# GRAPH THEORETIC APPROACHES TO UNDERSTAND RESILIENCE OF COMPLEX SYSTEMS

by

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Modern society is critically dependent on a network of complex systems for almost every social and economic function. While increasing complexity in large-scale engineered systems offer many advantages including high efficiency, performance and robustness, it inadvertently makes them vulnerable to unanticipated perturbations. A disruption affecting even one component may result in large cascading impacts on the entire system due to high interconnectedness. Large direct and indirect impacts across national and international boundaries of natural disasters like Hurricane Katrina, infrastructure failures like the Northeast blackout, epidemics like the H1N1 influenza, terrorist attacks like the 9/11, and social unrests like the Arab Spring are indicative of the vulnerability associated with growing complexity. There is an urgent need for a quantitative framework to understand resilience of complex systems with different system architectures. In this work, a novel framework is developed that integrates graph theory with statistical and modeling techniques for understanding interconnectedness, interdependencies, and resilience of distinct large-scale systems while remaining cognizant of domain specific details. The framework is applied to three diverse complex systems, 1) *Critical Infrastructure Sectors (CIS) of the U.S economy*, 2) *the Kalundborg Industrial Symbiosis (KIS), Denmark* and 3) *the London metro-rail infrastructure.* These three systems are strategically chosen as they represent complex systems of distinct sizes and span different spatial scales.

The framework is utilized for understanding the influence of both network structure level properties and local node and edge level properties on resilience of diverse complex systems. At the national scale, application of this framework on the U.S. economic network reveals that excessive interconnectedness and interdependencies among CIS significantly amplify impacts of targeted disruptions, and negatively influence its resilience. At the regional scale, analysis of KIS reveals that increasing diversity, redundancy, and multi-functionality is imperative for developing resilient and sustainable IS systems. At the urban scale, application of this framework on the London Metro system identifies stations and rail connections that are sources of functional and structural vulnerability, and must be secured for improving resilience. This framework provides a holistic perspective to understand and propose data-driven recommendations to strengthen resilience of large-scale complex engineered systems.

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## NOMENCLATURE

| | |
|---|---|
| *A* | Direct Requirements matrix |
| *ABM* | Agent Based Modeling |
| *B* | Modularity matrix |
| *BEA* | Bureau of Economic Analysis |
| *C* | Clustering coefficient |
| *CIS* | Critical Infrastructure Sectors |
| *D* | Maximum distance between two cumulative distribution functions |
| *DHS* | Department Of Homeland Analysis |
| $E_{glob}$ | Global efficiency |
| *EIO* | Economic Input-Output |
| *EIP* | Eco-Industrial Parks |
| $E_{loc}$ | Local efficiency |
| *ER* | Erdős–Rényi model |
| *EU* | European Union |
| *F* | Final Demand of an industrial sector |
| $f_c$ | Fracture Coefficient |
| *GLRT* | Generalized Likelihood Ratio Test |

| | |
|---|---|
| *GOF* | Goodness Of Fit |
| *HOT* | Highly Optimized Tolerance |
| $(I\text{-}A)^{-1}$ | Leontief inverse |
| *IO* | Input-Output |
| *IS* | Industrial Symbiosis |
| *KIS* | Kalundborg Industrial Symbiosis |
| $k_{min}$ | Lower bound of the power law distribution |
| *L* | Characteristic path length |
| *LCA* | Life Cycle Assessment |
| *LRT* | Likelihood Ratio Test |
| *MFA* | Material Flow Analysis |
| *MLE* | Maximum Likelihood Estimation |
| *NEA* | Network Environ Analysis |
| *OECD* | Organization for Economic Co-operation and Development |
| $P_G$ | Number of connected node pairs in graph *G* |
| $P_{G\|g}$ | Number of connected node pairs in graph *G* after removal of an edge *g* |
| *PPD 21* | Presidential Policy Directive |
| *Q* | Modularity function |
| *q* | Inoperability |
| *r* | Redundancy |
| *RODS* | Rolling Origin and Destination Survey |
| $S_{C1}$ | Total strength of nodes in the first component |

| | |
|---|---|
| $S_{C2}$ | Total strength of nodes in second component |
| $SD$ | Systems Dynamics |
| $S_T$ | Total strength of all nodes |
| $SW$ | Small World |
| $TFL$ | Transport For London |
| $UW_{ud}$ | Unweighted-Undirected network |
| $V$ | Value added |
| $W_d$ | Weighted-Directed networks |
| $X$ | Total output of an industrial sector |
| $Z$ | Transaction Matrix |
| $\varepsilon$ | Scaling factor for Power-law distributions |

## PREFACE

I am deeply grateful to my advisor Vikas Khanna. It is an honor to be his first Ph.D. student. Collaborating with Dr. Khanna has been a great learning experience for me. I am indebted to him for providing me guidance throughout my research while making sure I had the space and freedom to exercise my creativity and implement my ideas. He has taught me, both consciously and unconsciously, the tenets of good research, and I am extremely thankful for that. I appreciate all his contributions of time, ideas, and funding to make my Ph.D. experience productive and stimulating. His enthusiasm for scientific exploration is contagious and inspirational for me, especially the times all is not going your way.

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# 1.0 INTRODUCTION

## 1.1 COMPLEX SYSTEMS: IMPERATIVE TO BUILD RESILIENCE

In a highly interconnected world, impacts from events are significantly amplified [1]. For example, impacts arising from natural disasters like Hurricane Katrina and Hurricane Sandy, infrastructure failures like the northeast blackout, epidemics like H1N1 influenza, terrorist attacks, and social unrests like the Arab spring have large consequences cutting across national and international boundaries [2-4]. Figure 1 shows the increasing trend of economic damages due to natural disasters over the years [5]. Isolated disasters within an interdependent system trigger a chain of events that amplify the direct and indirect impacts within the system. The Northeast Blackout of 2003 is a prime example of such cascading impacts where disruption on a single power plant resulted in an electric grid failure, which in turn affected communication, transportation and water supply infrastructure for 55 million people [6]. To minimize such cascading impacts [7], there is an urgent need to adopt a systems approach to comprehend complexity of engineered systems and its implications for resilience [8-10].

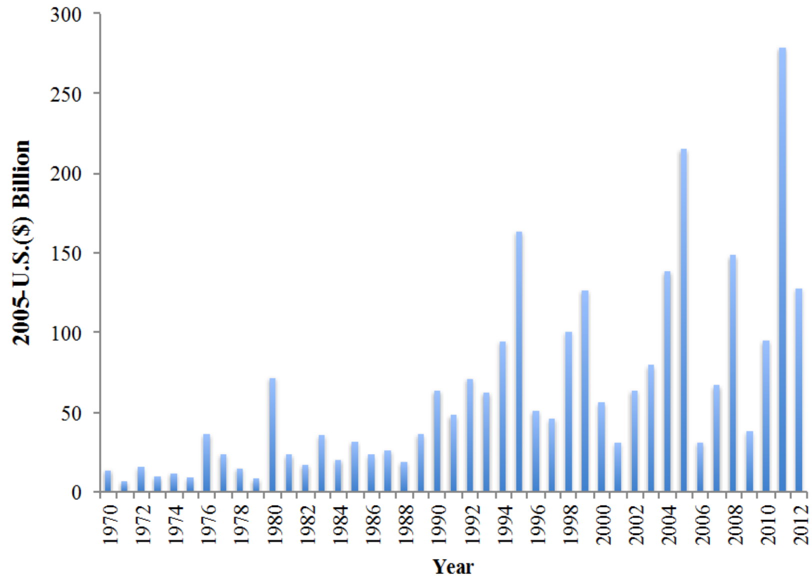


**Figure 1. Economic Impacts of Natural disasters in 2005-U.S. ($) Million from 1970 to 2012 [5].**

The recent increase in catastrophic disasters with large-scale cascading impacts indicates the increasing interdependence of engineered systems [11-13]. In order to develop engineered systems that are able to survive disasters without experiencing cascading failures, many researchers have advocated for a social-ecological approach. This approach considers engineered systems nested within ecological systems that are dynamically transforming in response to each other [14, 15]. Such a 'human-environment' systems approach allows engineers to design systems that are able to absorb unforeseen social and ecological stresses, and maintain their structure and function [16, 17]. This capacity of the system is commonly termed resilience [18, 19]. A system that structurally disintegrates and loses its functionality when it suffers a shock can hardly be called sustainable and resilient, even if it is highly eco-efficient with low resource intensity and emissions [20, 21]. Therefore, the solution to this "wicked problem" of designing sustainable complex systems relies on understanding fundamentals of resilience. This realization has triggered a considerable increase in research investigating resilience and has popularized the subject. Figure 2 illustrates the evolution in sustainability thinking.

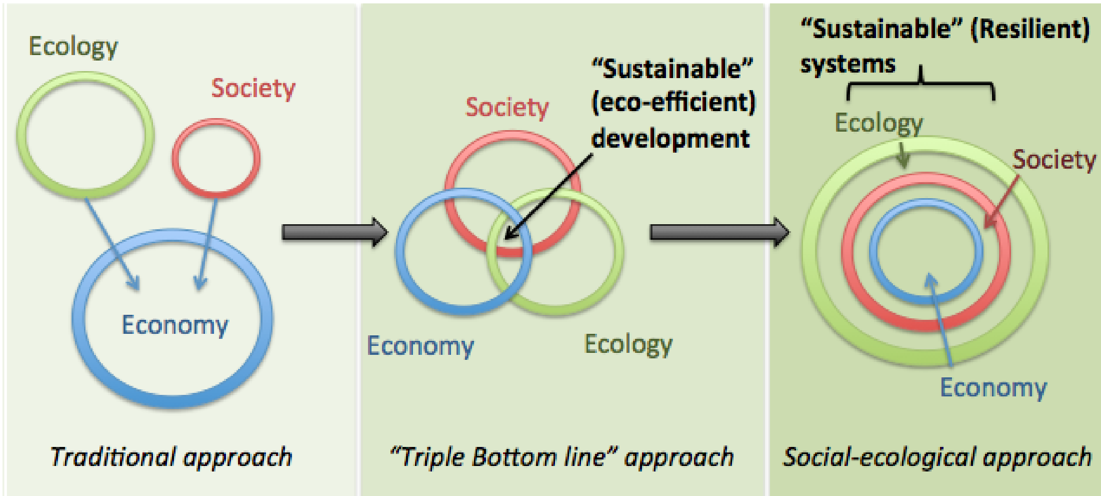


**Figure 2. Evolution of the perspective on sustainability.**

The concept of resilience is a complex one, and it is challenging to create metrics that measure resilience in a quantitatively rigorous manner [22, 23]. Bulk of the scientific literature on resilience assessment takes a qualitative approach in order to recommend design strategies that increase resilience [14, 24]. Yet such studies are unable to address the cyclical nature of tradeoffs between these recommended design strategies and resilience, for example- if one builds resilience principles such as redundancy and diversity, one is paradoxically increase complexity that in turn may impact resilience. On the other hand, studies that have developed quantitative frameworks to measure resilience for specific systems cannot be extended to other complex systems with different vulnerabilities and interconnections within and with other systems [25, 26]. There is an urgent need for a quantitative framework to understand resilience of complex systems with different system architectures and relationships between the interacting components [27].

## 1.2 RESILIENCE ASSESSMENT OF COMPLEX SYSTEMS: CASE STUDIES

There is no consensus on the definition of complex systems, but researchers agree that complex systems consist of interactions between many different components that adapt to the patterns created by these components [28, 29]. In order to study a representative sample of complex systems, distinct infrastructure and industrial systems are chosen as case studies. A graph theoretic framework is developed and applied to the following three distinct complex systems to understand and quantify their resilience: *the U.S. economic system*, *the Industrial symbiosis (IS) system at Kalundborg*, and *the London metro network*. Analysis of these three complex systems with varied scopes, system boundaries, relationships between the system components and overall network topologies will aid in developing the theoretical understanding of resilience.

The three case studies are selected not just for understanding fundamentals of resilience they provide, but also with the intention to recommend strategies to improve resilience of these systems. Although the three case studies at hand are considerably different, the aim is to understand their network architecture and its implications for resilience while remaining cognizant of their functionality. Previous studies have called for comprehensive resilience assessment of all three case studies, however a quantitatively rigorous is yet to be developed and applied to them. Application of this methodology has provided insights that can inform policy makers and decision maker, and arm them with data to take tough decisions.

*U.S. Economic Input-Output (EIO) Network:* The first case study aims to understand the network architecture of the U.S. EIO network, with focus on coupling of Critical Infrastructure Sectors (CIS), and its implication for the resilience of economic systems. The inherent complexity of the economic system causes a domino effect where stress on one sector directly and indirectly impacts multiple other sectors upstream and downstream in the supply chain. In an effort to mitigate the impact of natural and technological disasters on the nation's safety, prosperity and health, the recent U.S. Presidential Policy Directive (PPD 21) on *Critical Infrastructure Security and Resilience* establishes a national policy to manage risk and develop resilience of CIS [30]. In addition, it identifies 16 CIS whose incapacity due to hazards, ranging from natural disasters to cyber-attacks, would have a debilitating impact on the nation's security, economy, health and safety. Therefore, it signifies the importance of building resilient CIS for improving the overall resilience of the economic system. The U.S. economy exemplifies an excellent context to understand interdependencies, vulnerabilities, and resilience of large-scale complex systems.

*Industrial Symbiosis network:* The second case study focuses on understanding and designing heuristics to improve resilience of IS networks by identifying vulnerabilities and evaluating its evolution. IS networks comprise of industries with synergetic relationships, where one industries waste is another industries raw material [31]. IS networks are highly complex and resource efficient with substantial economic and environmental benefits for the participating industries. However, they are fragile because of the coupled nature of connections between the participating industries. A disturbance affecting even one industry can result in a complete breakdown of the IS system. For this reason, the focus is on understanding interconnections and vulnerabilities to build resilience in the IS system at Kalundborg (referred to as KIS), Denmark, which is one of the most studied eco-industrial parks. KIS is good proxy to study resilience of IS parks because of the large quantities of publicly data and research available on it, which is lacking for newer IS system that are mushrooming in newly industrialized countries like China and India, among others.

*London Metro network:* The third case study focuses on understanding the implications of spatial organization of a city and the network structure of its metro-rail system (also called metro system) for the resilience. Rapid urbanization in megacities, especially from developing countries, has boosted the demand for transportation, and further strained existing fragile transportation infrastructure like metro system. Moreover, spatial organization of megacities also impacts the performance of transportation systems. For this reason, metro network structure is examined to understand resilience of metro systems in polycentric cities by integrating graph theory approach with geospatial analysis. Specifically, the London Metro System (also known as the *Tube*) is studied since it is a good example of a large-scale metro network in a city with a polycentric spatial organization.

For each of these case studies, a systems framework is developed that primarily employs graph theory techniques to understand resilience of unique complex systems in a quantitative fashion. Since the resilience of a system is essentially a function of the vulnerability in the system, the graph theory framework developed considers vulnerability at both the level of the individual system components and the overall system level.

## 1.3 RESEARCH OBJECTIVES

The core goal of this research was to develop a graph theoretic framework to elucidate attributes of network structures that aid in building resilience, and subsequently, formulate design strategies that bolster resilience in new and pre-existing complex systems. Three case studies were used to understand the resilience of complex systems: 1) CIS in the 2007 U.S. Economic Input-Output (IO) network, 2) IS network at Kalundborg, Denmark, and 3) London Metro-rail infrastructure network, UK. This approach combined the use of relevant biophysical data, for instance-- economic flows between industries for case study 1, water exchange between industries in case study 2, and passenger flow between stations in case study 3, with graph theory based tools and techniques to advance resilience in built environment systems. The research spanned multiple case studies, each of which provided key insights for developing strategies specific to the system type with the graph theoretic framework. The overall objectives were to:

1. Model interdependencies and interconnectedness of CIS in the U.S economy to understand its implications on resilience of economic systems by integrating graph theory based analysis of complex networks with the *2007 U.S. IO Benchmark model*. (Chapter 3)
2. Determine vulnerabilities and evaluate the evolution of the KIS network to understand its resilience by integrating the concepts of graph theory with biophysical information about symbiotic resource flows. (Chapter 4)
3. Analyze the network topology of the London metro system by graph theory based techniques to identify specific network properties that would improve resilience of metro systems in polycentric urban regions. (Chapter 5)
4. Assess and compare network properties essential for resilience building ascertained from the analysis of the distinct complex systems in the case studies. (Chapter 6)

## 1.4 INTELLECTUAL MERIT

This research has led to creation of a novel quantitative framework that integrates graph theoretic modeling approaches with other mathematical models for understanding resilience of a complex system. This hybrid resilience framework provides a holistic perspective to understand and propose data-driven recommendations to strengthen resilience of large-scale engineered systems, which is especially necessary for disaster preparedness and pre-hazard planning of new and existing interdependent infrastructures. In addition to its ability to explore resilience of infrastructure systems through a social-ecological approach, this framework can be extended to develop computational and visualization tools for specific infrastructure projects and sectors.

The aim of this research is to fill fundamental research gaps regarding resilience within the sustainability literature. The quantitatively rigorous approach developed in this research is useful for providing necessary insights to policy makers and stakeholders for building resilience. Moreover, this research has resulted in creation of system-specific metrics that identify and rank system components whose disruption have the greatest impact on the entire structure and function of the system. This information is particularly useful when it comes to design and development of effective disaster preparedness and infrastructure protection plans. Application of this approach on individual case studies has been particularly insightful for understanding that there is no universal theory of resilience, and resilience strategies significantly differ for distinct complex systems.

## 1.5 BROADER IMPACTS

With growing concerns over global environmental change that have prompted strict directives from international, national and local governing agencies to reduce emissions and resource consumption, there is an unprecedented amount of urgency to understand network architecture of resilient complex systems. This work impacts the broad academic community and aids policymakers in developing informed systemic interventions at several levels. This work takes the form of three peer-reviewed articles that are at various stages of publication during the final writing herein:

1. Understanding Resilience in Industrial Symbiosis Networks: Insights from Network Analysis, **Journal of Environmental Management,** 2014. [32]
2. Interconnectedness and Interdependencies of Critical Infrastructures in the U.S. Economy: Implications for Resilience, **Physica A: Statistical Mechanics and its Applications**, 2015. Accepted
3. Exploring Resilience of the London Metro-rail system using Graph Theoretic Approaches, **Scientific Reports**, 2014. To be submitted.

## 1.6 DOCUMENT STRUCTURE

The background of the work, including a detailed review of prior research in the area is presented in Chapter 2. Chapter 3, 4 and 5 focus on addressing the specific objectives. Chapter 3 presents the background, methodology and results for the case study on critical infrastructure sectors in the U.S economy. Chapter 4 presents the background, methodology and results for the case study on the Kalundborg Industrial Symbiosis network in Denmark. Chapter 5 presents the background, methodology and results for understanding the resilience of the London metro system.

