1. INTRODUCTION

An important concern in transportation planning is to ensure or at least improve the resiliency of traffic networks. Disruptions to transportation networks can be very costly and they can productivity and quality of life of a region, emergency response, evacuation planning and rerouting of freight. Disruptions include those that are purely incidental events such as an accident involving a semi-truck on the freeway to those that result from targeted attacks on the infrastructure – e.g., a truck bomb on a major bridge.

Current methods to analyzing the resiliency of transportation networks generally fall into one of three categories: the four-step transportation planning model and microsimulation. This paper discusses the merits and shortcomings of these approaches and the capacity for each to facilitate network resiliency analysis. The paper also introduces a couple of alternative graph-theoretic techniques (one that is raster-based and the other based on segments) for doing transportation network analysis. Both are imbedded in a Geographic Information System allowing for easy manipulation of the data and visualization of results. The grid-based technique and a failure simulation is first demonstrated using a small hypothetical network. Then both methods are applied to a portion of the Washington, D.C. highway and arterial network. Directions for future research in this area are also provided.

2. CURRENT APPROACHES TO MODELING TRANSPORTATION NETWORKS

The most traditional approach to modeling transportation networks is the four-step planning model that was developed some five decades ago. This model is based on the traditional four-step modeling process, which captures each of the following: *trip generation* or number of trips produced in and attracted to each zone in the transportation study area; *trip distribution* or number of trips going between each origin and destination, or each pair of zones in the study area; *mode choice* or travelers choice of mode (e.g., drive alone, car pool, transit), and *traffic assignment* or travelers choice of routes between each origin and destination. This technique, while valuable in certain respects, is not well-suited for resiliency analysis where the effects of link failures are assessed. The process of preparing and running a scenario is time-consuming and it is not something that can be done in real-time.

With advancements in computing power, our understanding of micro-level travel behavior and improvements in data collection, microsimulation is becoming more popular as a technique for modeling the properties of transportation networks. While there are many varieties of these models, they each share some common characteristics and capabilities. First, the models capture micro-level behavior, which in turn gives rise to macro-level phenomenon like traffic flows and congestion levels. Second, micro-level behavior is characterized by rules that are assumed to guide individuals' decisions and individuals are classified in terms of the rules they utilize. For example, one type of person may base their decisions of what route to take on information they gather through traveler information services while another individual may be apathetic to knowledge of traffic conditions before they travel. Third, most micro-simulation models also include a visualization component that allows the user to see how traffic is evolving under different assumptions built into the model.

While modeling the effect of a disruption, like an accident, is fairly easy to do within a micro-simulation framework, the very act of constructing a model of this type is both time-consuming and challenging. The process entails detailed coding, calibration of innumerous parameters and validation of spatio-temporal conditions of the baseline network. Further, rules for individual-level behavior, and classes of travelers, need to be defined in such a way that they correspond to the actual population of the region being modeled. Oftentimes, this requires surveys of individuals to get at this with some precision.

The first step to any comprehensive plan for securing critical infrastructure is the establishment of a methodology by which standards and metrics can be set. There needs to be a common language by which stakeholders can quantify continuity by measuring resiliency. What follows is an initial step towards establishing such a methodology to move forward.

Infrastructure Assessment

One of the significant obstacles in dealing with critical infrastructure is assessing and setting baselines for such large complex sprawling networks. Further, infrastructures are often interdependent and dynamic. Fortunately there has been considerable work done on methods for quantifying critical infrastructure. Infrastructures can be assessed based on several factors a few of which include:

- Density – how much infrastructure is there in any discrete location – i.e. 15 fiber optic conduits, 3 electric transmission lines, 2 gas pipelines.
- Capacity – how much volume, flow, or traffic are the infrastructures in any discrete location able to handle – i.e. the fiber lines have a 10 Gbps[1] capacity, the electric transmission lines are 720 Kv, and the gas pipeline are 42 inches in diameter.
- Bottleneck identification – algorithmic approaches to identify areas with high amounts of capacity but little diversity to route it.
- Structural analysis – another algorithmic approach that calculates all possible paths across an infrastructure and finds those discrete locations that are most frequently used in routing.
- Weighted structural analysis – expands the all possible path analysis to include to identify those locations are frequently used in routing and have low levels of capacity, or alternative routing paths in the event of failures that could be under capacitated.

