based on the estimation. Third, the performance of the system confronted with combinatorial disrupted stations varies with the disruption level and is highly dependent on the combination of hubs. This finding is consistent with the results of previous research, highlighting that the protection of hubs acting as the bridges for branch lines to the rest of the network is extremely important, indicating that providing more belt lines or alternative lines will improve the system's ability to maintain survivability. At last, even though the fluctuation of ridership through a week affects the survivability to some extent, a well-prepared emergency plan for the entire week is currently acceptable. The effect of the ridership change remains limited to certain disruption levels, at least in the Beijing subway system.

6.2 Future Research Directions

This study introduces an accessibility-based measure and a simulation-based approaches to assess the survivability of the Beijing subway system. The achievements of the study can be the base of some future research.

With more detailed information about the passengers' origin-destination flow, the model to estimate the passenger flow after disruptions can be updated. In this study, the spatial interaction model used is based upon the population around the stations and the distances between the stations and adjusted with the actual daily ridership; thus the relative criticality of the stations along the same line might be biased.

The study can also be improved by modeling the reaction of the passengers toward disruptions more accurately. In order to estimate the amount of traffic flow as accurate as possible, many assumptive conditions have been put forward in former research. In this study, considering the modern operating and broadcasting systems of the subway, the passengers are assumed to make their decision according to the spatial interaction model.

Finally, one important factor is how the subway management company is managing the system. The outcomes of a disruption include not only the direct impact but also the response of the managers. If the entire subway system is shut down because of one bombing at a station, the survivability of the system will be meaningless.

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