The overall implications of this work, as well as prospects for future work, are discussed in Chapter 6. Collected data and supporting information are available in the Appendices, with Appendix A providing data and assumptions for case study on the U.S. economy, Appendix B providing detailed information regarding the network analysis of the Kalundborg Industrial Symbiosis network, and Appendix C providing additional information for London Metro system case study.

## 2.0 BACKGROUND AND LITERATURE REVIEW

### 2.1 DEFINING RESILIENCE OF COMPLEX SYSTEMS

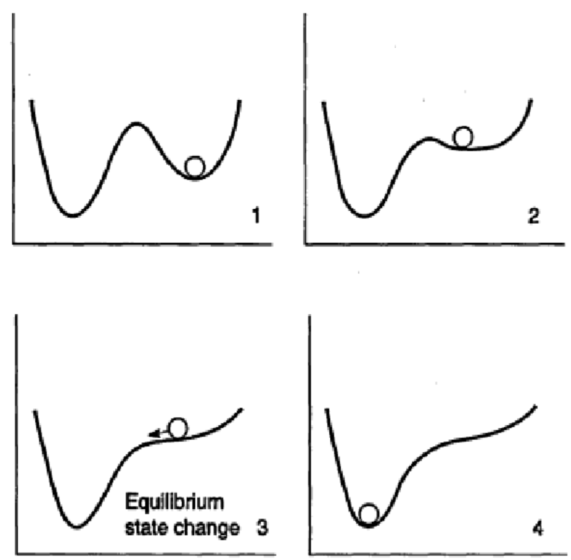


**Figure 3. Ball and trough representation of a system [19].**

The system modifies its equilibrium state as it goes from 1-4. System in snapshot 1 is resilient to changes, but in snapshots 2 and 3 it loses resilience, where even a small perturbation can change the state of the system.

Resilience in complex systems is examined differently on the basis of the assumption regarding the presence of single or multiple equilibrium states in the system [19]. Just as noted in the differing perceptions of sustainability, one definition of resilience aims at stability of a system by promoting efficiency, constancy and predictability, features desired by engineers to design fail-safe systems [19]. These systems are designed to have stability near a single equilibrium state, and resilience is measured in terms of how quickly the system returns to its steady state after it is perturbed to move away from the equilibrium [19]. For instance, an assembly line of a car is designed to have a single steady state. If the linear design of the system aimed to provide maximum efficiency breaks down, resilience of the assembly line will be measured in terms of the time taken for it to recover its functionality [26]. This type of resilience is known as the *engineering resilience*.

On the other hand, the second type of resilience called *ecological resilience* describes the behavior of dynamic systems by emphasizing persistence, change and unpredictability, features essential to design safe-to-fail systems [19]. Thus, contrary to engineering resilience, ecological resilience considers multiple equilibrium states as illustrated in Fig 3, and is defined as the magnitude of stress a system can experience and absorb before it moves to another equilibrium state [19]. Ecological systems are able to cope with stresses because of their robustness, similarly social systems are also able to cope and persist with change when considered in isolation. However, in reality these social and ecological systems are coupled, and dynamically interwoven with each other [26]. A disruption on either of these coupled complex systems can cascade to the other system, and trigger a change in its equilibrium state. Thus, one needs to look beyond robustness against known stresses [11], and develop the ability to adapt and self-organize in the face of unknown stresses [33]. The capability of the system to absorb disruptions while maintaining the structure, function and control components is the widely accepted definition of resilience, and is also known as the *social-ecological resilience* [13]. To arm decision makers with information on design of resilient, sustainable complex systems, it is essential to identify structural properties that are responsible for resilience using empirical data [34].

## 2.2 RESILIENCE: RELATION TO SUSTAINABILITY

To understand the relevance of resilience in the context of sustainability it is necessary to discuss the predominantly accepted definition of resilience. Resilience is frequently described as the capability of any system to absorb disruptions while maintaining its structure and function [15, 20, 21, 35, 36]. It is the adaptability and plasticity of the system in response to stresses [15], irrespective of whether they arise endogenous or exogenous to the system. Thus, a resilient system is able to maintain its functionality by modifying its structure in response to stress. On the other hand, a system that is unable to maintain its structural cohesion when under stress, can hardly be sustainable [20, 21]. Therefore, the solution to the “wicked problem” of designing sustainable complex systems appertains to understanding the fundamentals of resilience.

Even though consensus has reached on the significance of resilience to develop sustainability, there still exists difference in opinion regarding the influence these two concepts have on each other [13, 33, 37]. This disagreement is embedded in the definition of sustainability used. An accounting perspective on sustainability is synonymous to efficiency; where biophysical approaches such as life-cycle assessment (LCA), material flow analysis (MFA), etc. assess the impact in terms of consumption of natural resources or pollution prevention [35]. This approach on sustainability has resulted in studies arguing that resilience is either not an important feature of the system, or it is one of many responsible for sustainability [38]. On the other hand, others aspire to move away from the simple cause-effect relationship assumed by the accounting approach, and understand sustainability with respect to the system-wide interactions that result in complex dynamics [35]. Researchers applying a systems approach to sustainability either endorse resilience as a prerequisite for sustainability or consider them interchangeable [21, 39, 40]. However, attempts are being made to integrate these differing perspectives on sustainability assessment by building models of complex systems using their biophysical information like network environ analysis (NEA) [20, 41]. Such research ventures focused on understanding the nature of resilience of complex adaptive systems for the purpose of furthering sustainability are paramount.

## 2.3 ILLUSTRATING COMPLEX SYSTEMS AS NETWORKS

Lately, many fields of research are using complex networks to explore real-world systems such as life sciences- brain network [42], genome [43]; engineering- air transport network [44], power grid [45]; social sciences- twitter network [46]; and computer science- world wide web [47], to name a few. Many real-world systems have been described as models of complex networks, where *nodes* or *vertices* are system components connected by *links* or *edges* that are interactions between them, to understand the impact of network structure on the network dynamical behavior. Representing systems as networks not only allows visualization of the system, but also allows analysis of the structure of the system by using fundamentals from statistics and graph theory [48], which is required to study emergent properties like resilience and has been neglected in the studies of traditional disciplines (Figure 4).

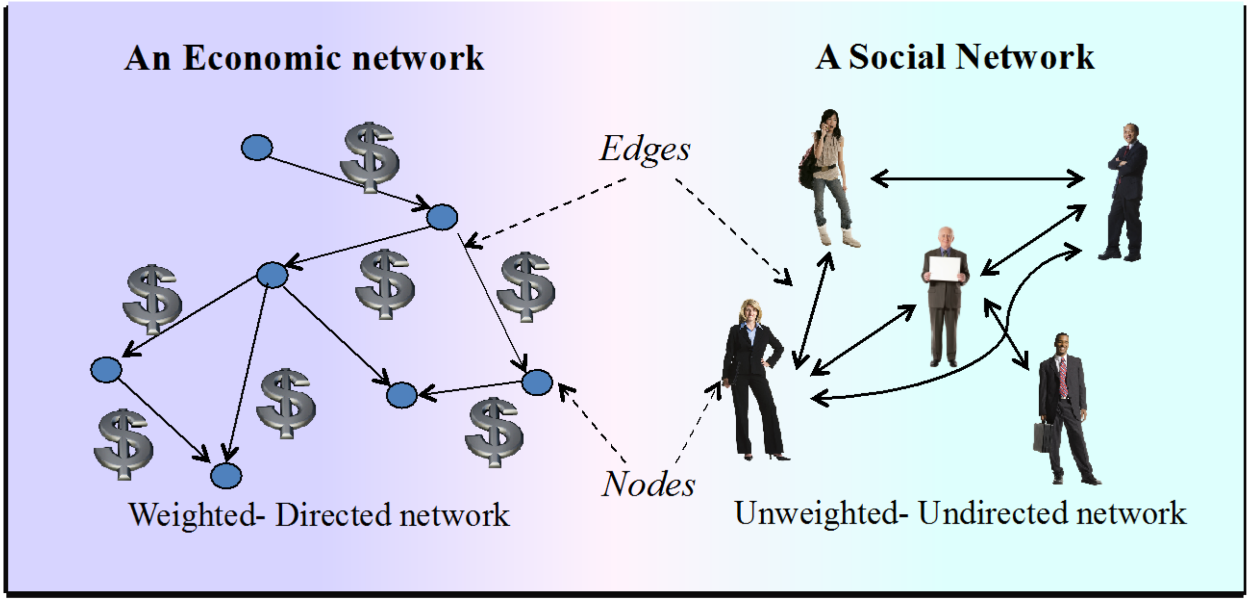


**Figure 4. Illustrating Complex Systems as Networks.**

Networks have often been used to model complex systems to visualize interactions between various components and study emergent properties.

Growth of computerization has played a significant role in the emergence of complex networks. Prior to the age of computerization, analysis of complex topology was restricted to Erdös-Rényi (ER) random networks [48]. In 1950s Erdös and Rényi, mathematicians and founder of random graph theory, described a network with complex topology using a random graph [49]. Yet, due to lack of super-computational power and detailed topological information about large-scale real-world systems there was a period of lull in the field [50]. However, the emergence of big data analysis caused by increased computing power and computerization of data acquisition has stimulated widespread interest in identifying properties associated with different types of complex networks. This led to the discoveries of the *small-world* effect and the *scale free* network, which has shed light on the topological properties of many complex networks.

Development of the *small-world* effect and the *scale-free* network topology has led to considerable advances in the field of graph theory. Watts and Strogatz introduced the concept of *small-world* effect in 1998 [51]. This concept gets its name from the common phrase "What a small world!" often used by strangers when they meet for the first time, but happen to have a common friend. Analogously, in a *small-world* network, nodes are not connected directly to each other but most nodes can be reached indirectly from all other nodes by a small number of steps [50]. Which implies that each node has about the same number of connections, and as a consequence the connectivity or degree distribution peaks at an average value and decays exponentially. Thus, making it a homogenous network. Most social networks exhibit properties of *small-world* networks, but others like the brain network [52], network of cortical neurons [53], information systems [54] are few examples of *small-world* networks from literature. The specifics regarding properties of *small-world* networks are discussed in chapters 4 and 5.

Many real world networks have also been identified with the *scale-free* topology. Connectivity or degree distributions for networks with scale free topologies follow a power-law form, irrespective of their size [48]. Power-law implies that most nodes in the network have very few connections with other nodes, while a handful of nodes have many connections in the network. Thus, a scale-free network topology is non-homogenous since all nodes do not have the same number of connections [50]. Moreover, Barabasi and Albert framed '*the rich get richer*' model to propose that *scale-free* networks are self-organizing in nature [55, 56]. Since, most real networks are dynamically growing by addition of new nodes, in a *scale-free* network these new nodes preferentially attach to existing nodes with large number of connections [55]. Implications of degree distribution following a power law are discussed in chapters 4 and 5.

In addition, topological properties of systems can be generalized and compared on the basis of the difference in their network structures [51, 57, 58]. Recent studies have attempted to understand the contribution of network structure for robustness to identify the innate systemic vulnerability due to the pattern of interactions [1, 59]. For instance, a network with a scale-free topology tends to be robust to random failures/removal of nodes, however it is vulnerable to targeted attacks on the network [57]. If a network is unable to adapt to a shock that ultimately renders it dysfunctional, then the system is not resilient. Thus, identifying structural properties that reduce systemic vulnerabilities are key for understanding resilience and moreover, designing for resilience.

Network analysis employs methods and metrics such as centrality and connectivity indices to understand the network structure and the underlying complex set of relationships among the nodes [60]. Since these metrics are able to quantify emergent properties of complex systems, network analysis provides good indicators for resilience assessment. However, it is noted that interpretation of these network metrics are context dependent [61]. Therefore, increase in connectivity might improve resilience for one system, but might decrease resilience for another scenario. Application of network analysis for understanding resilience of complex adaptive systems is at its initial stage [61, 62], but an increase is expected with progress in collection and availability of empirical data means greater model accuracy in the future.

The three networks used as case studies represent diverse strains of complex systems with differing scales of magnitude and the relationship between interacting system components. At the national scale, the connectedness of the U.S economic network is examined to ascertain systemic vulnerability of CIS, while at a regional scale, the fragility of ad hoc IS networks are studied. Likewise, the investigation of urban transportation system further provides a unique spatial perspective on resilience. In addition, urban metro/subway transit networks are a part of the economic transportation sector, which is one of the CIS in the economy.

## 2.4 BACKGROUND: COMPLEX SYSTEMS USED AS CASE STUDIES

Background and Motivation for selecting the three complex systems as case studies to assess resilience based on graph theoretic approaches is discussed next.

### 2.4.1 Case Study 1: Critical Infrastructure sectors in the U.S. Economy

Infrastructure assets, systems and networks that provide essential services and form the nation's backbone are referred to as CIS. The U.S. Department of Homeland Security (DHS) identifies 16 CIS whose incapacity due to hazards, ranging from natural disasters to cyber-attacks, would have a debilitating impact on the nation's security, economy, health and safety [63]. The recent U.S. PPD 21 on *Critical Infrastructure Security and Resilience* recommends steps to manage risk and strengthen the security and resilience of CIS [30]. While the definition for resilience may vary across disciplines and systems, the PPD defines CIS resilience as "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions". This report highlights the importance of building resilient CIS for improving the overall resilience of the economic system.

According to a National Research Council report, natural disasters affecting the U.S. in 2011 alone yielded close to $55 billion in economic damages [18]. The historical data on economic impacts of natural disasters worldwide exhibits an upward trend (illustrated in Figure

1), suggesting that this number will continue to soar [5]. Cascading impacts arising from increasing number of natural, man-made and technological disasters may continue to rise as complexity grows. There is an urgent need to identify, understand and analyze functional interdependencies and structural vulnerabilities in economic systems [3, 64-67].

#### 2.4.1.1 Modeling Critical Infrastructure Interdependencies

Many researchers have devoted themselves to the challenging task of modeling and simulating interconnectedness and interdependencies of complex CIS. They have indicated that before modeling interdependencies between CIS, it is necessary to identify and characterize the nature of their interactions. Zimmerman categorizes interdependencies as *functional* and *spatial* [68]. Functional interdependencies refer to situations in which infrastructure systems are dependent on one another for their operation (e.g. the functioning of the railroad system is dependent on communication systems). Spatial interdependencies occur due to geographic proximity of infrastructures (e.g. underground collocated lines of telecommunication, power, water, and sewage infrastructures can affect one another.). Zimmerman's functional interdependencies broadly encompass the following classes of interdependencies categorized by Rinaldi: *physical interdependencies*, i.e. based on infrastructure outputs; *cyber interdependencies*; and *logical interdependencies*, such as banking, taxation, etc. [68, 69]. There are additional interdependencies types defined by other researchers [70-73]; however, the classification of interdependencies based on Rinaldi and Zimmerman are quite comprehensive. Also, while modeling spatial interdependencies between various CIS is equally essential, such a study must be done at a regional level with high-resolution data.

Some studies have utilized empirical approaches to analyze interdependencies among CIS based on data from incident records (media reports, newspapers, official ex post assessment, etc. to quantify societal impacts caused by cascading failures [74-81]. Others have used agent based and system dynamics based approaches to model interdependencies among CIS as complex adaptive systems (CAS) that are able to handle the inherent complex behavior of CIS [82]. Some tools based on ABM and SD models include Aspen, Aspen-EE, CommAspen, and N-ABLE developed by Sandia National Laboratories [83-89]. While the aforementioned methods have been extensively applied to understand the structure and behavior of CIS per se, researchers have not explored the possibility of using these methods for understanding the implications of CIS interdependencies on resilience of economic systems. Also, the above-mentioned methodology is restrictive because of the lack of CIS-related data, which hampers calibration of model parameters and functions, and inhibits validation of results. [90].

Among approaches used to model CIS interdependencies, graph theory based approaches are one of the most frequently employed techniques to understand and quantify the coupling phenomena between different infrastructures as a set of nodes linked by edges [72, 91, 92]. Graph theory has proven useful for both providing topological understanding of CIS connectedness using graph level metrics and statistics, as well as for identifying individual infrastructure vulnerabilities based on node level metrics [92]. EIO models have also been used to model CIS interdependencies based on empirical economic data and understand the complex nature of economic relations between them [93, 94]. EIO models have been successfully used to analyze the impact of various disruptive events. Some examples include simulating the impact of terrorist attacks on Virginia's interdependent transportation systems [95], the impact of high-altitude electromagnetic pulse attack on different economic sectors [93], the reduction in demand of air transportation after terrorist attacks [96], the impact of the 2003 Northeast Blackout [97], the impact of hurricane Katrina on power transmission and telecommunication systems [98], the economic impact of cyber-attacks on oil and gas sector [99], and the economic impact of Peak-oil-induced increase in oil prices [100]. While EIO models have certain inherent limitations such as their linear nature and rigid structure, researchers argue that strengths of EIO models for assessing higher-order impacts of disruptions and ranking vulnerable interdependent infrastructure sectors outweigh their weaknesses [101, 102]. EIO models are particularly well suited for modeling infrastructure interdependencies as they are based on observed empirical data [73, 90, 103-105]. While these studies are able to determine cascading impacts and systemic vulnerabilities, more attention is needed to develop design strategies for improving resilience based on topological properties of infrastructure networks [106].

#### 2.4.1.2 Integrating Graph Theoretic Approaches with EIO data

Recent studies have used IO data for national economies to analyze the overall economic structure using graph theory tools and techniques [107]. The available IO data on different countries have different levels of aggregation. For example, the U.S. IO network is divided into approximately 400 industrial sectors, while structured analysis (STAN) data provided by OECD comprises of merely 39 sectors. This is very important, because the analysis of IO data of the same country but with different levels of aggregation can lead to different conclusions, and models based on the more aggregated data has less predictive capability. For instance, studies that have assessed degree distributions of detailed U.S IO networks for different time periods have consistently concluded that connectivity of industrial sectors follow a power law [108, 109], on the other hand McNerney's study that utilizes coarser IO data compiled by OECD does not exhibit the same behavior [110]. Therefore, for credible modeling of cascading impacts and analysis of network structures it is necessary to use the highest resolution IO data available for the country's economy.

Xu and colleagues attempted to understand the interconnectedness of economic sectors and its implication on the functionality and resilience based on the impact of shocks on the U.S. economic IO tables [108]. Following their lead, Han and Goetz explored economic complexity of local economies of U.S. counties to predict resilience [109]. Studies focusing on cross-country comparison of network structure have used aggregated IO tables. McNerney, Fath and Silverberg compared the topology of industrial networks for twenty OECD nations in terms of their node and link size distributions and community structure, and found similar underlying network structures for most economies [110]. Contreras and Fagiolo [111] analyzed how shocks propagate in twenty two European economies based on aggregated IO data sets from Eurostat. Indeed, focus of researchers on robustness to estimate dependencies among industrial sectors of economic networks has helped understand resilience. However much work is still required to understand the nature and extent of interdependencies between specific CIS that amplify impacts caused due to perturbations, and its influence on economic resilience.