[1] Gigabyte per second (OC-192)

- Interdependency –
    - Colocation – two or more infrastructures are located in the same discrete location.
    - Structural – the most frequently utilized routing paths of two or more infrastructures are located in the same discrete location.
    - Functional – the loss of one infrastructure will cause failures in a dependent infrastructure – i.e. the loss of electric power causes traffic light failures resulting in cascading traffic congestion, hampering emergency response.
- Cost – creating a baseline figure of cost for the infrastructure in its current configuration – i.e. the cost of leasing fiber per month from a network provider.

These are but a few of the possible approaches to assessing infrastructure, but they provide a first cut and the basic aspects of infrastructure that are important to understand. Each approach provides a list of discrete locations and assets that could be critical to the operation of one or multiple infrastructures. To know if the assessment created the correct output the analysis needs to be verified.

Verification

There a multitude of ways to assess infrastructure and identify potential vulnerabilities, and there needs to be a means to identify which approach works best in each environment through a verification process. One means of verification is through failure simulation. Once infrastructure has been assessed and the most critical infrastructure components identified and ranked a failure of each component can be simulated. After the failure the impact can be charted and subsequently compared to other components to verify their criticality. Would the failure of a location with the highest density of infrastructure cause more impact than an area with the highest capacity, or would a failure at a bottleneck cause the greatest repercussions to continuity. Failure simulation provides a means to verify the criticality of any of these scenarios to the continuity of the infrastructure. Once baseline verification has been performed a combination of assessment methods can be investigated. For instance the greatest impact to continuity could come from the most frequently used routing path that contains a high density of three different infrastructures.

A second aspect that needs to be considered in a verification process is after an initial failure the structure of the network changes. What was once the second most critical asset in the network may have changed. To determine if it has or not a combinatorial optimization needs to be run where after the first failure has been incurred all possible second most critical assets need to be tested to determine which has the greatest impact on the infrastructure's continuity. In the best case scenario real time analysis can be performed to react to failures and determine how to best allocate resources in the network, but proactive analysis before events is still critical to ensure continuity.

Consequence

An integral part of both assessment and verification is determining what the consequences of a failure are. Consequences can be calculated through a variety of methods and ultimately are specific to an individual scenario, the infrastructure involved and the users dependent on it. That said there are some broad areas into which consequence can be categorized:

- Population affected – how many people will be affected by a failure or lack on continuity in an infrastructure – i.e. after a transmission line failure and subsequent blackout how many people will be without power.
- Businesses affected – how many business locations will be affected in a failure scenario for aggregation purposes these consequences can be grouped by SIC or NAICs codes.
- Interdependent infrastructures affected – what infrastructures with dependencies to a failed infrastructure will be impacted by an event – i.e. a transmission line failure causes traffic signals to loose power causing cascading gridlock in transportation infrastructure.

These are just three broad categories under which consequence could be grouped. For specific critical sectors consequence can be more narrowly defined and quantified. If the Federal Reserve Banks Fedwire settlement system suffered a continuity failure what would the impact be on the financial sector and specifically the banking community, domestically in the United States and internationally? There are plenty of specific examples of consequence within each sector, and each needs to have the ability to fit in a larger framework with metrics to quantify how mitigation will augment continuity to decrease consequence. Once consequence has been measured it is possible to attach a dollar figure to that consequence and a probability of that consequence that can in turn establish a justified level of investment in continuity.