The definition of social-ecological resilience-- the ability to absorb shocks by adapting and re-organizing for maintaining its structure, function and control components of the system, is applicable to economic systems as well. In economic systems, adaptation and re-organization follow a number of recovery patterns shaped by exogenous forces like the markets or novel technological innovations, which are extremely difficult to model or predict. For this reason, resilience of economic networks tends to focus on the ability of the system to resist changes to its structure and remain at its equilibrium state during the initial decline, rather than recovery process. The understanding behind this is that an economic system whose network structure causes greater cascading impacts is less resilient. Also, an economic system with a network structure that experiences smaller cascading impacts makes a faster recovery, and thus is more resilient. Thus, identifying structural properties to reduce cascading impacts is a key for understanding resilience and moreover, designing for resilience.

The focus is on understanding the implications of CIS interdependencies on resilience of economic systems. To accomplish this, a systems approach is adopted that combines the empirical economic input-output (EIO) data with graph theory based tools and techniques for industry-level interdependency analysis to advance our understanding of resilience in economic systems. This research is absolutely pivotal for understanding the network structure and system properties that decrease systemic vulnerability by reducing the cascading impacts propagating throughout the system, and ultimately build resilience of economic networks.

### 2.4.2 Case Study 2: Industrial Symbiosis at Kalundborg, Denmark

Recently, there has been a revival of interest in Industrial Symbiosis, or IS, – a mutually beneficial relationship between industries that achieve productive use of waste and by-products – due to its growing appreciation among policy makers for its ability to improve economic and environmental issues, that consequently promotes sustainable development [112]. IS is being pursued in both developing and developed countries of the world for stimulating sustainable development from a local to a global scale. A recent publication *The Roadmap for a Resource Efficient Europe* supports and encourages IS for maximizing resource consumption by all EU member countries, and is a core economic directive for the future. Likewise, Organization for Economic Cooperation and Development (OECD) recognizes IS as a tool for furthering green growth and eco-innovation, and recommends its application [113-114]. Asian economies such as China and India have been extensively implementing Eco-Industrial Parks (EIPs) [115-117]. Especially China has developed the largest EIP network by incorporating 15 National

Demonstration EIPs and 45 National Trial EIPs [115]. Thus, such widespread utilization and furtherance of IS by most economies in the world has engendered a demand for developing a sound theoretical framework of IS.

#### 2.4.2.1 Previous Research on Industrial Symbiosis parks

Studies on foundations of IS have been performed since the early nineties; however, increasing waste disposal costs, environmental degradation and raw material scarcities have led to mounting interest in sustainable development in recent years. Much research has been carried out on genesis and evolution of IS networks [118], redefining the IS system and its system boundaries [112], and impacts of implementing IS networks [119] [115]. Moreover, other works have attempted to correlate social factors and performance of the IS system itself by looking at the coordination and organization of the actors and the information available to them for initiating synergies [120] [117] [116].

One of the oldest known examples of IS is the eco-industrial park in Kalundborg, Denmark. Industrial symbiosis at Kalundborg (KIS) creates an exchange network of waste, water and energy among companies based on contractual dependency. KIS began in the early 1960s and is one of the oldest known IS networks. It originated with a strategy to reduce exploitation of groundwater in the face of growing groundwater deficit in the area and increasing water demand by the industries; subsequently, it has developed from a water exchange network to a network with more than 20 different by-product synergies [121, 122].

In accordance with the definition of IS, the synergistic flow of by-product and waste streams between the power plant, the oil refinery, the district municipality, and other industries in the region of Kalundborg has not only led to an increase in the resource efficiency but also in the economic gains of the participating industries. Although such IS systems are efficient, complex networks, a disturbance at even one industry may lead to a domino effect and cascading impacts on the rest of the network. Additionally, since most of the exchanges were established because of social interactions between managers and owners of industries at Kalundborg [123] [31], the network is not strategically planned and coincidental in nature which makes it vulnerable to unforeseen and catastrophic events. Several studies exist in the literature that focuses on the application of industrial ecology concepts to quantify resource savings and emissions reduction at the KIS network [31, 123] [121]. However, none of these studies have focused on examining the resilience of the highly interconnected and symbiotic industrial network in a rigorous quantitative manner. Resilience is the capability of the system to absorb disruptions before it changes its properties that controls its functionality. This property allows an IS network to endure the impact of unforeseen events [20].

#### 2.4.2.2 Modeling Industrial Symbiosis parks as Networks

IS systems demonstrate self-organizing capability, similar to complex adaptive systems like natural ecosystems, to maintain their functionality to counter stresses [124]. Understanding resilience of such complex networks will aid in assessing the capacity of the system to retain its function by maintaining its structure while under stress [21]. However, there is a notable disparity in the understanding of resilience in the context of engineered systems. It has been argued that a close relationship exists between resilience and sustainability where the former concept is a prerequisite for the latter [21, 39, 40]. On the other hand, some researchers consider resilience equivalent to sustainability [15, 40, 125] and while a few others consider resilience inadequate for attaining sustainability in specific instances [15, 38]. However, among all the uncertainty surrounding the relationship between resilience and sustainability, the need for developing resilient and efficient IS networks for improving sustainability, is a certainty.

There also exists a rich body of literature in the area of network analysis. For example, concepts of Social Network Analysis have been employed to determine the morphology of KIS [126]. Network Environ Analysis (NEA), a system-oriented modeling tool that examines the structure and flows of materials in an ecosystem has also been used for Ecological Risk Assessment studies for prediction of possible ecological impacts arising from stresses on the system [127]. However, there has been little to no emphasis on applying the concepts of network analysis for understanding resilience. A simple cause-effect type of computation among the actors may neglect the information of indirect effects and system-wide properties arising due to the interactions [127] that will be assessed through a systems approach. Thus, a network perspective is useful for developing in-depth understanding and plugging gaps in the foundations of IS studies.

This work attempts to bridge the gap between IS networks and their ability to cope with disruptions by adopting a networks approach. The 2002 snapshot of the water synergy network at Kalundborg is extensively used to reveal industries with the highest vulnerability, using network metrics like centrality indices and network efficiency, to design resilient IS systems for the future. The present work aims to deliberate on a universal theoretical framework for the advancement of resilient IS networks.

### 2.4.3 Case Study 3: Transportation Infrastructure systems: Urban Metro systems

Urban metro transit systems have greatly benefitted metropolitan areas in the past, both economically and environmentally, and will play an even more important role with the growth of megacities (cities with population of over 10 million) around the world. Cities account for no more than 1% of the Earth’s surface area, yet consume 75% of its natural resources and occupy over 50% of the global population [128, 129]. Further, increasing trends of urbanization and changing spatial organization of cities point towards challenges for the urban ecosystem that are accompanied with growing dependence on an urban lifestyle [128, 130, 131]. There is a great necessity for creating sustainable and resilient urban infrastructures that are capable of supporting large percentages of the globe's population.

Public transportation infrastructure including metro systems have known to impact the economy through direct impacts such as direct cost savings for businesses and households due to reduced traffic congestion and shift in consumer spending due to cost savings for public transportation passengers, that indirectly encourage regional business growth [132]. In addition, environmental benefits of shifting urban travelers from privately owned vehicles to metro rail transportation are straightforward. Urban metro transit systems are successful in reducing traffic-generated emissions of greenhouse gases caused by combustion of fossil fuels [133]. However, by 2050, it is estimated that two-thirds of the world's population will live in urban areas. Such rapid urbanization tends to exert pressure on urban infrastructure and services that have not been able to grow at the same rate to support the increasing population [134]. Transportation infrastructure in megacities, especially in developing countries, is extremely vulnerable to congestion derived infrastructure stresses and environmental challenges. For this reason, the development of resilient transit systems is crucial for long term sustainability of megacities in the future [135].

#### 2.4.3.1 Analyzing Large-scale Transportation systems via Graph theoretic approaches

Graph theory has been extensively used for the investigation of transport networks. Road transport systems were the first to be researched with a graph theory approach mainly combined with an economic approach to assess the regional economic impacts of the US interstate highway system and various freeways built in cities in the 1960s and 70s, prior to the era of computerization [136]. In this era, Garrison and Marble[137-139], and Kansky [140] pioneered the use of graph theory by creating specific indicators to analyze road transport networks. Recently there has been a return of graph theory for the study of road networks [141], with studies creating new indicators to measure properties of road transportation networks [142], understanding their robustness [143], and studying the impact of their network structure on travel distance, trip assignment and even mode choice [144]. A graph theoretic approach was not applied to public transportation networks until the 1980s [136]. Lam and Schuler [145] were the first to apply graph theory to public networks, but Vuchic and Musso [146] made the most significant contribution by creating network indicators specific for public transit systems such as directness of service, average inter-station spacing and line overlapping [133, 147].

Over the last 15 years, significant progress has been made in supplementing the quantification of reliability and robustness within large-scale transportation systems, and network analysis has emerged as the tool of choice [143, 146, 148]. Application of network analysis to metro systems has enabled quantification of topological properties that influence its resilience, as has been the case for complex systems in economics (trade networks, etc.) and engineering (electric grid, etc.), among others. Using network analysis, Latora and Marchiori identified the *small-world property* of the Boston transportation system, suggesting that the topology of the transportation network enmeshes desirable levels of interconnectivity and redundancy [54]. Previous studies have also adopted a networks approach to comprehensively compare various metro systems across the globe based on new network indicators [148-151]. Derrible and Kennedy applied new and existing metrics to make more decisive claims about the organization of the network that directly relate to the robustness, resilience and efficiency of metro systems [148]. Ip and Wang also developed quantitative measures for resilience and friability of cities in the mainland China railway network [152]. Most of the above mentioned studies attempt to understand and identify network properties that influence reliability and robustness of metro systems based on its topology and geographic location. These studies have been unable to incorporate urban dynamics in terms of passenger flow patterns in these network models of metro systems to develop a comprehensive understanding of its resilience.

For this reason, a novel graph theoretic approach is utilized to quantitatively assess the influence of the network structure, the spatial locations of specific network components, as well as the patterns of intra-urban movement, on the resilience of metro-rail infrastructure. Specifically, the comprehensive *London underground* metro system is examined as a case study for our analysis.

# 3.0 INTERCONNECTEDNESS AND INTERDEPENDENCIES OF CRITICAL INFRASTRUCTURE IN THE U.S. ECONOMY: IMPLICATIONS FOR RESILIENCE

The following chapter is based on an article accepted in *Physica A: Statistical Mechanics and its Applications* with the citation:

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The chapter combines the manuscript and supporting information currently in print with *Physica A: Statistical Mechanics and its Applications.* Additionally, extraneous supporting information submitted with the manuscript appears in Appendix A.

## 3.1 INTRODUCTION

Modern society is critically dependent on the stability and performance of complex infrastructure networks for almost every social and economic function. Infrastructure assets, systems and networks that provide essential services and form the nation's backbone are referred to as critical infrastructure sectors, or CIS. DHS identifies a list of 16 CIS whose incapacity due to hazards, ranging from natural disasters to cyber-attacks, would have a debilitating impact on the nation's security, economy, health and safety [63]. The far-reaching importance of CIS is a result of increasing interconnectedness between them (as is the case with energy supply, telecommunications and transportation), which may result in unpredictable consequences and risks. Additionally, individual industry sectors in an economic system are inherently interdependent and interconnected, and disruption on any single sector can trigger a ripple throughout the economy affecting sectors that are directly and indirectly interacting with the triggering sector [69].

In recent times, impacts arising from natural disasters like Hurricanes Katrina and Sandy, infrastructure failures like the Northeast blackout, epidemics like the H1N1 influenza, terrorist attacks like the 9/11, and social unrests like the Arab Spring have had large consequences across national and international boundaries [2-4]. Impacts from these events have been significantly amplified because of the interdependencies and feedback mechanisms between our society, the environment and the CIS [1]. According to a National Research Council report, natural disasters affecting the U.S. in 2011 alone yielded close to $55 billion in economic damages [18]. The historical data on economic impacts of natural disasters worldwide exhibits an upward trend, suggesting that this number will continue to soar [5]. Cascading impacts arising from increasing number of natural, man-made and technological disasters may continue to rise as complexity grows. There is an urgent need to identify, understand and analyze functional interdependencies and structural vulnerabilities in economic systems [3, 64-67].

The recent PPD 21 on *Critical Infrastructure Security and Resilience* recommends steps to manage risk and strengthen the security and resilience of CIS [30]. While the definition for resilience may vary across disciplines and systems, the PPD defines CIS resilience as “the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions”. This report highlights the importance of building resilient CIS for improving the overall resilience of the economic system.

Economies are self-organizing, complex systems comprised of industrial sectors, firms, and consumers that interact with and react to one another [28]. Resilience for economic systems has been previously defined in terms of its structural robustness as the ability to maintain its functionality in response to disruptions [36, 108]. Based on this definition, key sectors/hubs for the economic system are identified that are a source of vulnerability to comment on its resilience. However, previous studies stop short of assessing the subsequent cascading impacts on rest of the sectors resulting from a disruption on one of these key sectors. To address this issue, the concept of ecological resilience is adapted to define resilience of complex industrial and infrastructure systems as their ability to resist structural and functional change, and minimize deviation from its original state during initial decline after disruption [19, 20, 32]. As per this definition, an economic system is not considered resilient if it suffers large cascading impacts because of its topology, which is governed by the patterns of interconnectedness and interdependencies between industrial sectors.

Previous work has focused on the challenging task of characterizing, modeling, and simulating interconnectedness and interdependencies of complex CIS. Zimmerman categorizes infrastructure interdependencies as *functional* or *spatial* [68]. *Functional interdependencies* are those in which infrastructure systems are dependent on one another for their operation (e.g. the functioning of the railroad system is dependent on communication systems). *Spatial interdependencies* occur due to geographic proximity of infrastructures (e.g. underground collocated lines of telecommunication, power, water, and sewage infrastructures can affect one another). While modeling spatial interdependencies between various CIS is equally essential, such a study must be done at a regional level with high-resolution data. The focus is restricted to understanding and quantifying functional interdependencies between CIS and other industry sectors.

Previous work has focused on utilizing empirical approaches based on data from incident records (media reports, newspapers, official ex post assessment, etc.) to quantify CIS interdependencies [8, 74-81]. Other modeling and simulation techniques such as agent based modeling (ABM) and system dynamics (SD) have also been employed to model interdependencies and complex adaptive behavior of CIS [82]. Some tools based on ABM and SD models include Aspen, Aspen-EE, CommAspen, and N-ABLE developed by Sandia National Laboratories [83-85, 87, 89, 153]. While the above-mentioned methodologies are valuable, their application is restrictive because lack of CIS-related data hampers calibration of model parameters and functions, and inhibits validation of results [90].

An attractive and alternative method for modeling CIS interdependencies is via the use of EIO model, originally developed by Nobel laureate Wassily Leontief. Unlike other methodologies the EIO model is based on comprehensive empirical data published by national and international agencies such as Bureau of Economic Analysis (BEA) in the U.S. and Organization for Economic Co-operation and Development (OECD) globally. The EIO model divides the economy of a particular region into industries or sectors and tracks the monetary transactions between them. It is a static and linear model of all purchases and sales between economic sectors for a specific time period based on the technological recipe of production. EIO models are useful for modeling short-term cascading impacts caused by perturbations on the interconnected industry sectors, and identifying functional interdependencies between them [94, 154-156].

At the core of an EIO model is the transaction table also known as the flow or transaction matrix (*Z*) that accounts for all payments to and from a sector in any given year (shown in Table 1). It is represented as $z_{ij}$ where sector *j* pays sector *i* the monetary value of the goods and services provided by sector *i* to sector *j*. In addition to the inter-industry transactions, sector *i* also sells $f_i$ worth of goods to the consumers as final demand. The value added, $v_i$ contains information on employee compensation, profit of business owners, and government tax paid by sector *i*. The column at the right and the row at the bottom represent the total throughput of each sector in monetary terms, $X_i$. The direct requirements matrix *A*, a normalized Z matrix containing direct coefficients $a_{ij} = z_{ij} / X_j$, represents the inputs required by a sector as resources from all other sectors to produce one dollar of output. For a changed final demand $F_{new}$, the direct economic activity is $A \times F_{new}$, while the total economic activity is calculated by

$$X = (I - A)^{-1} \cdot F_{new} \tag{1}$$

The term $(I - A)^{-1}$ is called the Leontief inverse or the total requirements matrix. The above-mentioned equation is the demand driven model useful in modeling shocks that affect the final demand *F* of an industry. Similarly, to assess cascading impacts of a disruption that reduces total output of sectors, a mixed-model or supply-constrained model has been developed [157]. This model is further discussed in the methods section (Chapter 3.2).

**Table 1. Tabular representation of the economic input-output (EIO) model**

| | Inter-industry transaction matrix, $\boldsymbol{Z}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Purchasing Industrial sector, $j$ | | | | | | | | | |
| Selling Industrial sector, $i$ | *Sector* | 1 | 2 | .. | .. | .. | .. | $n$ | Final demand, $f_i$ | Total Throughput, $x_i$ |
| | 1 | $z_{11}$ | $z_{12}$ | ➔ | | | | $z_{1n}$ | | |
| | 2 | $z_{21}$ | $z_{22}$ | ➔ | | | | $z_{2n}$ | | |
| | • | • | • | Inter-industry flows | | | | • | | |
| | • | • | • | ➔ | | | | • | | |
| | n | $z_{n1}$ | $z_{n2}$ | ➔ | | | | $z_{nn}$ | | |
| | Value-added, $v_j$ | | | | | | | | | |
| | Total Industrial Input, $x_j$ | | | | | | | | | |

EIO models have been successfully used to analyze the impact of various disruptive events. Some examples include simulating the impact of terrorist attacks on Virginia's interdependent transportation systems [95], the impact of high-altitude electromagnetic pulse attack on different economic sectors [156], the reduction in demand of air transportation after terrorist attacks [96], the impact of the 2003 Northeast Blackout [97], the impact of hurricane Katrina on power transmission and telecommunication systems [98], the economic impact of cyber-attacks on oil and gas sector [99], and the economic impact of Peak-oil-induced increase in oil prices [100]. While EIO models have certain inherent limitations such as their linear nature and rigid structure, researchers argue that strengths of EIO models for assessing higher-order impacts of disruptions and ranking vulnerable interdependent infrastructure sectors outweigh their weaknesses [101, 102]. EIO models are particularly well suited for modeling infrastructure interdependencies as they are based on observed empirical data [73, 90, 103-105]. IO based framework has also been coupled with subjective information from sector-specific domain experts about infrastructure dependencies for critical infrastructure risk analysis [158].

Recent work has analyzed the overall economic structure by applying graph theory methods to EIO data [107]. These studies identified key industries that form the backbone of the economic network (industries and transaction between them represented as nodes and edges) at different levels of aggregation [108, 110, 159]. For instance, Xu and colleagues identify certain critical sectors in the 2002 benchmark U.S. EIO network whose removal has a great impact on the economy [108]. Recent work by Contreras and Fagiola examined shock propagation using diffusion models in aggregated EIO networks from different European economies to demonstrate high vulnerability of highly densely connected economies [111]. EIO models have also been integrated with P-graph approach to determine optimal allocation of resources in an economic system under climate change induced disaster condition [160]. These studies represent important contributions and essential first steps toward understanding resilience of EIO networks based on interconnectedness of industrial sectors. While this prior research has identified hub industries (that can be considered CIS) and explored the implications of the EIO network structure on resilience, much work is still needed to understand the nature and extent of interdependencies between specific CIS that amplify impacts caused due to perturbations and its influence on economic resilience.

Understanding patterns of connections and vulnerabilities in networks is essential in order to restrict cascading impacts, or systemic vulnerabilities, especially in densely interconnected networks [1]. Representing EIO tables as networks permits analysis of network structure by using fundamentals from statistics and graph theory [48]. There are instances in the literature where EIO networks at different production levels have been described as *small-world* and *scale-free* structures [107, 161, 162]. Networks with small-world topologies are homogenous in nature, where each node has about the same number of connections, and as a consequence the connectivity or degree distribution peaks at an average value and decays exponentially. Connectivity or degree distributions for networks with scale free topologies are heterogeneous in nature and follow a power-law form, irrespective of its size [48]. While Carvalho identifies power-law behavior for out-degree distribution as well as *small-world* property in the commodity-by-commodity U.S. EIO network, a detailed graph-theory based topological analysis of the U.S. EIO inter-industry transaction network including investigation of statistical properties and their implications for resilience have largely gone unassayed [161].

The goal of our present work is to understand the implications of CIS interdependencies on resilience of economic systems. To this end, the underlying topology of the U.S. economic network is analyzed by identifying patterns of interconnectedness and interdependencies between the economic sectors. The CIS interdependencies are also modeled by simulating hypothetical disruptions on CIS and quantifying the resulting cascading impacts on the economic network. To accomplish these objectives, a systems approach is adopted that combines the empirical economic input-output data with graph theory based tools and techniques for industry-level interdependency analysis to advance our understanding of resilience in economic systems.

The rest of the chapter is organized as follows. The materials and methods section describes the methodologies applied to determine the topological properties of the U.S. EIO networks. It also describes the IO technique utilized to simulate hypothetical shocks on CIS, and the specific graph theory algorithm used to detect sub-community structure in the U.S. economic network. In addition, this section also describes the statistical method used for understanding the network topology. The results and discussion section presents results on the U.S. EIO model based interdependency analysis of CIS, and the topological properties of the U.S. EIO network. It also discusses the implications of these results for resilience in the U.S. economic network. The conclusion section summarizes the main findings, and provides strategic suggestions based on the analysis.

## 3.2 MATERIALS AND METHODS

### 3.2.1 Construction of the economic network from IO tables

EIO data is converted into graphs by creating adjacency matrices for our analysis. An adjacency matrix is a *'n x n'* matrix whose *(i, j)* entry is 1 if the *ith* and *jth* node are connected to the each other, and 0 if they are not, for a network with '*n*' number of nodes. Such a matrix would represent an un-weighted and undirected graph, which can be converted to a weighted-directed graph if magnitude and direction of the flow between *ith* and *jth* node is known.

The 2007 version of the make and use tables for the U.S. economy published by the Bureau of Economic Analysis (BEA), a division of U.S. Department of Commerce, are utilized to create the '389x389' industry-by-industry transaction matrix [163]. Miller and Blair described a general methodology to construct symmetric IO tables from the make and use tables [157], while Guo and his colleagues have provided a detailed algorithm for specifically deriving U.S. EIO tables [164]. A complex weighted-directed network is constructed by considering the industrial sectors as nodes and the monetary transactions between them as edges. Additionally, an unweighted-directed network is also constructed by disregarding the weights of the flows between the nodes to analyze the connectivity of sectors. To the best of our knowledge, the 2007 U.S. benchmark IO accounts are the most recent version and have not been examined from a graph-theoretic perspective by other studies.

### 3.2.2 Network topology of the economic network

Network topology is the structural organization or the overall pattern of connectedness of the system components (nodes and edges). In real-world networks, there are a number of common recurring patterns of connections that have a profound effect on the way these complex systems behave. Below the procedure for analyzing the topology of the U.S. EIO network is discussed by separately looking at its unweighted and weighted forms. Topological analysis of both these configurations provides unique insights on interconnectedness and interdependency patterns of industrial sectors.

#### 3.2.2.1 Unweighted EIO network analysis

Degree distributions of the unweighted network is analyzed to determine topological features. Degree $k_i$ of node $i$ is the total number of connections that node $i$ has with other nodes. Degree distribution is the probability distribution $p(k)$ of node degrees in a network. In terms of probability, $p(k)$ is the probability that a randomly chosen node has a degree k. For instance, a regular lattice network topology, where all nodes have the same number of edges, will have a degree distribution plot with a single sharp spike at the average degree. Degree distribution analysis of an unweighted network helps to determine whether the network is small world or scale free. If a degree distribution follows a power law of the form $p(k)\ \alpha\ k^{-\varepsilon}$, where ε is a constant parameter of the distribution known as the scaling factor, then the network is considered to have a scale-free topology. If degree distribution peaks at an average and decays exponentially, then it is likely to be a small world network [50]. However, the degree distribution analysis for small world is not customary, because it is not as reliable as methods based on graph theory metrics.

Watts and Strogatz introduced the concept of *small-world* effect in networks, characterized by a small characteristic path length- the average shortest path length for the network, and a high clustering coefficient- a measure of clustering in the network [51]. For this reason, nodes in a small world network are not connected directly to each other but most nodes can be reached indirectly from all other nodes by a small number of steps [50]. Expanding on this understanding to real-world systems, Latora and Marchiori asserted that in physical terms the flow of information in a small world network is extremely efficient [54]. For this reason, efficiency of information propagation is computed at both global (network) and local (node) levels. A high value for these measures will suggest a small-world topology. Global efficiency refers to the overall network efficiency, while local efficiency is the average efficiency of each node's sub-graph comprised of its neighbors. Both these metrics are described in greater detail in Appendix A.

**3.2.2.2 Weighted EIO network analysis**

In parallel with the analysis of degree distributions of the unweighted U.S. EIO network, statistical analysis of industry throughput or strength distributions provides insights from the weighted network. Strength $s_i$ of node $i$ is the sum of weights of edges connected to node $i$. Strength distribution is the probability distribution $p(s)$ of strength in a network, and characterizes the spread of strengths for all industrial sectors in the EIO network. Power-law or other heavy-tailed distributions are specifically tested to check whether they are a good fit for the industrial strength data. A good fit with these distributions would suggest that there are a handful of dominant industries involved in large transactions, while the majority of industrial sectors are involved in transactions of far smaller size. In order to verify whether the strength data follows a power-law, a statistical framework is adopted that estimates the scaling factor, ε, by using maximum likelihood estimation (MLE) in tail region of the distribution (above some lower bound $s_{min}$) The scaling factor, ε, for power-law distributions mostly lies in the range of $2 < \varepsilon < 3$, however this is not a rule [165]. For this reason a comprehensive power-law detection methodology is employed, which is discussed in detail in the Appendix A.

### 3.2.3 Simulating Hypothetical disruptions on CIS

Hypothetical shocks are simulated on select CIS to quantify the impact of initial disruptions on CIS on the rest of the U.S. economic network, and subsequently, to understand interconnectedness and interdependencies between CIS. CIS as defined by the U.S. DHS are first mapped to the relevant sectors of the U.S. IO model as shown in Table 8 in Appendix A. It must be noted that multiple IO sectors may comprise a single CIS (for instance energy CIS includes Petroleum refineries sector, Oil and gas extraction sector, and Electric power generation, transmission, and distribution sector). For the purpose of our present study, disruptions on critical IO sectors are modeled that represent each CIS. Both demand and supply driven models have been utilized for modeling disruptions that impact final demand or the value-added component of the industry sectors. However, these are restrictive in modeling disruptions that cause a direct reduction in the total output of the disrupted sectors due to sudden shocks, like natural disasters, shortage of a key resource, or facility closure [166]. The mixed-model IO methodology is utilized to assess the short-term direct and indirect impacts on unconstrained sectors caused by reduction in output of certain supply-constrained sectors in the economy. These supply-constrained sectors are the ones that experience the shock in the form of sudden reduction in their economic throughput.

Earliest mention of mixed-model IO methodology for economic impact assessment was by Stone [167]. Based on this previous work, Johnson and Kulshreshtha proposed a detailed methodology to exogenize a given set of outputs [168, 169]. Mixed-models have been used previously for various purposes. Examples include the work by Leung and Pooney to study the impact of a new fishery policy on the Hawaiian economy [170]. Papadas and Dahl applied the mixed IO methodology to determine the importance of 16 distinct U.S. farm commodities for the U.S. economy [169]. More recently, mixed models have also been extended for assessing macro-economic effects of Peak Oil phenomena on different economies [166]. The extensive application of the mixed-model IO methodology on distinct industry types, including agriculture, mining, fisheries and petroleum sector, provides justification for our adoption of this methodology to simulate shocks on disparate CIS [171-175].

Methodologically, Miller and Blair describe in detail the mixed model as a modification of the demand-driven model shown in equation 1 by exogenously specifying the final demand for non-supply constrained sectors, and endogenously specifying the total throughput of sectors that experience supply constraint (or the sudden shock) [157]. Subsequently, using basic algebra for partitioned matrices, equation 2 is derived. There are $n$ sectors in the economy; out of which the first $k$ sectors are endogenous elements, and the last $(n-k)$ sectors are exogenous elements.

$$\begin{bmatrix} P & 0 \\ R & -I \end{bmatrix} \begin{bmatrix} X \\ F \end{bmatrix} = \begin{bmatrix} I & Q \\ 0 & S \end{bmatrix} \begin{bmatrix} \bar{F} \\ \bar{X} \end{bmatrix} \qquad (2)$$

$\bar{F}$ is the $k$-element column vector of elements $F_1$ through $F_k$, representing exogenous final demands of non-supply constrained sectors.

$\bar{X}$ is the $(n - k)$ element column vector of elements $X_{k-1}$ through $X_n$, representing exogenous total outputs of the supply-constrained sectors.

$X$ is the $k$-element column vector of elements $X_1$ through $X_k$, the total output of non-supply constrained sectors (to be estimated).

$F$ is the $(n - k)$ element column vector of elements $F_{k-1}$ through $F_n$, the final demand of supply-constrained sectors (to be estimated).

$P$ is the $k \times k$ matrix containing the elements from the first $k$ rows and the first $k$ columns in $(I - A)$.

$R$ is the $(n - k) \times k$ matrix containing elements from the last $(n - k)$ rows and the first $k$ columns in $(I - A)$.

$Q$ is the $k \times (n - k)$ matrix of elements from the first k rows and the last $(n - k)$ columns in $-(I - A)$.

$S$ is the $(n - k) \times (n - k)$ matrix of elements from the last $(n - k)$ rows and columns of $-(I - A)$.

Equation 2 is rearranged as:

$$M\begin{bmatrix} X \\ F \end{bmatrix} = N\begin{bmatrix} \bar{F} \\ \bar{X} \end{bmatrix} \qquad (3)$$

where

$$M = \begin{bmatrix} P & 0 \\ R & -I \end{bmatrix} \qquad (4)$$

and

$$N = \begin{bmatrix} I & Q \\ 0 & S \end{bmatrix} \quad (5)$$

The total output ($X$) for the first $k$, supply constrained sectors and the final demand ($F$) for the last $n$-$k$, non-supply constrained sectors is determined using

$$\begin{bmatrix} X \\ F \end{bmatrix} = M^{-1} N \begin{bmatrix} \bar{F} \\ \bar{X} \end{bmatrix} \quad (6)$$

The term inoperability ($q_i$) is defined as the normalized degraded production to quantify the fractional degradation or deviation from the normal state of an industry sector.

$$q_i = \frac{\left(X_i - \bar{X}_i\right)}{X_i} \quad (7)$$

The value of $q_i$ falls between 0 and 1, where 0 means no change in economic activity and 1 means total disruption of the system. This concept is similar to the one introduced by Haimes and Jiang to measure the impact of the disruption on the infrastructure systems [154]. Inoperability aids in ranking the industry sectors in terms of their vulnerability to the disruption [176].

### 3.2.4 Community detection in U.S. economic network

The graph theoretic concept of modularity-based community detection is applied to identify natural fault lines in the U.S economic IO network along which it separates. Previously, studies have applied this methodology to identify clusters in economic IO networks [110]. Community detection is utilized to further our understanding of the overall pattern of connectedness of economic sectors, and its effect on resilience of the economic system. Combining insights from community detection with the mixed-model IO methodology helps assess vulnerability of individual communities to disruptions on individual CIS. This is determined by mapping the economic impact suffered by individual sectors to their respective communities. Based on this information and the knowledge of connection patterns in modularity-based community structures, interdependencies of CIS and the systemic vulnerability arising from tightly coupled CIS are understood. Identifying industrial communities within the larger economic structure helps determine the extent of coupling between each CIS, which is very important, because greater coupling of CIS may amplify cascading impacts of initial shocks on any industrial sector.

While there are many different methods to find communities [177, 178], here communities are detected based on modularity optimization method for directed-weighted networks developed by Leicht and Newman [179]. Modularity optimization method identifies communities by maximizing Q, the modularity function, which is defined as

*Q= (fraction of intra-community edges) – (expected fraction of such edges).*

This definition of modularity signifies that a cluster or community is valid when there are more edges inside a community than what is expected by chance for a random network. Therefore, modularity based community detection works on the premise that connections within a community are denser, and sparser between them.

Many clustering techniques have utilized the concept of modularity for identifying clusters in large networks [178]. Since modularity optimization is a NP-complete problem, developing an algorithm for maximizing modularity is a challenging task [177]. The spectral optimization methodology, an accurate and fast algorithm to maximize the value of Q, is used to find the best division of the U.S. economic network [179]. The expression of modularity, Q, for the directed-weighted economic network reads

$$Q = \frac{1}{m}\sum_{ij}\left(A - \frac{s_i^{in} \cdot s_j^{out}}{m}\right) \cdot \delta(C_i, C_j) = \frac{1}{m} B_{ij} \cdot \delta(C_i, C_j) \tag{8}$$

where, $A_{ij}$ is the weight of an edge from node $j$ to node $i$, $s_i$ is the strength of inflows for node $i$, $s_j$ is the strength of outflows for node $j$, $m$ is the total number of edges in the network. $\delta$ is the Kronecker delta symbol that is equal to 1 if nodes $i$ and $j$ are in the same community ($C_i = C_j$), and 0 otherwise. Spectral optimization technique for modularity maximization assigns nodes to different communities based on the sign of the eigenvector, corresponding to the largest positive eigenvalue of the modularity matrix B, whose elements are

$$B_{ij} = A_{ij} - \frac{s_i^{in} \cdot s_j^{out}}{m} \tag{9}$$

In order to identify the natural fault lines in the network by identifying natural groupings of nodes, the repeated bisection graph-partitioning algorithm is applied [179]. This method starts by dividing the network in two and then repeating the division while optimizing for maximum modularity of the communities. A good division of a network results in a high modularity score, thus Q is maximized over all possible divisions of the economic network to identify communities of industrial sectors.

## 3.3 RESULTS AND DISCUSSION

### 3.3.1 Topological properties of the U.S. economy

Frequency distributions of total, in, and out degrees (Figure 22 in the Appendix A) of the unweighted-directed U.S. economic network suggest that high fraction of the nodes have a high degree, which implies that the U.S. economic network is densely interconnected since a sizeable fraction of industrial sectors in the economy are directly connected to most other sectors. This explains the low characteristic path length, *l*, of 1.212 and the high clustering co-efficient, *c*, of 0.790 for the network, which are requisites for a small-world topology. These values also compare well to a synthetically generated small-world network of the same size ($l_{SW}$ = 1.245 and $c_{SW}$ = 0.755). In addition, both global efficiency and local efficiency for our network is extremely large at 0.966 and 0.975 respectively. High interconnectedness of the industrial sectors causes these efficiency measures for our network to be close to 1. Based on these findings one can conclusively claim that the U.S. EIO network has a small-world topology. Since most industrial sectors in an economic system are highly functionally interdependent, it is not surprising that the U.S. EIO network exhibit a small-world effect. Incidentally, previous studies on unweighted local firms and international trade economic IO networks have also argued that they are small world topologies [107, 162].

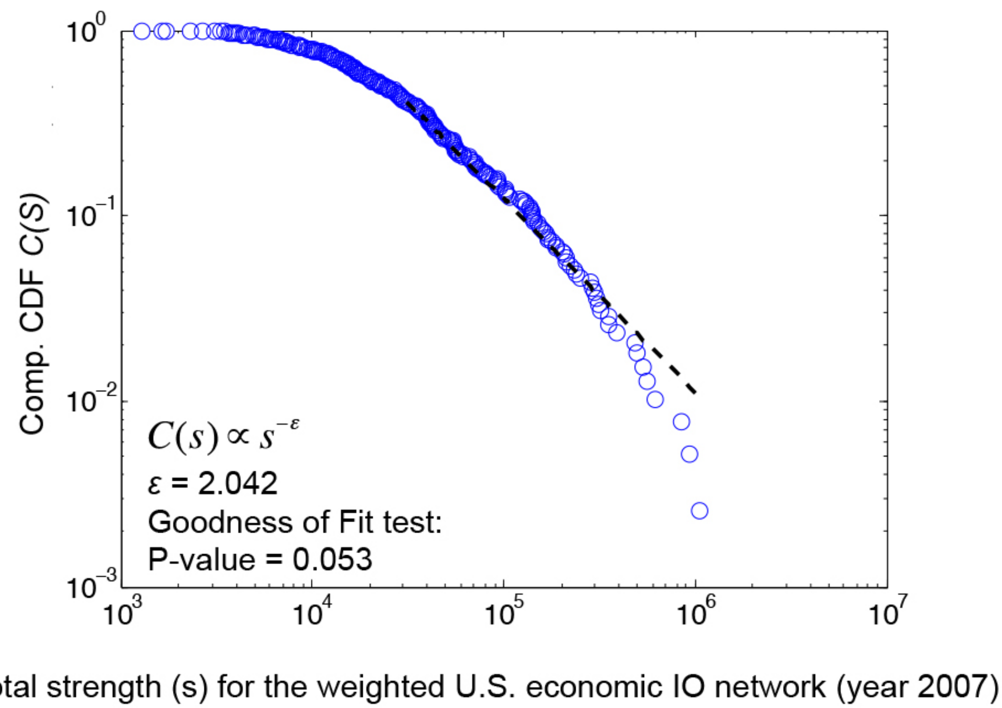



**Figure 5. Cumulative Distribution Function of Total-strength and the maximum likelihood power-law fit for 2007 US economic input-output (EIO) weighted network.**

A small-world network topology for the U.S. EIO network implies that a disturbance or failure at any industrial sector would get transmitted to rest of the sectors in less than 2 steps (since the characteristic path length, $l$, is 1.212). For instance, a shock on a seemingly unimportant sector like *Dry-cleaning and Laundry services* impacts the rest of the sectors in the economy, even though the effect might be negligible. In addition, such a shock would be responsible for a reduction in the overall economic throughput. While this insight is based on the topological assessment of the unweighted U.S. EIO network, the weighted network is analyzed to determine the overall pattern of interdependencies among sectors in the US economy.