Fiscal Evaluation

3. GRAPH-THEORETIC APPROACHES TO NETWORK ANALYSIS

A much simpler but perhaps less detailed approach to modeling transportation networks is based on graph theory. Graph theory has a long history starting with the work of Euler in 1736, but implementations to spatial network resiliency is far more recent. Investigations of the spatial and resiliency aspects of networks have their own trajectories. Spatial applications of graph theory have a long lineage in both geography and regional science. Garrison (1968) did in-depth network analysis on the interstate highway system, analyzing the importance of nodes and links on location and development. This same vein of research was greatly expanded through Garrison's student Kansky (1963) and later with the work of Chorley and Haggett (1968). In addition, Nyusten and Dacey (1968) and later Taffee and Gauthier (1973) expanded this research, applying network analysis to telephone networks and general infrastructure. This tradition of network analysis was picked up again by geographers to begin to analyze the Internet's network of networks. Wheeler and O'Kelly (1999) examined the basic graph measures of several domestic US providers and analysis of city connectivity of the aggregated providers. Gorman and Malecki (2000) investigated the network topologies of several firms and how graph theoretic measures could be used to investigate competitive advantage and the nature of interconnection between networks. Later studies have looked at the structure of networks and city connectivity as a time series finding large changes in bandwidth capacity (Malecki, 2002; Townsend, 2001), but little change in graph measures of connectivity (O'Kelly and Grubesic, 2002). While connectivity indices have changed little over time the overall structure of the network has. Gorman and Kulkarni (2004) found that the aggregated US backbone network has increasing self-organized from 1997 to 2000 creating a more efficient but more sparsely connected network. This research confirmed at a spatial level of analysis what was being found at a topological level in the study of complex networks.

In studies of large complex network of thousands and millions of nodes physicists and computer scientists have begun to incorporate spatial dimensions to their work. Work by Yook, Jeong, and Barabasi (2001) has examined the role of linear distance in complex networks. They found that the spatial layout of the global Internet router network formed a fractal set, determined by population density patterns around the globe (Yook et al 2001). A similar study at Boston University found the same effect when population was controlled for with the per capita GDP of regions (Lakhina et al 2002). Barthelemy (2003) found that in spatial networks with scale free properties long distance links connect predominantly to hubs. Further, if the total length in a network is fixed, the optimal network which minimizes both the total length and the diameter lies in between the scale-free and spatial networks (Barthelemy 2003).

The analysis of the resiliency of networks also has a long history of analysis with applications to fields as diverse as landscape ecology (Urban and Keitt 2001) and telecommunications engineering (Colbourn 1999). In additon to several discipline specific approaches there has been considerable recent work on the resiliency of general complex networks. A widely discussed work by Albert et. al. (2000) found that complex networks[2] were robust to random failures but vulnerable to targeted attack. The research illustrated that when nodes with a significant percentage of the networks connections are targeted for attack the network degrades rapidly leading to catastrophic failures and network balkanization.

The initial work by Albert et. al. was quickly followed by several other approaches to vulnerability of large complex networks. Callaway et al (2000) modeled network robustness and fragility as a percolation and Cohen et al (2001) using similar percolation models, both findings reinforcing the fragile-robust dichotomy discovered by Albert et. al. (2000). The research has not been without criticism, and many computer scientists and engineers have argued the network topology models generated in these studies are not accurate (Chen et al. 2002, Alderson et al. 2003, Li et al. 2004). In fact the same heavy tail connectivity distribution can result from a wide variety of network topologies, some more and less resilient than others (Li et al. 2004, Schintler et al. 2004).

While combining the themes of spatial network analysis and resiliency has received considerable recent attention work in this area dates back over thirty years. Some of the

[2] Specifically scale free complex networks with power law connectivity distributions.

earliest resiliency work involving spatial dimensions was Reed's (1970) graph theoretical analysis of the urban city network formed by the Indian airline network. In this analysis Reed successively removed nodes from the network and calculated the impact on the average distance[3] in the network. While similar work had been done previously by mathematicians Reed's was one of the first applications of the work to a critical infrastructure. The work was well ahead of its time calculating tiers of cities based on their criticality and finding that the loss of top tier cities could balkanize the network resulting in large scale failures (Reed 1970).

Analysis of the resiliency of spatial networks has again been picked up largely in relation to the analysis of critical infrastructure networks. Utilizing a model of node connectivity and path availability Grubesic et al (2003) found that the disconnection of a major hub city could cause the disconnection of peripheral cities from the network. Building upon the complex network literature Gorman et. al. (2004) found that incorporating spatial variables into algorithms, such as global connections between cities and Euclidean distance, to determine the criticality of nodes in the network was more effective than the binary connectivity measures used in the previous studies citied.