Frequency distributions of total, in, and out strength (Figure 23 in Appendix A) for weighted EIO network indicate that most industrial sectors have a low total-weighted degree, and an extremely small number of sectors including CIS have very high weighted degree. While a visual inspection of U.S. EIO network total strength distribution suggests a power law (Figure 5), additional statistical testing using maximum likelihood estimation and goodness-of-fit (GOF) rules out power-law as the underlying distribution (p-value in Table 2). A similar result is observed for in-strength, however, out-strength distribution does follow a power law as per the GOF test presented in the Appendix A.

**Table 2. Underlying strength distributions in the U.S. economic input-output (EIO) network.**

Statistics including the p-value for the goodness of fit test with power-law model, log likelihood ratios for the four alternate models and the p-value for each of the genera likelihood ratio tests (LRT), are presented to determine the model that best fits the data.

| Strength Distributions in Weighted-directed Economic network | | P-value for GOF with Power-law model | LRT: *Log-normal* | | LRT: *Exponential* | | LRT: *Stretched exponential* | | LRT: *Power-law with exponential cut-off* | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | LR | P-value | LR | P-value | LR | P-value | LR | P-value |
| U.S. Economic IO network (year 2007) | Total-strength | 0.05 | -2.67 | 0.06 | 63.03 | 0.99 | -0.02 | 0.06 | -3.62 | <u>*0.01*</u> |
| | In-strength | 0.02 | -2.66 | 0.06 | 52.93 | 0.99 | -2.99 | 0.06 | -4.01 | <u>*0.01*</u> |
| | Out-strength | <u>*0.24*</u> | -5.63 | 0.01 | 40.29 | 0.99 | -5.75 | 0.01 | -769.41 | <u>*0.00*</u> |

*P-values for distributions that fit the economic network data are underlined.*

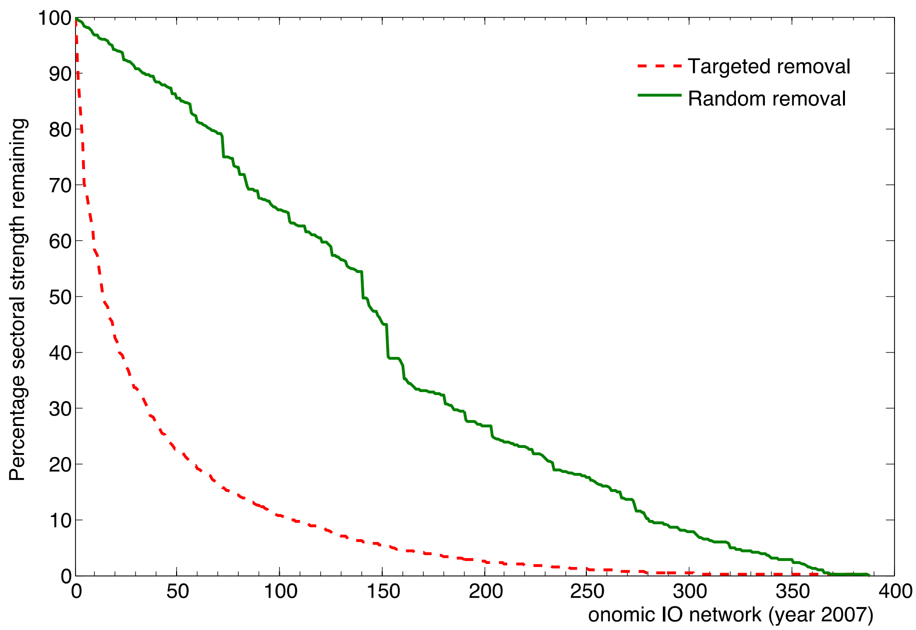



**Figure 6. Robustness analysis of the 2007 U.S. economic input-output (EIO) network.** Targeted removal represents attacks on influential sectors based on highest total weighted degree, while random removal represents accidental failures of sectors.

Table 2 presents the results of generalized likelihood ratio test (GLRT) comparing the power-law distribution with four alternate distributions: lognormal, exponential, stretched exponential (Weibull) and power-law with exponential cut-off. Results for the GLRT depicted in Table 2 suggest that power law with an exponential cut-off is a better fit for total strength, in-strength and out-strength distributions for 2007 U.S. economic IO network. Previous assessment of empirical data has revealed that most real world networks tend to deviate from pure power-law distributions [165]. Additionally, it has been noted that networks whose distributions follow a pure power-law exhibit similar network based insights to networks with heavy-tailed distributions like power-law with exponential cut-off [165]. While the presence of power-law in unweighted networks suggests a scale-free topology, there is no evidence in the literature suggesting that weighted networks whose strength distribution follows a power-law exhibit scale-free behavior as well. It has been argued that scale-free networks tend to be robust against random failures but are vulnerable to targeted attacks on key nodes [57]. The results of robustness analysis for the weighted U.S. EIO network are presented in Figure 6. The results in Figure 6 suggest high vulnerability of the U.S. EIO network as indicated by the degradation in the total weighted strength of the network to targeted removal of sectors with highest total strength, compared to removal of sectors that are randomly chosen. This result indicates that while the system is extremely vulnerable to shocks on a few extremely influential industrial sectors like CIS, at the same time the U.S. EIO network is robust to shocks on most other nodes because of their low importance.

Methodology used to assess the robustness of the U.S. EIO network has a few shortcomings that one should bear in mind. Firstly, since robustness is understood in terms of the impact of systematic removal of industrial sectors on the original network, the cascading impacts resulting from node removal at each step are not considered. Secondly, the economic system's adaptive response to node removals is not considered in our robustness analysis. While both these are valid criticisms of the methodology, result for robustness analysis (Figure 6) is able to provide the "vulnerable, yet robust duality" of the economic system. These shortcomings could be addressed using more dynamic models to capture the adaptive response of the system, but is beyond the scope of our current work.

### 3.3.2 Disruptive scenarios on CIS

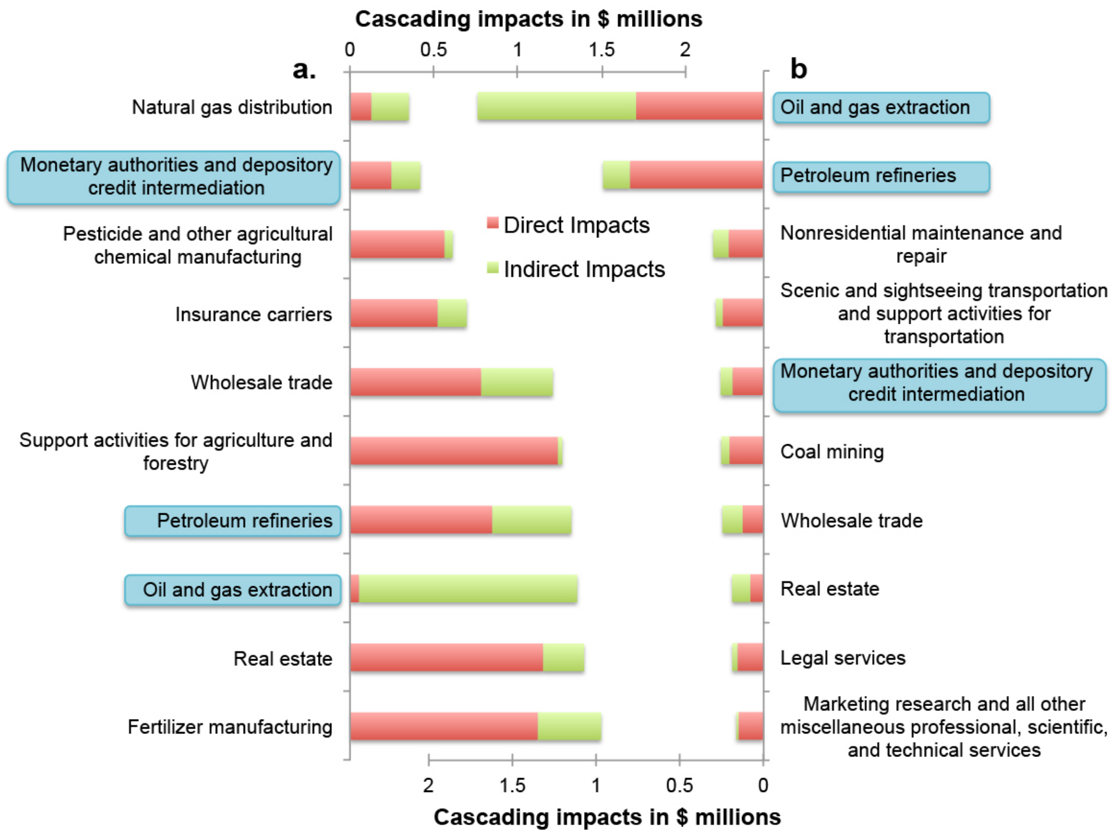



**Figure 7. Top 10 industrial sectors experiencing greatest direct and indirect economic impacts due to disruption of $10 million on a. *Food & Agriculture CIS (Grain farming)* and b. *Energy CIS (Electric power generation, transmission, and distribution) CIS*.**

CIS are highlighted in blue. Results for two of the seven CIS are presented here, while the results for the remaining CIS are included in the Appendix A.

Figure 7 shows the top 10 industry sectors suffering the highest economic impact because of a hypothetical shock of $10 million on two CIS, food and agriculture and energy CIS. It is interesting to note that three CIS are amongst the top 10 sectors that suffer the highest economic impact because of an initial economic shock of $10 million on the food and agriculture CIS. The results in Figure 7 highlight the tight coupling and interdependence of the food and agriculture

CIS with energy CIS (oil and gas extraction and petroleum refineries) and finance CIS (monetary authorities and depository credit intermediation). Similar results are observed for an initial shock of $10 million on the electric power generation transmission, and distribution CIS. The results in Figure 7 also show the direct (due to direct linkages between the industries) and indirect (due to indirect linkages) impacts for the various industry sectors. Additional results for hypothetical disruptions on the remaining CIS are presented in the Appendix A (Figure 25). Moreover, sectors vulnerable to disruptions on CIS are identified in terms of inoperability, and are presented in the Appendix A as well (Figure 26).

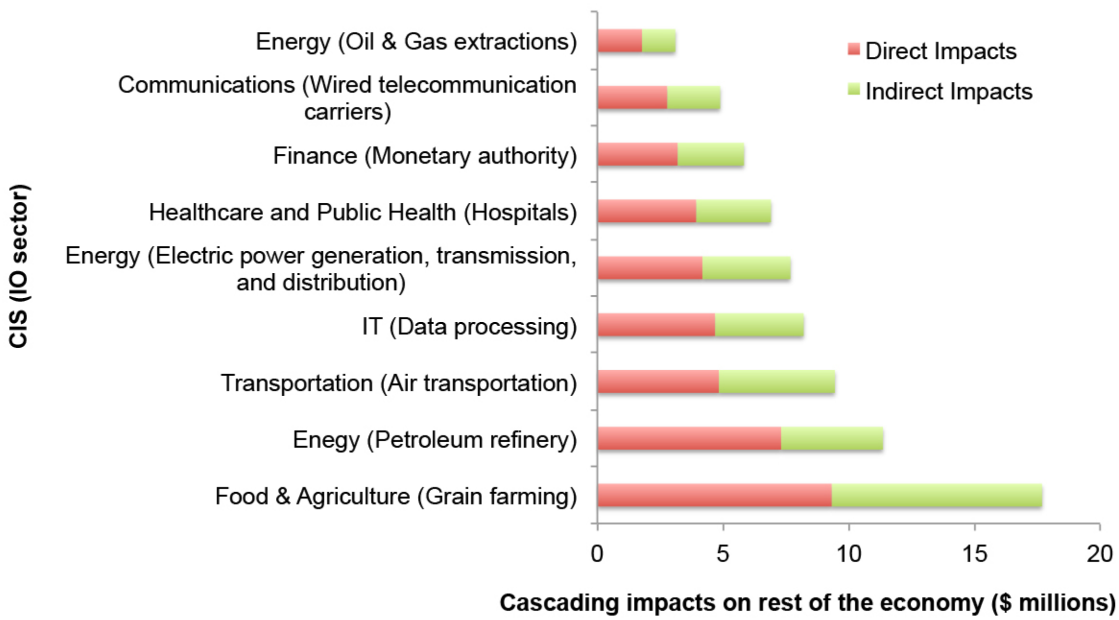



**Figure 8. Impacts, both direct and indirect, of hypothetical shock of $10 million on CISs on the rest of the U.S. economy (based on 2007 U.S. EIO network).**

Figure 8 presents the economy-wide impacts arising from an initial $10 million shock on individual CIS. The results in Figure 8 indicate that initial shocks on Agriculture (Grain farming) and Energy (Petroleum refinery) CIS have the largest impacts on the economy, even surpassing the initial economic shock of $10 million on these individual CIS. A sector whose disruption causes high cascading impacts signifies that it is highly interdependent and critical for others sectors in the economy. Identification of industrial sectors that trigger widespread economic impacts throughout the system may allow creation of policy measures aimed towards protection of structurally significant industrial sectors that can compromise the resilience in economic systems.

It is worth noting that the U.S. EIO model used in this work has its own inherent limitations. Some of these include the linear and static nature of the model and the lack of any potential adaptation due to market forces following a sudden shock. However, the numbers presented in Figure 7 and Figure 8 are not meant to be predictive in nature and the results of disruptive scenarios provide an understanding of the interdependencies and interconnectedness between CIS and other sectors in the U.S. economy. Furthermore, it has been argued that since IO models are static in nature, they are unable to account for feedback effects. However, insights from these models are still informative to understand the short-term effects of disruptions before any adaptation due to market forces and/or policies occur.

### 3.3.3 Community structure of the U.S. EIO network

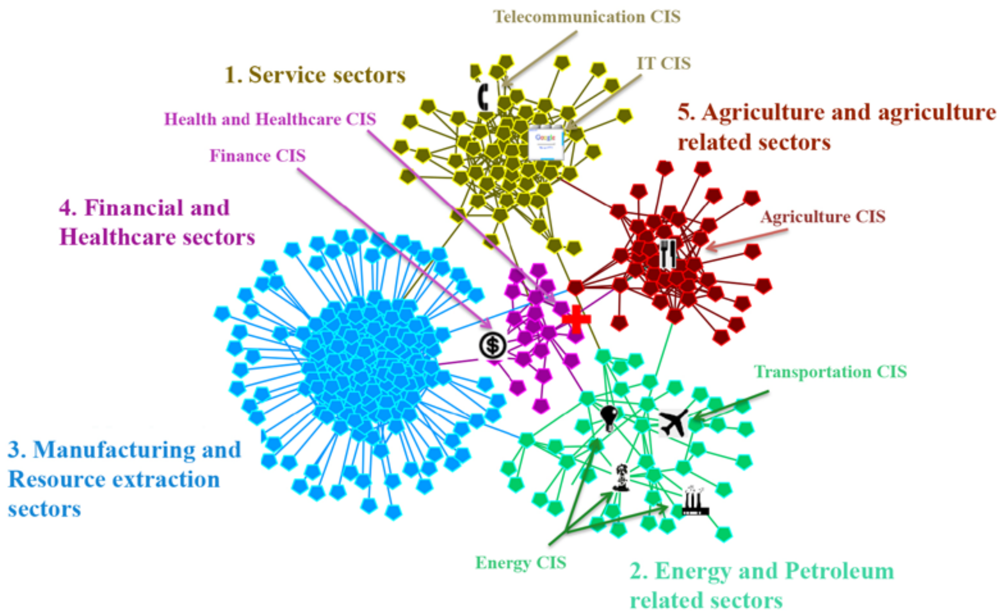



**Figure 9. Community structure of the 2007 U.S. economic input-output (EIO) network.**

Five distinct communities are detected. This is just a schematic representation; in real life this network exhibits greater complexity.

Partitioning of the U.S. economic IO network yields 5 industrial communities made up of industry sectors that are closely associated. Even though the clustering algorithm comes from applied mathematics, specifically graph theory, its application to economic networks enables us to identify industrial communities that make sense from an economic perspective. Community detection methodology based on modularity is able to detect the natural fault-lines, and clusters the industrial sectors into the following communities: 1) *Service sectors* 2) *Energy and Petroleum related sectors* 3) *Manufacturing and Resource extraction sectors* 4) *Financial and Healthcare sectors* and 5) *Agriculture and agriculture related sectors*.

**Table 3. Cascading impacts of disruptions on CIS on Industrial communities.**

Communities that suffer the highest cascading impacts and do not contain the disrupted CIS are represented in bold.

| Disrupted CIS (*IO sectors*) | Industrial Community Corresponding to the CIS | Community Experiencing Highest Cascading Impacts | Magnitude of Cascading Impacts in $ Millions |
|---|---|---|---|
| Food & Agriculture CIS (*Grain farming*) | 5. Agriculture and agriculture related sectors | ***2. Energy and Petroleum related sectors*** | 5.418 |
| Transportation CIS (*Air transportation*) | 2. Energy and Petroleum related sectors | 2. Energy and Petroleum related sectors | 6.303 |
| Energy CIS (*Oil & Gas extraction*) | 2. Energy and Petroleum related sectors | 2. Energy and Petroleum related sectors | 1.474 |
| Energy CIS (*Petroleum refineries*) | 2. Energy and Petroleum related sectors | 2. Energy and Petroleum related sectors | 9.439 |
| Energy CIS (*Electric power generation, transmission, and distribution*) | 2. Energy and Petroleum related sectors | 2. Energy and Petroleum related sectors | 4.409 |
| IT CIS (*Data processing, hosting, and related services*) | 1. Service sectors | 1. Service sectors | 4.088 |
| Communications CIS (*Wired telecommunications carriers*) | 1. Service sectors | 1. Service sectors | 3.178 |
| Finance CIS (*Monetary authorities and depository credit intermediation*) | 4. Financial and Healthcare sectors | 4. Financial and Healthcare sectors | 2.427 |
| Healthcare and Public Health CIS (*Hospitals*) | 4. Financial and Healthcare sectors | ***1. Service sectors*** | 3.150 |

CIS are located in these five industrial communities as shown in Figure 9. CIS that are present within the same community are strongly interconnected to each other. For example, energy and transportation CIS, healthcare and finance CIS, and information technology and telecommunication CIS are extremely interdependent and tightly coupled. Results from the mixed IO model based hypothetical economic shocks is combined with the results from community detection to determine which industrial communities experience the greatest cumulative cascading impacts due to disruptions on each of the CIS. These results are shown in Table 3. The community that contains the disrupted CIS is expected to experience the highest cumulative cascading impacts because of its closer association with industry sectors within the community. While this is true for most CIS, this is not the case for *food and agriculture* and *healthcare CIS*. As can be seen from Table 3, the community experiencing the highest cascading impacts because of a disruption on the food and agriculture CIS is the *energy and petroleum related sectors*. This suggests the strong coupling and interdependence between *food and agriculture CIS* and the *energy and petroleum related sectors*. This finding is further corroborated and consistent with the results presented in Figure 7 where the two energy CIS (oil and gas extraction and the petroleum refineries sectors) are among the top 10 sectors that are most affected due to the disruptions on food and agriculture CIS. Such high level of interdependency results in amplification of impacts throughout the economy and increasing systemic vulnerability.

Additionally, *service sectors* community experience the highest cascading impacts because of a disruption on the healthcare CIS. Such insights on the interconnectedness and interdependencies are useful for identifying specific CIS that unintentionally increase systemic vulnerability in economic networks. In addition to reducing interdependencies between CIS, securing and protecting sectors that are a source for systemic vulnerability is essential for building resilience in the U.S. economic system.

## 3.4 CONCLUSIONS

The methodology presented in this paper integrates EIO modeling with a graph-theoretic framework to understand the implications of interconnected and interdependent CIS on the resilience of the U.S. economy. This framework identifies CIS interdependencies that play a significant role in amplification of impacts from the initial disaster. There is an urgent need to understand structural and functional interdependencies between infrastructure systems for improving disaster resilience of economic systems. This work adds to the rapidly growing body of literature that utilizes quantitative models for improving post-disaster recovery and reconstruction, and evaluating pre-hazard preparedness and mitigation strategies [90, 102, 103, 180, 181]. While previous work has focused on creating and refining mathematical models for critical infrastructures analysis, our work provides a fundamental understanding of the structure of CIS within the U.S. economic network and its implications for economic resilience.

Increasing instances of large-scale economic impacts triggered by natural and technological disasters has motivated international, national and local policymakers to understand the relationships between critical industry sectors for the development of resilient economic systems. Topological analysis of the unweighted U.S. EIO network reveals its small-world properties, while the weighted case demonstrates that economic throughput for sectors follows a *power-law with an exponential cutoff* distribution. For an unweighted economic network, small world property implies that a shock will transmit throughout the economy quickly since it is densely interconnected. However, an unweighted economic network disregards the strengths of these interconnections between industrial sectors; thus, topological properties of the weighted economic network are more informative. *Power-law with an exponential cutoff* distribution of industrial sector strength for the weighted economic network indicates that there are a few CIS involved in bulk of the economic transactions, and the economic network may be extremely vulnerable to shocks and disruptions on these key CIS. This attribute of the economic network is also clearly evident from the hypothetical disruptions on CIS that show high cascading impacts throughout the U.S. economic network. On combining insights from hypothetical disruptions with community detection, it is observed that excessive interconnectedness and interdependencies of CIS result in high systemic vulnerability of the economic network.

Since the U.S. economic system is a self-organizing, decentralized network, it is impractical to suggest a network topology as a panacea for developing resilient economic networks. There are examples of network topologies in the literature that assure resilience, however these topologies are applicable to planned systems. An economic system is complex and evolves over time in response to market forces, technological innovation, and policy decisions. Out of these approaches, policy directives could act as feasible measures for advancing resilience building. Comprehensive analysis of the structural organization of CIS and the overall economy is critical for improving resilience of the economy. This information can guide policymakers to design new policies that reduce systemic vulnerability of economic networks, and reevaluate policies that might indirectly increase coupling between CIS.

Another reason for reducing interdependencies between CIS comes from the work of Carlson and Doyle on Highly Optimized Tolerance [182]. The HOT framework claims that robustness of complex systems that exhibit "robust, yet fragile" behavior (with throughput distribution following power-laws) is not a matter of chance but must be managed by using design strategies [183]. Similar to the U.S. economic system, a HOT system is robust, but at the same time they have a probability (although very low) of experiencing catastrophic cascading impacts due to perturbation on influential system components such as CIS. For this reason, robustness barriers must be created around CIS based on the understanding of interdependencies between them. Based on our analysis, policymakers should place robustness barriers to restrict cascading failures within the U.S. economy.

Finally, in addition to the national imperative of understanding the inherent interdependency of CIS in economic systems to develop a resilient U.S. economy, it plays an important role globally as well. The 2009 global financial crisis has exposed the vulnerabilities in the global economic system by producing the first decline in global GDP since World War II. Since the U.S. economy is the biggest sub-system of the global economic system, any sort of economic disruption in the U.S. may adversely affect the rest of the economies [184]. Thus, the urgency to limit U.S. economy's systemic vulnerability, and ultimately developing resilient U.S. economic system is unprecedented.

# 4.0 UNDERSTANDING RESILIENCE IN INDUSTRIAL SYMBIOSIS NETWORKS: INSIGHTS FROM NETWORK ANALYSIS

The following chapter is based on an article submitted in *Journal of Environmental Management* with the citation:

Chopra, Shauhrat S., and Vikas Khanna. "Understanding resilience in industrial symbiosis networks: Insights from network analysis." *Journal of environmental management* 141 (2014): 86-94.

The chapter combines the manuscript and supporting information to be published in *Journal of environmental management.* Additionally, extraneous supporting information submitted with the manuscript appears in Appendix B.

## 4.1 INTRODUCTION

Industrial Symbiosis- a mutually beneficial relationship between industries that achieves productive use of waste and by-products- promotes sustainable development by providing economic benefits while minimizing environmental degradation caused by the participating industries. IS was investigated with much curiosity from the 1925-1960’s in the field of Economic Geography [185-188] to understand geographically localized synergies of by-products, however it fell out of the radar until appreciation for its ability to mitigate environmental impacts rekindled a renewed interest many decades later [189]. Growing interest in the field of IS and attempts to develop theoretical approaches to understand the resilience of IS networks is being pursued with equal vigor in both developing and developed countries of the world. *The Roadmap for a Resource Efficient Europe* supports and encourages all European Union (EU) member countries to employ IS for maximizing resource efficiency [112, 190]. Similarly, Organization for Economic Cooperation and Development (OECD) recognizes IS as a tool for fostering green growth and eco-innovation and recommends its application [113, 114]. Moreover, developing economies from Asia such as China and India have been extensively exploring and experimenting with Eco-Industrial Parks (EIPs) [115-117].

While IS networks are highly complex and resource efficient with substantial economic and environmental benefits to the participating industries, they can also be vulnerable to unanticipated perturbations. A disturbance affecting even one industry (or node in the system) may lead to a domino effect, resulting in cascading impacts on the rest of the network [36, 120]. Additionally, since most synergies in an IS network may be a result of social interactions between managers and owners of industries, the resulting network may not be strategically planned and be coincidental in nature, which makes it vulnerable to unforeseen and catastrophic events [31, 117, 123, 191]. The need for understanding the theoretical framework of IS for guiding their resilient design has been identified, but has only received limited attention [192, 193]. Resilience has drawn attention in studies aimed at advancing risk adaptation in supply chain management [194, 195] and to ascertain mechanisms promoting resiliency in ecological networks [13, 15, 19, 26]. Zhu and Ruth compare and contrast the concept of resilience in ecological systems and supply chains to inform its application for IS systems [62]. Borrowing the understanding of ecological resilience, resilience is defined in this case as the capability of a system to absorb disruptions while maintaining its structure and function [20, 21, 35, 36]. This property allows an IS network to absorb known or unknown stresses that would otherwise disintegrate the system and leave the participating industries dysfunctional.

Past research on IS has focused primarily on genesis and evolution of IS networks [31, 121, 123, 124, 196, 197], defining the IS system and its boundaries [123] and the impacts of implementing IS networks [119, 198-200]. Most of these studies adopt a biophysical approach to quantify resource savings and emissions reductions in IS systems by applying the concepts of industrial ecology [31, 121, 123]. Amongst biophysical approaches, life cycle assessment (LCA) is frequently being used as a decision making tool to estimate and compare the environmental impacts of various synergetic exchanges in an IS context. [201-206]. There have also been attempts to recognize the importance of social factors for coordination and organization of actors for initiating synergies [116, 117, 120]. Social Network Analysis is one such technique applied on Kalundborg IS to understand its organizational framework [126]. Furthermore, research on the design of IS for specific regions and industry types, for instance modeling coal-chemical IS in China, has provided a viable option to mitigate emissions and achieve high value-added utilization of resources [114]. However, except for Zhu and Ruth's recent work on robustness of

IS networks to removal of industries from the network, none of the other studies have focused on studying the resilience of highly interconnected and symbiotic industrial network in a rigorous quantitative manner [62]. There still exists a void in the resilience assessment of IS systems, since most of the synergies are "strictly business" and ad-hoc in nature that may render the system fragile and highly vulnerable to perturbations [121, 196].

IS systems demonstrate self-organizing capability, similar to complex adaptive systems like natural ecosystems, to maintain their functionality to counter stresses [124]. Understanding resilience of such complex networks will aid in assessing the capacity of the system to retain its function by maintaining its structure while under stress [21]. However, there is a notable disparity in the understanding of resilience in the context of engineered systems. It has been argued that a close relationship exists between resilience and sustainability where the former concept is a prerequisite for the latter [21, 39, 40]. On the other hand, some researchers consider resilience equivalent to sustainability [15, 40, 125] and while a few others consider resilience inadequate for attaining sustainability in specific instances [15, 38]. However, among all the uncertainty surrounding the relationship between resilience and sustainability, the need for developing resilient and efficient IS networks for improving sustainability, is a certainty.

Most existing methods for sustainability assessment including those based on life cycle thinking employ biophysical approaches to quantify the resource flows and environmental impact of products and processes. However, these methods assume a simple cause-effect relationship and may ignore the indirect effects due to the system-wide interactions between the network components [192, 193]. On the other hand, network analysis employs methods and metrics such as centrality or connectivity indices to understand the network structure and the underlying complex set of relationships among the nodes [62]. However, network analysis has not been applied extensively to enhance understanding of resilience in engineered networks. This gap is bridged by integrating the concepts of network theory with information about resource flows to understand resilience and vulnerabilities in industrial symbiotic networks. The Kalundborg Industrial Symbiosis (KIS) located in Kalundborg, Denmark is the focus of this study due to availability of public information for this Eco-Industrial Park. The 2002 snapshot of the water synergy network at KIS is studied, due to availability of data for this period, to reveal industries with the highest vulnerabilities, using network metrics like centrality indices and network efficiency, and suggest strategies for designing resilient future IS systems. In addition, the evolution of the Kalundborg industrial symbiosis network is explored, and time trends in node-level metrics and connectivity indices are analyzed for gaining an understanding of the resilience. This work aims to deliberate on a network-based approach for understanding resilience in IS networks and plugging the gaps in foundational framework for IS.

The rest of the article is organized as follows. Section 2 provides a detailed description of the IS at Kalundborg. It also describes the metrics and the methods used to assess vulnerabilities in the system through disruptive scenarios, the evolution of resilience over time, and calculation of hypothetical economic and ecological savings resulting from synergistic exchanges. Section 3 presents the results of the study. A discussion of the results and strategies for the design of resilient IS system is in Section 4. Lastly, a summary of the main findings is provided in Section 5.

## 4.2 MATERIAL AND METHODS

### 4.2.1 System Description

IS at Kalundborg, Denmark consists of a synergistic network of waste and by-product streams among companies based on contractual dependency [31, 191]. KIS originated in the early 1960s as a strategy to reduce exploitation of groundwater in the region in the face of a growing groundwater deficit and an increasing water demand by the industries [207]. Subsequently, it has developed from a water exchange network to a network with more than 30 different by-product synergies [121, 122]. The synergistic flow of by-product and waste streams between the power plant, the oil refinery, the district municipality, and other industries in the region of Kalundborg has not only led to an increase in the resource efficiency but also to the economic gains of the participating industries [121, 191, 198].

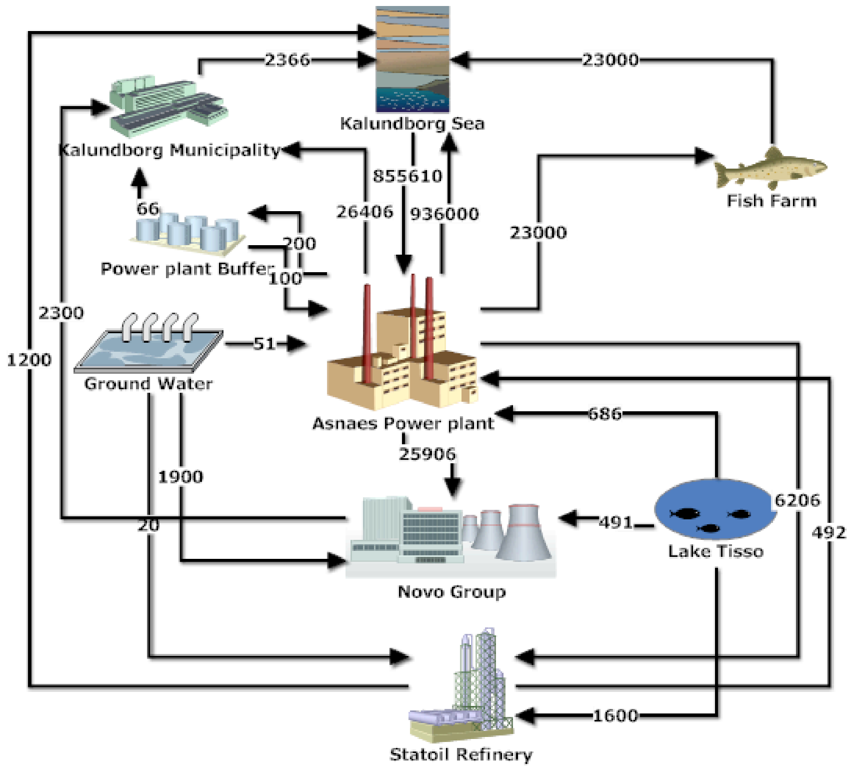



**Figure 10. 2002 Kalundborg Industrial Symbiosis- Water synergy system.**

Flows expressed in 1000 $m^3$.

As shown in Figure 10, IS at Kalundborg includes disparate industries such as the Asnaes power plant, the Statoil refinery, the Novo Group- a pharmaceutical company, as well as the local municipality that exchange by-product and resources amongst themselves. Since not all participating industries require the same quality of water, the water synergy network includes raw water from surface water and groundwater, as well as used industrial water in the form of wastewater and cooling water. The power plant, the refinery and the pharma group primarily use groundwater and surface water from Lake Tisso for industrial purposes. In addition power plant uses seawater from the Kalundborg Sea as cooling water for electricity production. Subsequently, wastewater and the cooling water is reused as well as recycled within industries to reduce the extraction of groundwater and surface water. For instance, wastewater and cooling water from Statoil refinery, as well as salty cooling water, boiler feed water, and steam from the Asnaes power plant are channeled to industries that present a requirement for the corresponding grade of water quality. The cooling water is stored at the power plant buffer, which is responsible for treatment and recycling of wastewater for daily operations. The cogeneration plant provides the Novo group facility and the Statoil refinery with steam and electricity by converting cooling water sourced from the sea. Moreover, Asnaes power plant delivers waste heat trapped in the cooling water to the local municipality for residential heating. In addition, the availability of heated cooling water also benefits the fish farm. If these by-product and waste streams were not symbiotically exchanged in the system, these resources would be considered a waste, and the subsequent increase in demand for virgin resources would over burden the already exploited and depleted natural capital of the region

Bearing in mind that KIS originated primarily as a water synergy network, over time it has evolved into a complex system with multiple industries exchanging around 30 distinct by-products. These by-products synergies include resources like wastewater, sludge, fly ash, drain water, straw, sea water, etc. and highly processed resources like bioethanol, C5/C6 sugars, sulfur fertilizers, gas, heat, gypsum, lignin, etc. The complete KIS network is considered including all by-product synergies to understand the trend in systemic resilience from 1960-2010. The study also analyzes the water exchange network for understanding the impact of stresses on the system, since the physical flow data is available for these synergies.

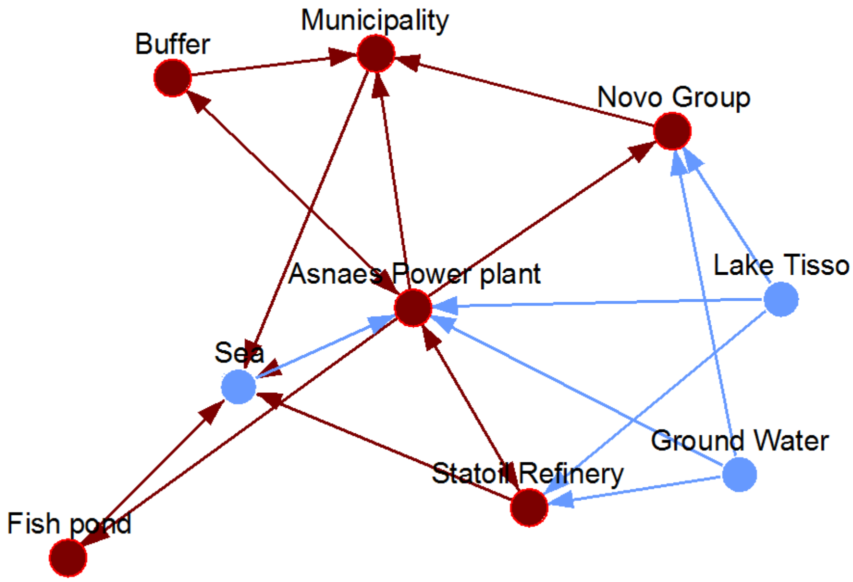



**Figure 11. 2002 Water Network- weighted and directed used for analysis.**

Nodes in blue represent sources of water and nodes in red represent the industries.

The industries and sources of water are considered as nodes and the symbiotic exchanges between them are depicted as edges of the water network. To visualize and analyze the KIS water network, an adjacency matrix representing the structure and interconnectedness in the network is constructed. Details of the adjacency matrix are available in the Appendix B (Figure 27). A weighted and directed adjacency matrix accounting for the magnitude and direction of flow is constructed and used for vulnerability analysis, a network based approach to identify and rank vulnerabilities in the system. By considering water and steam exchanges between the nodes, a 9-node water network shown in Figure 11 is constructed using actual reported data for the year 2002 [121]. This visualization is made using ORA software [208]. A series of un-weighted and directed networks were created to represent the multiple by-product exchanges between the industries for determining and understanding the trend in resilience of the KIS system over time.