4. MODIFIED GRAPH THEORY TECHNIQUES: GRID-BASED AND SEGMENT-BASED APPROACHES

One of the most significant shortcomings in current spatial approaches to graph theory is the loss of spatial data when a network is decomposed into edges and vertices. Previous approaches have succeeded in capturing the location of vertices and the distance of edges, but the path takes by an edge is lost. In an effort to find a method for capturing spatial path data of physical networks ideas were borrowed from the field of image analysis. In image analysis researchers often decompose large images into pixels and perform analysis based on pixel adjacency. Since the number of pixels in a high-resolution image can be quite large image analysis implemented theories from circuit theory to implement large graph processing algorithms (Roth 1955, Branin 1966, Zahn 1977). Utilizing the computational power of the algorithms researchers were able to overlay images with grids and produce connectivity graphs based on pixel adjacency (Wallace et al. 1994). This approach allowed the efficient spatial capture of an image with Cartesian coordinates for analysis. The approach has been used in computer graphics (Taubin 1995), 3-D surface flattening (Wandell et al. 2000), and data clustering analysis (Jain et al. 1999).

The approach allows the creation of graph while capturing the Cartesian coordinates of an image. This facet of the approach provides a possible angle for capturing the spatial properties of network including the exact path of edges. Building upon the work in image analysis a grid-based approach is possible for network analysis. To accomplish this task a grid is laid over the network of interest. This is most easily accomplished in a geographic information system where each part of a network already has a precise spatial coordinate based on its vector attributes. To understand conversion of the grid into a

[3] The average number of hops it takes t get from one node to any other node in the network, in this case cities.

connectivity graph a toy problem is useful for illustration. Figure 1 shows a simple network with a grid overlay.

The above grid is laid over the network vector file and the cells are marked as either containing a network point or not (in the case above indicated by red numbers[4]), attributes can also be assigned based on a variety of factors. Once the cells have been assigned a number and a designation of whether they contain a network link or not, a connectivity edge list can be created. The cell adjacency list for the network above would be:

1,7
7,13
13,19
19,25
21,17
17,13
13,9
9,5

A few considerations go into defining the dimensions of the grid. A grid with a finer resolution is desired to ensure that each cell contains only part of one link and not multiple links. The size of the grid also depends on the nature of the "what if" scenarios that are intended to be modeled. Larger cells may be desired if one is interested in exploring the impact of a large-scale disruption to some part of the network although this can also be simulated with a grid dimension of finer resolution by simultaneously removing a block of smaller cells.

The grid-based network is used to conduct failure simulations. First, each cell in the network is ranked according to some indicator that is believed to measure the criticality of that cell or its importance to the connectivity of the entire network. These indices need not be limited to graph-theoretic variety and can be formulated to capture the weighted network properties (e.g., capacities or length of links). Second, cells are removed in sequence based on their criticality and after the removal of each cell network connectivity is examined.

One of the limitations of the grid-based approach is the curse of dimensionality problem. As the density of a network increases, the grid resolution need to adequately capture the network topology expands and the computational power to run simulations grows exponentially. Further, the method cannot easily be applied to weighted networks and there are also computational issues associated with this as well.

The segment-based approach attempts to address these shortcomings. It entails defining a network in terms of links and nodes at a level of resolution that can be reasonably handled from a computational perspective. Weights are added to links based on attributes of interest – e.g., capacity, where in the case of capacity for example a segment with greater carrying capacity is viewed as a more attractive link in a route between two points. Shortest paths between origins and destinations in the network as defined by the

[4] This process can be done with vector line files or raster point files

user are calculated and the resulting criticality of any given segment is based on the number of shortest paths that utilize that link. The resiliency of the network is assessed by conducting failure simulations of critical links and rerunning the shortest path analysis.

5. PROTOTYPE DEMONSTRATION OF GRID-BASED APPROACH

The grid-based approach is first applied here to a generic network. A 150 by 150 grid is used in the simulations and cell-adjacency is based on rook rules. A program called UCINET is used to conduct network analysis on the graph defined and to rank the criticality of links based on a variety of graph-theoretic indices.