### 4.2.2 Network metrics

**Table 4. Network metrics utilized for the Kalundborg Industrial Symbiotic System**

| Network Metric and Type | Formula | Definition | Implications for resilience |
|---|---|---|---|
| **Stress Centrality**<br><br>Shortest Path analysis (Koschützki et al., 2005) | $C_s(v) = \sum_{s \neq v \in V} \sum_{s \neq t \in V} \sigma_{st}(v)$<br>$\sigma_{st}(v)$: number of shortest paths from node s to node t containing the node v. | Stress centrality, $C_s(v)$, estimates the absolute number of shortest paths containing a node (Koschützki et al., 2005) | Stress centrality focuses on determining the local criticality of the node *v* in the system, which for a resilient system should be low |
| **Betweenness Centrality**<br><br>Shortest Path analysis (Koschützki et al., 2005) | $C_B(v) = \sum_{s \in V} \sum_{t \in V} \delta_{st}(v)$<br>where,<br>$\delta_{st}(v) = \frac{\sigma_{st}(v)}{\sigma_{st}}$<br>$\delta_{st}(v)$ : ratio of $\sigma_{st}(v)$ over the total number of shortest paths between nodes *s* and *t* in the network | Betweenness Centrality is the ratio of the number of shortest-paths between nodes *s* and *t*, passing through *v*, $\sigma_{st}(v)$, over the total number of shortest paths between *s* and *t* in the network, $\sigma_{st}$ (Koschützki et al., 2005) | Betweenness centrality determines the global importance of the node *v* in the IS network. A node with high betweenness centrality indicates that it is important with respect to the influence it has over the flow of information between other nodes. |
| **Degree Centrality**<br><br>Neighborhood of a node (Koschützki et al., 2005) | In-deg:<br>$C_{iD}(v) = d^{-}(v)$<br>$d^{-}(v)$: edges that terminate with node *v*<br>Out-deg:<br>$C_{oD}(v) = d^{+}(v)$<br>$d^{+}(v)$: edges that originate with node *v* | Degree centrality, also known as Freeman's Degree, (in-degree and out-degree centrality) of a node represents the number of edges pointing in or out of the corresponding vertex (Koschützki et al., 2005) | A node with high in or out degree centrality signifies that the node is connected by many edges in an unweighted network. From a weighted network perspective, high in or out degree suggests large flows to and from a node, respectively. It is one of the ways to determine a node's importance in the network and system's vulnerability. |
| **Network Efficiency**<br><br>Based on the Lotora and Marchiori (LM) (Latora and Marchiori, 2004), and the Nagurney and Qiang (NQ) measures (Nagurney and Qiang, 2010) | $E(G) = \frac{\sum_{i \neq j \in G} d_{ij}}{\eta_W}$<br>*E(G)* : measure of efficiency of the network<br>*I(g)*: Importance of the node 'g' in the network G, based on removal of node 'g' from the network.<br>$d_{ij}$: the weight of edge from node i to node j.<br>$\eta_W$: number of connected pairs of nodes | Network efficiency of a IS network is used to calculate the importance of each of the node by examining the change in the network efficiency on removal or change in the flows from the nodes (Crucitti et al., 2003; Latora and Marchiori, 2004; Nagurney and Qiang, 2010) | Removal of a node in the network leads to the reduction in the total throughput in the network, which decreases the efficiency of the network. Removal of the node that causes a larger change in *E* has a greater significance in the network.<br>This measure is also used to recognize the robustness of the network to disruptions. |

Table 4 presents a summary of network metrics utilized in this study to understand the network structure and topology of the IS system at Kalundborg. Centrality measures like degree centrality (in-degree and out-degree), betweenness centrality and stress centrality are used that provide information regarding the most central nodes in the system based on different structural properties of the network such as neighborhood interactions and shortest-path analysis [48, 209]. Additionally, hypothetical disruptive scenarios are introduced on the IS system, a method similar to the approach taken by Albert and co-workers to assess the overall impact on the network through removal of network components [57]. Reduction in throughputs of critical nodes or industries due to disruptive scenarios may impact the network efficiency and integrity of the system to a larger extent compared to other nodes in the network. In addition, network efficiency, another metric, considers weights of the synergistic exchanges as well as the network topology, and ranks the industries on the basis of their importance in the network [210-212]. This is discussed in detail next.

### 4.2.3 Vulnerability analysis of the KIS water network by simulating partial and complete disruptions.

In order to understand the vulnerabilities and assess the resilience of the water network, the change in network efficiency for the 2002 snapshot of the water network is calculated in response to partial and complete disruptions. A partial disruption is defined as an untargeted disruption on a node like pipeline damage, shortage of a resource, minor technical failures, drought, etc. that causes a short-lived impact and leads to reduction in total flow in the system. 10% reduction in the annual input and output exchanges of Asnaes power plant, Statoil refinery, surface water from Lake Tisso and the groundwater nodes are simulated. On the other hand, the analysis is restricted to 10% reduction in the seawater withdrawal by other industries at KIS and a disruption is not applied on the flow of water from the industries to the sea since a decrease in the flow of treated water to the sea is not likely to limit the withdrawal levels.

The scenario of complete disruption is also analyzed which is defined as a targeted disruption, such as deliberate attacks on critical nodes of the system, or an untargeted disruption, like unexpected economic collapses such as bankruptcy, and natural disasters such as storms and droughts that are frequent in Denmark, possibly leading to an irreparable amount of damage to the nodes (industries). A 100% reduction in the input and output water flows is simulated for Asnaes power plant, Statoil refinery, surface water from Lake Tisso and the groundwater nodes.

Similar to the partial disruption scenario, the simulation is restricted to reduction of output flows from the Sea node to other industries.

Changing input/output flows from an industry in the system will affect input and output flows from the industries upstream and downstream of that industry since it will limit the supply and reduce the productivity of the overall system. To determine the cascading effect on the network caused by the disruption scenarios on an industry, the ratio of change in the total output of the disrupted node is calculated and thereby calculating the effect it has on the subsequent industries in the network. Cascading effects due to disruption of industries causes change in the flows between the nodes of the network, thus bringing down the productivity of the whole network. The efficiency of the original network topology is compared with the disrupted network's topology to gain insights on the importance of different nodes in the network, and understanding of the robustness of the water synergy network to disruptions. The network efficiency measure described in Table 4 is developed specifically keeping IS networks in mind and its details are in Appendix B. Centrality calculations for the IS network is performed using SocNetV [213].

### 4.2.4 Evolution of the KIS from 1960 to 2010

The time-series data is analyzed for KIS from 1960 to 2010 available from the Kalundborg Symbiosis Institute to determine the trends in interconnectedness and the network topology [122]. The goal of this analysis is to shed light on the evolution of KIS network and gain an understanding of possible strategies for designing resilient industrial symbiosis networks. Using available data for KIS network configuration, directed and un-weighted networks representing different byproduct synergies are prepared. These include networks for water, energy, materials, and combined material and energy synergies for the four time periods: 1960-79, 1980s, 1990s and 2000-10.

Water-flow network considers water and steam based interactions in the network (wastewater, cooling water, etc.). Similarly, energy-flow network is constructed by taking all the different energy exchanges between the industries (like steam, gas, etc.). The material-flow network represents all by-product and waste exchanges between industries other than water and energy streams. The total-flow network is also constructed by including all three types (water, energy, and material flow) of exchanges at KIS. In general, an increase in the number of exchanges is observed over the years; however, in certain instances interactions are withdrawn for they might have become economically unviable over time, or an improvement in technology has avoided the synergies. The time trends are analyzed in these symbiotic networks in terms of the network topology and changes in node-level metrics: in-degree, out-degree, stress and betweenness centrality for KIS. Detailed network representation of KIS for the four time periods are available in Appendix B (Figure 29).

### 4.2.5 Hypothetical savings made by the industries in the KIS

The resulting monetary savings due to the biophysical exchange of waste and by-products at KIS are quantified for the year 2002. Two types of hypothetical savings are computed; the first one includes profit earned (savings made) by the industry as a result of participating in industrial symbiosis, while the second type monetizes preservation of virgin natural raw materials due to substitution by by-products and waste streams from the neighboring industries.

The direct economic gains made by the industries are accounted for by breaking down the synergies into ‘Giveaways’ and ‘Priced’. ‘Giveaways’ as the name suggests are synergies that occur without the recipient paying a price for them. In such a transaction, the donor industry saves resources and economic capital involved in the treatment of the waste or by-product, while the recipient industry saves economic capital that would have been used to procure virgin raw materials or inputs. On the other hand, 'priced' exchanges have a price linked to the exchange of the by-products. The donor industry sells the treated by-product and earns a profit on it, while the recipient industry saves on the price of the by-products that cost considerably lower than the virgin raw materials. The classification of synergies as "Giveaways" and "Priced" is adopted from the data provided by Jacobsen for KIS for the year 2002 [121]. The assumption that by-product streams cost a flat 50% of the substituted raw material's price is also based on the same study [121]. All the savings made by an industry, as a donor or a recipient, are added to compute the total monetary savings made by the industry. The economic savings made by each industry are compared to the total unweighted degree, which includes both the in-degree as well as the out-degree, for each of the nodes in the network.

A monetary value is also attached to natural resources avoided due to the use of waste or by-product streams for each of the industries. The price of substituted raw materials for each of the industries is calculated by summating all the waste or by-product streams accepted by them. For instance if an industry used wastewater instead of $1000 worth of groundwater, the industry saved $1000 worth of natural resources. Detailed data on market prices of commodities and resource flows used for quantifying the hypothetical savings is available in Appendix B (Table 12). Monetary value of avoided natural resource consumption by each of the participating industries is also provided in the Appendix B (Table 10).

## 4.3 RESULTS

### 4.3.1 Network Analysis of the 2002 KIS Water network

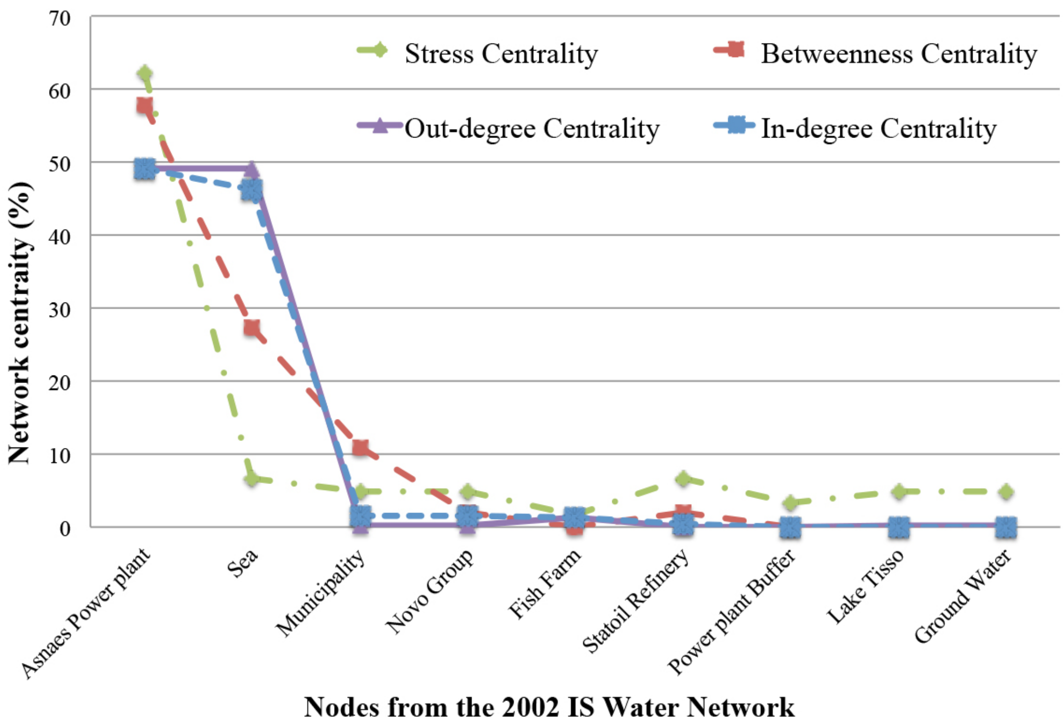



**Figure 12. Network based node-level metrics for 2002 snapshot of the Kalundborg Industrial Symbiosis system.**

Figure 12 presents the node-level metrics for the 2002 snapshot of the KIS water network. The results in Figure 12 illustrate the importance of various industries in the network as indicated by several network metrics for the water network. An apparent trend is visible as Asnaes power plant has the highest in-degree, out-degree, stress, and betweenness centrality suggesting its high importance in the system.

Both, Asnaes power plant and the sea have high degree centralities because of the largeamounts of in- and out-flow from these nodes. The power plant receives large quantities of water from the sea and directs steam, cooling water, and wastewater to other nodes in the network. The sea has a high in-degree because it receives discharge water from most of the industries in the network, and has a high out-degree because it is responsible for the supply of cooling water to the power plant, which accounts for 99% of all the water being supplied from the three water sources: the lake, the sea, and groundwater. Other nodes in the system like the Statoil refinery, the Novo group (pharmaceutical company), the Kalundborg Public works, Fish farm to name a few, have a comparatively much lower importance in the network as conveyed by degree, stress, and betweenness centrality.

Asnaes power plant also emerges as the most centrally located node in the network based on stress and betweenness centrality as well indicating the critical nature of the industry, thus a point of vulnerability for the IS network. It is worth mentioning that Asnaes power plant help facilitate the water exchange between the sea and other industries in the KIS water synergy network, hence reflected in its high betweenness and stress centrality. While Kalundborg Sea has high degree centralities, its stress and betweenness centralities are relatively lower primarily because it is either an origin or destination node for most water streams. From resilience perspective, identifying and securing the vulnerable nodes such as the Asnaes power plant against disruptions is critical for developing robust symbiotic networks.

### 4.3.2 Importance of nodes based on complete disruption

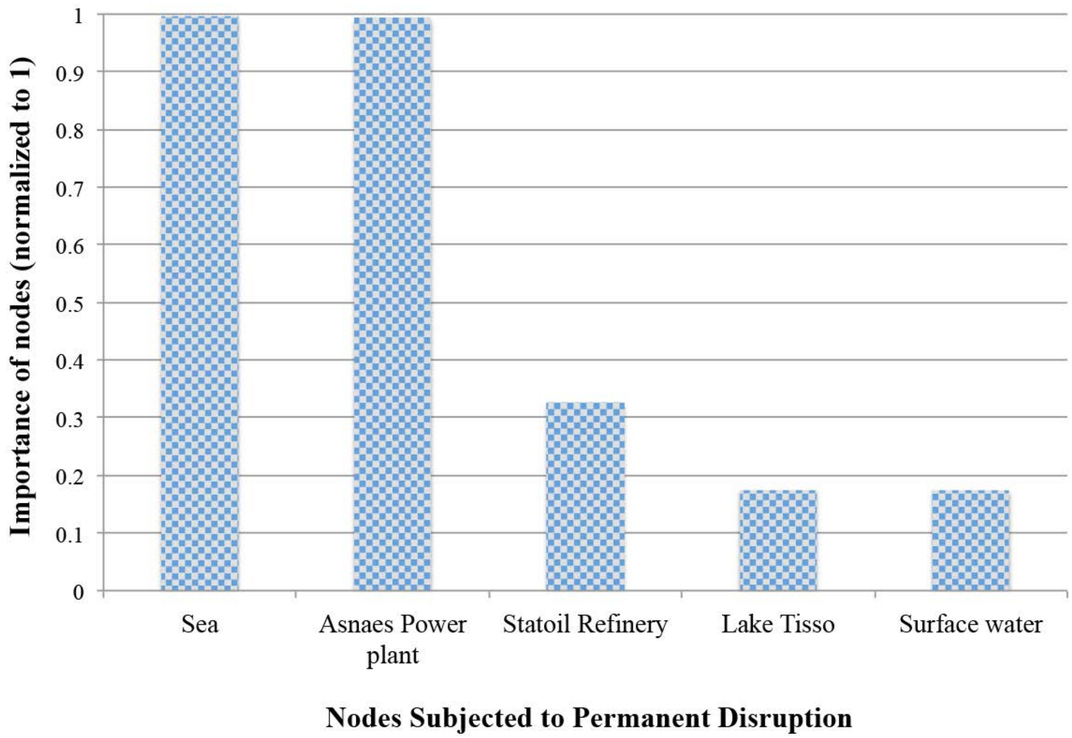



**Figure 13. Importance of nodes based on network efficiency after permanent removal of nodes from the KIS Water Network.**

System is vulnerable to attack on nodes with high importance. Importance is dimensionless and scaled to 1. The results for partial removal scenario are in Appendix B.

Figure 13 presents the results for the importance of nodes on the basis of change in network efficiency after their complete removal from the KIS water network. The robustness of the KIS water network is determined by evaluating the dependence on particular nodes to maintain the structure and function of the network. The complete removal of Asnaes power plant and the input from the sea as a result of targeted or untargeted disruption has a higher impact on the structure of the network than the removal of Statoil refinery, surface water, or ground water. Since, the sea solely supplies water to Asnaes power plant that accounts for 99% of the water consumed by the power plant, the disruption on either of the two nodes affects the other directly. This explains the high importance of these nodes as shown in Figure 13 based on the disruption scenarios.

With the removal of the Asnaes power plant only 7 of the 20 previously existing synergistic water flows were maintained. On the other hand, complete removal of inputs from the sea greatly reduces the flows between the nodes. In comparison, complete removal of nodes such as the Statoil refinery, surface, and ground water sources does not cause large gaps in the system, but still moderately reduces the amount of water exchanges in the network. Similar results are observed for the short-lived disruption scenario with Asnaes Power plant and the Sea emerging as the influential nodes and other nodes like Statoil refinery, surface water, and ground water exhibiting negligible importance in the network. The results for short-lived disruptions are available in the Appendix B. It is interesting to note the similarities in the results based on node-level metrics (Figure 12) and importance based on network efficiency (Figure 13) with Asnaes power plant and Sea emerging as the most important and critical nodes in the water synergy network.

### 4.3.3 Evolution of KIS network

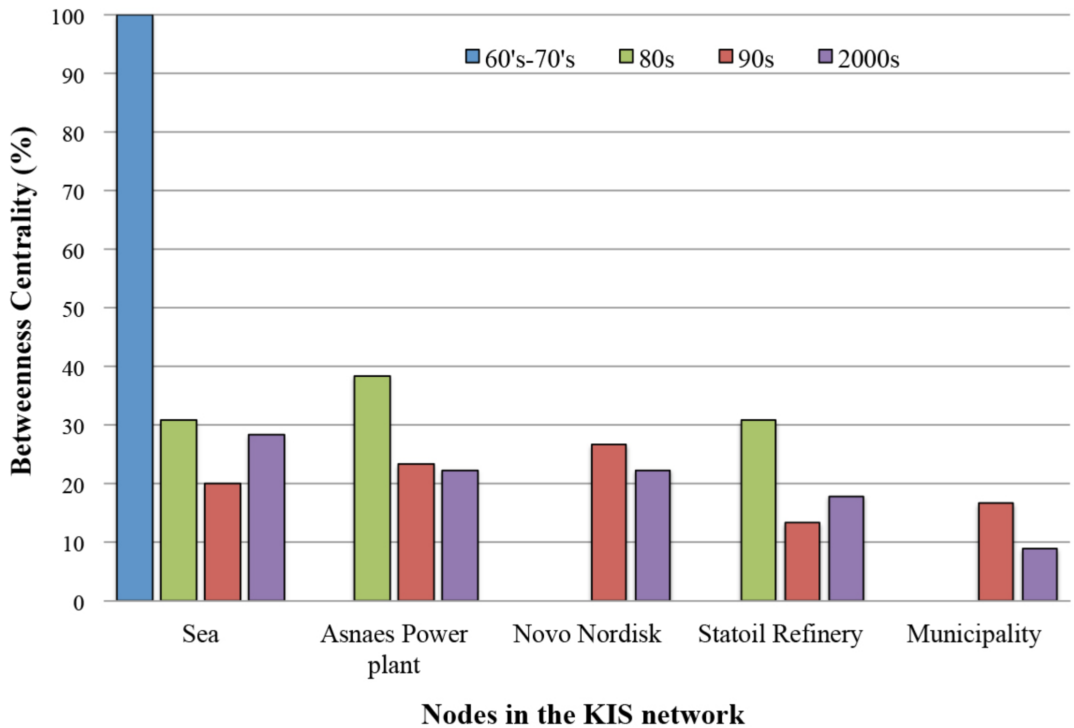



**Figure 14. Evolution of Betweenness Centrality of the industries/nodes for water synergies at KIS.**

Figure 14 presents the time trends in betweenness centrality for the KIS water synergy network. Result based on the shortest-path based centrality index demonstrates a gradual decrease in the betweenness centrality of nodes for water, energy, materials, and total flows network over time, signifying that KIS network is becoming less vulnerable to network disintegration caused by single points of failure. Furthermore, the results indicate an even distribution of the betweenness centrality over time, which represents decreasing vulnerability of nodes, and increasing interconnectedness in the KIS system. Trends for stress centrality, normalized in-degree and out-degree for water, energy, materials, and total flows network are available in the Appendix B and, demonstrate similar findings.