The indices used in this simulation include:

> Betweeness: measures the degree to which a node is an intermediate location through indirect relationships connecting other nodes.
>
> Closeness: measures how close a node is to all other nodes based on the shortest paths between that node and all other nodes.
>
> In-Degree: measures the number of links that have direct connections to a node.
>
> Clustering Coefficient: measures the degree of small-world network local clustering of a node.
>
> Reachability: measures the extent to which a node can reach all other nodes in a fragmented.

The connectivity of the network at each point in the simulation is measured by two indices: diameter and the degree of balkanization. Diameter is the longest geodescic path in the network. Balkanization measures the fragmentation of the network and specifically, the number of disconnected components.

Drops in the diameter of the network do not reflect improvements in connectivity but rather further balkanization of the network. This is because the algorithm that is used to do the simulations computes the diameter of the largest disconnected component.

The experiments provide some insight about which indices appear to be better than others as measures of how critical a node is to the connectivity of a network. Of all of the indices used to conduct the failure simulations, only betweeness causes an immediate degradation of the network. After the cell ranked highest according to this measure is removed, the network fragments into six disconnected components and the diameter drops from 267 to 156. The network continues to balkanize as additional cells are removed.

Using just the number of components as a measure of fragmentation can be deceiving. It doesn't say anything about the size of the fragments that break off with the removal of certain cells. Topology diagrams can also help to provide this information (see Figures 2 and 3). Each node is given a different color to represent which component to which it belongs. The original network (i.e., before any cells are removed) consists of five components. After removing the cell ranked highest according to betweeness the largest component of the original network breaks in half. The network continues to balkanize with the removal of additional cells although the pieces that break off in each case are rather small.

There are only modest, and in some cases no effect, on the diameter or balkanization of the network when the other measures of criticality are used to rank cells for removal. It is not surprising to find this for the clustering coefficient and degree as they are only measures of the local connectivity of a node. There are no readily apparent explanations why reachability and closeness do not perform well.

6. EMPIRICAL APPLICATION OF TECHNIQUES

The raster-based and segment-based approaches are next applied to the Washington, D.C. highway and arterial network. Computationally, it was not feasible to apply either method to the entire Metropolitan Statistical Area and this stems largely from the fact that the network spans a large geographic region and it is very dense in most regions. As a result, only the middle portion of the network is extracted for the purpose of demonstration.

Figure 4 shows the results of the raster-based technique for the unweighted network. The grid size that is used to conduct the analysis is 250 rows by 300 columns with 13,253 cells that contain segments of the road network. Betweenness scores are calculated for each link and different colors are used to represent the magnitude of these scores. This application demonstrates one of the dangers of utilizing a non-weighted graph and that is that the attractiveness any given link in the network is determined only by it's spatial position in relation to other links. It does not account for other factors such as capacity and travel time. This simulation shows perhaps erroneously that minor arterials in the District of Columbia are more critical than the Interstate beltway that circles the region.

The next simulation utilizes the segment-based approach and a network weighted by capacity. Capacity classification codes are used to create normalized index of capacity which is then inverted to make links with greater capacity appear shorter and hence more attractive. The network is comprised of 2,793 links. Figure 5 shows the results of the segment-based simulation and the criticality of links is again represented by different colors. What emerges this time is a characterization of traffic that appears to be more realistic where for example, the importance of the beltway is highlighted. One of the most critical links is then removed from the network and the simulation is rerun. The results are displayed in Figure 6 and the red circle shows which segment was deleted from the network. This simulation illustrates how a shock to the network affects the rerouting of traffic and where in the network additional stress is imposed due to the disruption.

7. CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

This paper presents some alternative methodologies for examining the resiliency of networks. One of the advantages of the technique is that it overcomes some of the challenges that are associated with the analysis of planar networks. The connectivity of a network at any point in a cell removal process can be measured by statistics like diameter but also visually represented with network topology diagrams. Betweeness appears to be a good measure of criticality although others should be explored and validated.

The prototype demonstration of the grid-based method revealed some shortcomings of the process. Most notably, in some of the cell rankings there were sequences of cells that comprise part of a single link connecting two nodes in the original network. If it is a link that is critical to the connectivity of a network, removal of only the first cell in sequence had any measurable impact. An approach for minimizing this problem may be to conduct recursive simulations, where the criticality of cells is recomputed each time a cell is removed from the network. Application of the technique to the Washington, D.C. area highlighted some of the computational problems of using the method on a large, dense network.

The grid-based network simulation method could be used to explore interdependencies across multiple networks, and to define critical nodes based on these interdependencies. This requires the development of indices that measure criticality based on interdependency.

The segment-based approach could be extended to examine dynamics within a network. This might be accomplished using a recursive procedure, where after each step the properties of the network are visualized using the Geographic Information Systems. Extension of the approach to look at infrastructure interdependencies also holds some merit.

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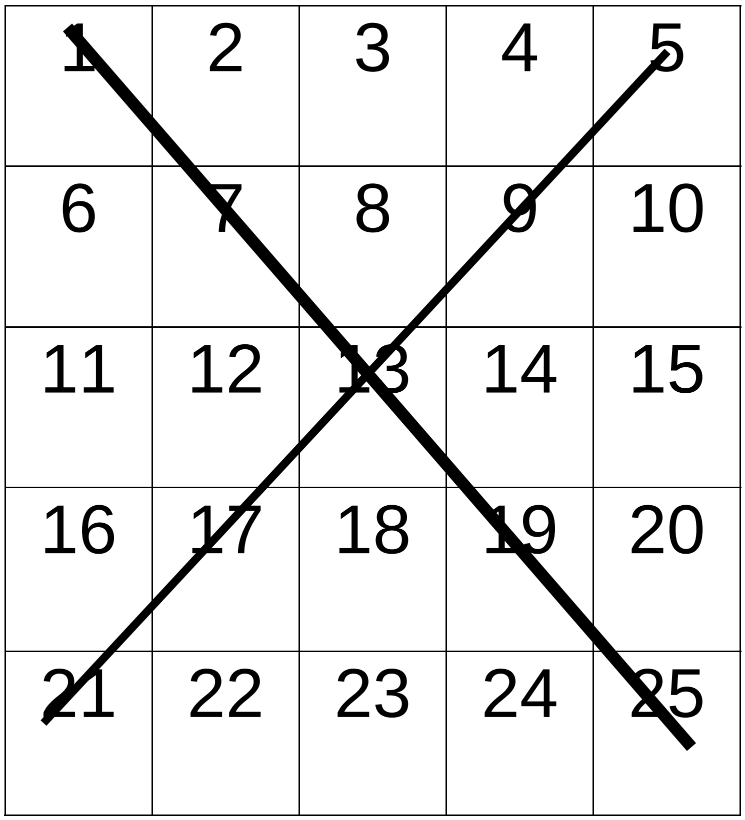
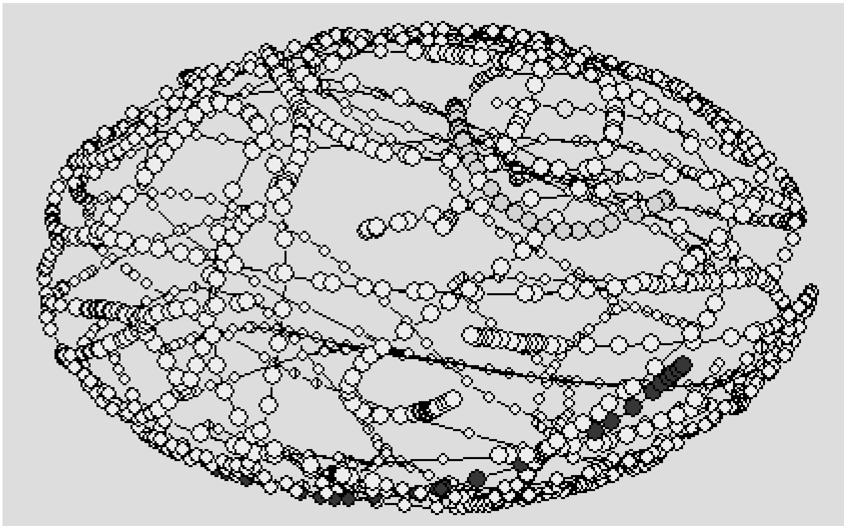
Figure 1. A method for cell adjacency graph creation





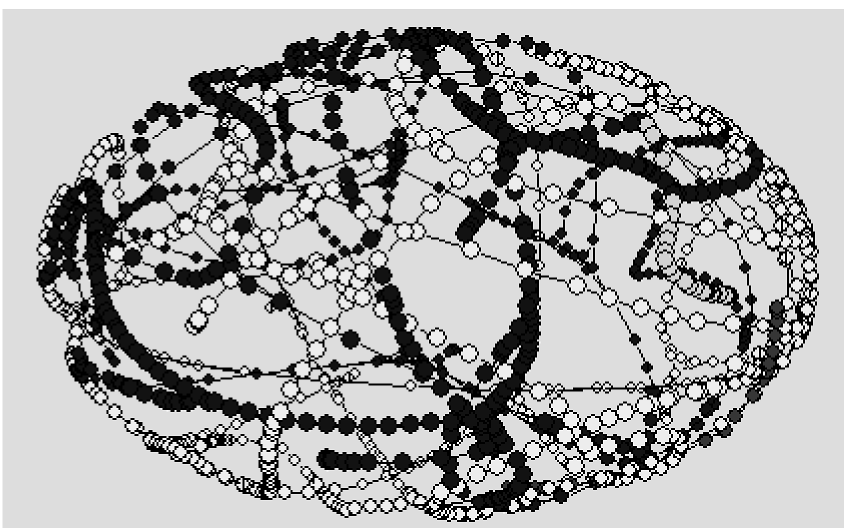


Figure 2: Washington, D.C. Network Using Grid-Based Approach

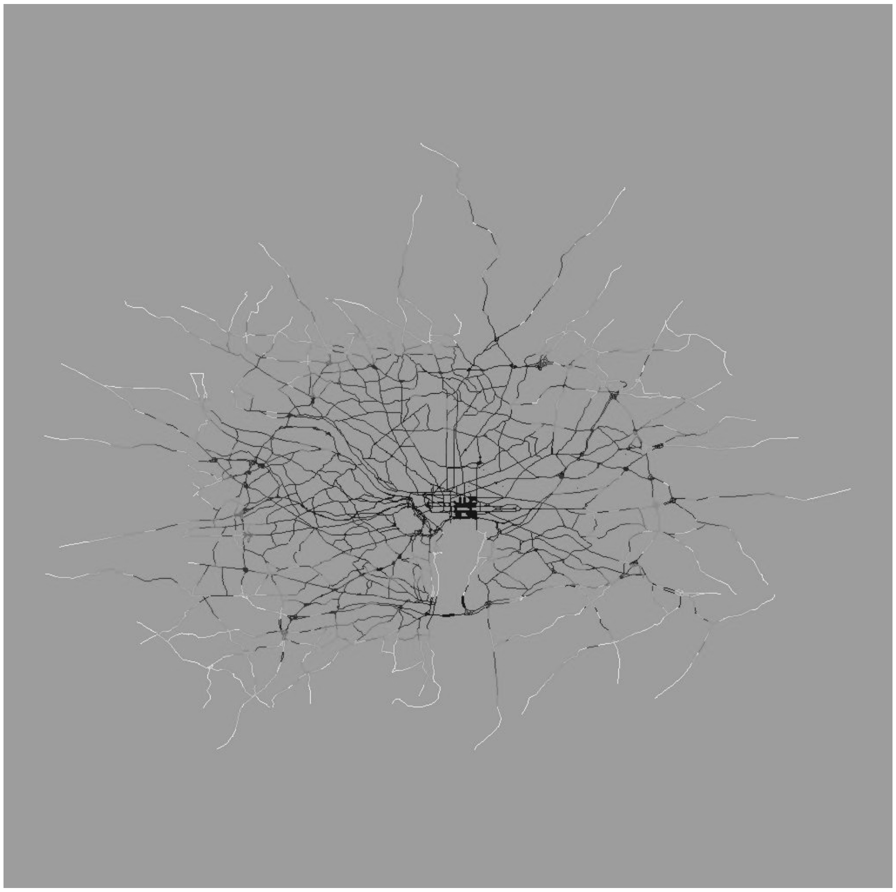


Figure 3: Washington, D.C. Network Using Segment-Based Approach Before Link Failure

Figure 4: Washington, D.C. Network Using Segment-Based Approach After Link Failure