The results for absolute in-degree and out-degree show an increasing trend over time for the water, energy, materials, and total flow networks. This is an expected finding since the KIS network has increased in size over time, both in terms of the number of participating industries and the interactions between them. Thus, these results suggest an increase in diversity of the types of industries, caused by an increase in the number of nodes in the network, and redundancy, caused by an increase in the number of similar by-product interactions for the industries over time. In contrast to the results for absolute in-degree and out-degree, normalized in-degree and out-degree show a downward trend, suggesting a decrease in vulnerability and a greater interconnectedness of industries in the KIS. Decreasing vulnerability, increasing redundancy, and diversity are important properties that have been previously suggested for building resilience [20, 35]. Additional results for the time trends in degree, stress, and betweenness centralities are available in Appendix B.

### 4.3.4 Savings made by the Industries in KIS.

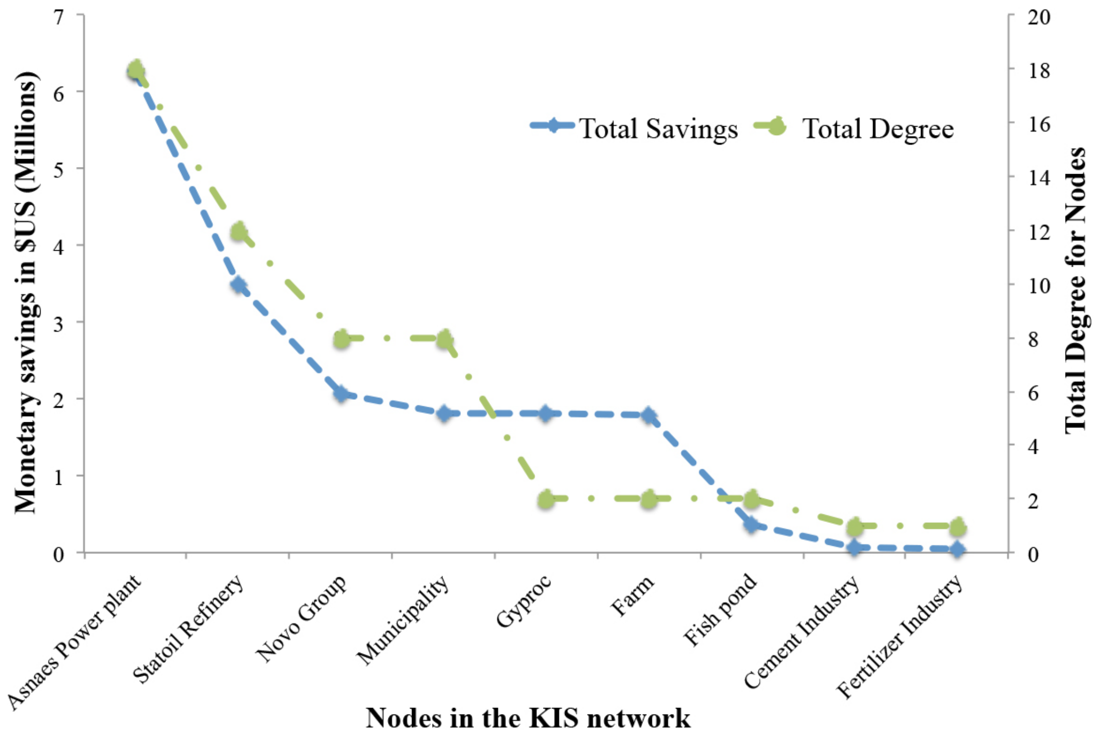



**Figure 15. Comparison of hypothetical savings made by the industries for year 2002 and the total degree centrality for each of the industries in the system.**

Figure 15 shows a plot of the total hypothetical savings made by the industries versus the total degree centrality. Some similarities are observed in the savings made by the industries in the KIS water network and their corresponding total degree centrality. Asnaes power plant, Novo group, and Statoil refinery have relatively high total degree centrality and also higher hypothetical savings. However, similar relationship is not observed for other industries, such as Gyproc and Farm.

It is important to keep in mind that the monetary value of the natural resource avoided due to the exchanges of waste streams and by-products is attributed as savings. The calculations of these savings are based on the market price of the substituted raw material. Industries like

Novo group, Statoil refinery and the municipality avoid the use of natural gas for steam generation by utilizing excess steam from the Asnaes power plant, thus, generating the highest monetary natural resource savings and also reduced environmental burdens. The reason behind the lack of a strong relationship between hypothetical savings and total degree centrality is also the quality of resource being exchanged by the industries. For example, the monetary value of natural gas is very different from the monetary value of wastewater. Nonetheless, the results in Figure 15 indicate that waste and by-product exchanges in an IS network are not only environmentally friendly but also economically viable for the industries in the long term. In addition, by-product synergies and symbiotic relationships between industries may aid them to offset their dependence on virgin natural resources and raw materials, and consequently be both environmentally and economically beneficial.

## 4.4 DISCUSSION

This work focused on studying the network properties of KIS with specific application to the water synergies. Using metrics based on network theory and disruptive scenarios of short-term failure and removal of nodes, structural vulnerabilities are identified in the KIS water network, a concept perceived as an antonym to resilience. A system with high vulnerabilities will inevitably have low resilience. On the other hand, resilience is an emergent property of the system that ensures functionality by adapting to disruptions on the system. The structural durability of an IS system is pivotal for ensuring its overall functionality. For instance, an IS network that loses its cohesiveness due to vulnerabilities, may fail and disintegrate, rendering the system dysfunctional. In the Kalundborg network, the Asnaes power plant emerges as the highest vulnerable node from a network topology perspective, calling for greater efforts to secure the node as it may have the largest cascading impact on the network, thus threatening its functionality. Researchers have argued that an increase in vulnerability of nodes may correlate with a decrease in resilience or adaptive capability of the network [13, 14]. Time trends for the KIS network topology revealed decreases in betweenness centrality of most nodes indicating that the network may be becoming less susceptible to single points of failure. However, due to absence of quantitative details on resource flows between industries for different time periods additional research is needed to make concrete claims about the overall resilience of the KIS network.

Nonetheless, snapshots of the KIS network over time are able to shed light on the evolution of the network to its current state. From the available data, it is notable that the size of the IS network has steadily increased, both in terms of the number of industries in the region and the synergetic exchanges between them. However, the results for absolute in and out degree change over the years presented in the Appendix B suggest that most of the new industries joining the KIS tend to primarily have synergetic exchanges with the Asnaes Power plant. Asnaes Power plant is also the most critical node as per the analysis presented in this work, and has the most number of synergetic interactions in the KIS network at any given period from 1960-2010. This property of “rich get richer” is called preferential attachment where new nodes in a network preferentially attach to more central nodes than to less central ones. Preferential attachment model of network formation results in a network structure that has a power-law degree distribution [55]. These networks tend to be robust to random removal of nodes, but are vulnerable to targeted removal of central nodes [57]. Small size of the KIS network restricts our investigation of degree distribution to comment on whether the KIS network follows a power-law distribution. However, analysis of our results for permanent disruption scenario suggests that the system is vulnerable to disruption on nodes with high degree centrality, complimenting with the findings of a recent study by Zhu and Ruth on the robustness of industrial ecosystems using generalized industrial ecosystem models [62]. Thus, identifying and safeguarding nodes that are extensively connected and have high amounts of by-product and waste flows in the system are necessary to ensure resilience to unknown stresses.

The analysis presented in our work provides some insights regarding strategies and guidelines for designing resilient IS systems. Firstly, seeing that resilience is a planned and strategically designed feature of a network, a multi-level deliberation of environmental, ecological, social, and economical aspects must be accounted for in a specific IS system. Moreover, since resilience is the ability of a system to respond to change, a systems-level understanding of the possible stochastic processes and perturbations is critical for developing adaptive capacity in an IS network. The results from the analysis of evolution of KIS network, where a decrease in vulnerability arising from single points of failure were noted, exhibited an increase in the number of participating industries and the interactions among them. This suggests that by increasing redundancy (more exchanges of similar resources) in the network, it may be possible to decrease vulnerability across nodes in the network. Redundancy in an IS context is maximized by encouraging multiple connections in the network, which means that more distinct industries with similar commodity synergies may aid in absorbing the impact of degradation of an industry in the network [190]. An increase in redundancy of synergies and industries in an IS may axiomatically promote resilience by favoring flexibility or plasticity of the network that provides alternative opportunities for synergies if a node or edge is removed, thus ensuring the adaptive capability of the IS. An IS with more number of industries with similar synergistic pathways provides flexibility to the network [190].

Another important trait that can aid in the design of a resilient IS network is the concept of multifunctionality. In the context of IS, multifunctionality refers to the ability to provide multiple functions and benefits from the same system [18, 214]. As shown by the hypothetical savings calculations in this paper, an IS system provides benefits in the form of economic profitability to the industries in the region as well as environmental benefits in the form of resource conservation. In addition, it also provides other broader social, environmental, and economic benefits to the region such as employment, reduced industrial emissions, etc. in the region. With many governments and international consortiums like OECD and EU beginning to realize these benefits of IS and promoting it, stakeholders such as industry owners, local community, regional policy-makers, environmental planners, etc., must be included in the genesis, planning, implementation, and evaluation of IS systems. Such an approach can enhance the adaptability of the system to disruptions through collective social-industrial initiatives, thus permitting the IS to be more resilient to the constant flux that the society, technology, and the ecology will be invariably going through [190]. An example of this approach is seen in the planning and coordination efforts undertaken by facilitators such as the Symbiosis Institute and the Environmental club, and the small, tightly knit community at Kalundborg, who have together fostered the system to adapt to the steadily increasing number of participating industries and the fluctuating number of synergetic exchanges. These modifications in the network structure of KIS are due to the changes in management of the industries and the technological advancements made by the participating industries [121, 122, 207]. Thus, multifunctionality as a design objective endows social embeddedness to the IS, which increases its ability to adapt to risk that may otherwise cripple it [117, 197, 215].

Finally, natural ecosystems exemplify a useful context in which to understand resilience. An ecosystem maintains its panarchy by readily re-configuring itself in response to stressful states, considering that the primary motive of ecological resilience is functionality [15, 216]. On the other hand, most man-made systems are governed by the concept of engineering resilience with a single equilibrium steady state that may maximize efficiency but is not fail-proof in the long run. Design patterns and structural features of natural ecosystems provide a convincing case that ecological networks can provide insights for building resilient engineered systems. An example from the literature regarding the fundamentals of ecological resilience of a system by Walker and co-workers describes the issue of grazing on the semi-arid grassland ecosystem of East and South Africa [15, 217]. Due to the dependence of varied species of herbivores on these grasses, a dynamic balance between various grass species is maintained to withstand intensive grazing and drought conditions. One set of grass species, with a higher photosynthetic rate, is able to provide the grazing herbivores the desired nutrients, whereas the other set of grass species are deep rooted but less productive in terms of available biomass for grazing, thus able to withstand grazing and drought pressures. The diverse set of grass species together are able to maintain a homeostatic balance to meet the functionality to provide grazing opportunities, since the grass species with high productivity are able to provide for the herbivore, and the drought resistant species is able to counter overgrazing and drought conditions. Thus, together these diverse species are able to serve both functions: productivity and drought protection. In the context of IS networks, also known as industrial ecosystems in the literature, the composition of industries also plays a role in building resilience. Increase in heterogeneity of critical nodes may lead to decrease in vulnerability, and increase in flexibility, redundancy, and multi-functionality of the system.

## 4.5 CONCLUSION

Resilience as an emergent property of a system's ability to absorb stress is vital for any system attempting to be sustainable, and more so in the case of systems comprised of tightly coupled components. IS networks are such highly interconnected systems where a disruption at even one industry can limit the productivity of all other participating industries, resulting in cascading impacts on the network. By adopting a network theory approach for KIS network, industries that are sources of systemic vulnerability are identified, and disruptions are simulated to assess the ability of the system to maintain its functionality. Also, on observing the evolution of KIS, the addition of diverse industries and exchange of redundant commodities between them resulted in decreasing vulnerability and single points of failures. Moreover, industries that are involved in greater number of symbiotic exchanges tend to incur greater economic benefits from IS. Reflecting on the insights offered by this study, features such as diversity, redundancy, and multifunctionality should be deliberated on while designing for resilient IS systems. With increasing adoption of IS and availability of empirical data, the aim is to further expand the theoretical framework for design of resiliency in complex, self-organizing systems.

## 5.0 EXPLORING RESILIENCE OF URBAN TRANSPORTATION INFRASTRUCTURE: A CASE STUDY OF LONDON METRO SYSTEM

### 5.1 INTRODUCTION

**Figure 16. Map of the London Metro Network [218].**

On August 14th, 2003, contact between an Ohio power-line and an overgrown tree resulted in an estimated $6 billion impact on the U.S. Economy [219]. What happened in between was an electric grid failure known as the Northeast Blackout that affected other dependent critical infrastructures responsible for communication, transportation and water supply for 55 million people [6]. Other recent events like Hurricanes Katrina, Rita and Sandy, the Indian Ocean tsunami, and the Tohuko, Japan earthquake and tsunami have also exemplified the vulnerability of our modern, highly interconnected society and economy to isolated incidents whose impacts are amplified and observed across national and international boundaries [1]. The threats that accompany a highly advanced and interconnected society and economy are convoluting [219-221]. Moreover, the modern society is increasingly dependent on the stability and performance of a complex system of interdependent infrastructure assets that form the nation's backbone. The U.S. Department of Homeland Security identifies 16 such CIS whose disruption would result in catastrophic impacts on the nation's economy and security [222]. Additionally, the PPD 21 on *Critical Infrastructure Security and Resilience* has highlighted the necessity of understanding the *resilience* of these expanding, large-scale and interconnected systems to disruption and disasters [223].

Developing resilient large-scale, critical infrastructures is not only a national imperative, but is critical for addressing the threat of natural disasters and man-made disruptions on communities locally as well as globally. On a microcosmic scale, consideration of how effectively urban infrastructures can supplement the creation and preservation of sustainable urban areas is of equal importance. This is demonstrated through increased urbanization and disproportionate consumption of natural resources within urban boundaries. Cities account for no more than 1% of the Earth's surface area, yet consume 75% of its natural resources and occupy over 50% of the global population [128, 129]. Further, increasing trends of urbanization and changing spatial organization of cities point towards challenges for the urban ecosystem that are accompanied with growing dependence on an urban lifestyle [128, 130, 131]. There is a great necessity for creating sustainable and resilient urban infrastructures that are capable of supporting large percentages of the globe's population.

A singular avenue for improvement of urban infrastructures exists within the transportation sector. As population and spatial boundaries of cities expand, commuters become increasingly reliant on transportation infrastructure. Moreover, the increasing number of extreme events and pressures of congestion make existing infrastructure vulnerable. Specifically, public transportation infrastructures like metro rail-systems that provide environmental and economic benefits for urban regions, must be capable of enduring heightened levels of stress [135]. Moreover, with spatial organization of major cities becoming more polycentric in nature [224, 225], it is essential to develop resilience strategies specifically for polycentric cities. Not only are urban planners from major cities promoting polycentric spatial organization for urban sustainability, but literature also demonstrates that cities from emerging economies in Asia, Africa and South America are growing in a polycentric fashion as well [226]. Analysis is required to both ensure that existing transportation networks are capable of withstanding and containing unexpected perturbations, and develop heuristic strategies for the creation of more resilient networks in the future.

Over the last 15 years, significant progress has been made in supplementing the quantification of reliability and robustness within large-scale transportation systems, and network analysis has emerged as the tool of choice [143, 146, 148]. Application of network analysis to metro systems has enabled quantification of topological properties that influence its resilience, as has been the case for complex systems in economics (trade networks, etc.) and engineering (electric grid, etc.), among others. Using network analysis, Latora and Marchiori identified the *small-world property* of the Boston transportation system, suggesting that the topology of the transportation network enmeshes desirable levels of interconnectivity and redundancy [54]. Previous studies have also adopted a networks approach to comprehensively compare various metro systems across the globe based on new network indicators [149-151, 227]. Derrible and Kennedy applied new and existing metrics to make more decisive claims about the organization of the network that directly relate to the robustness, resilience and efficiency of metro systems[148]. Ip and Wang also developed quantitative measures for resilience and friability of cities in the mainland China railway network [152]. However, majority of these studies have attempted to identify and understand network properties that influence reliability and robustness of metro systems based on its topology and geographic location. These studies have been unable to incorporate urban dynamics in terms of passenger flow patterns in these network models of metro systems to develop a comprehensive understanding of its resilience.

In order to bridge this gap in the literature, a novel network approach is developed in this study to quantitatively assess the influence of the network structure, the spatial locations of specific network components, as well as the patterns of intra-urban movement, on the resilience of metro-rail infrastructure. Specifically, the comprehensive *London underground* metro system is examined as a case study for our analysis. The London metro system is one of the most frequented and longstanding of its kind, accounting for 268 stations across 11 metro lines and 1.2 billion annual passengers [228]. Further, due to the polycentric organization of London, the London Underground acts as a paradigmatic case study, representative of what existing and developing world metro systems may resemble in future years [229]. *Transport for London's* (TFL) Rolling Origin and Destination Survey (RODS)–a passenger questionnaire that documents metro journey behavior of the London Underground–is used to compile passenger data that fully describes the network's passenger flow at five durations throughout the day [230]. The survey data, along with knowledge of the sequential organization of the London Underground's lines and stations, are used to take a multifaceted and weighted approach to comment on the resilience of the metro network.

Since there is a lack of consensus regarding the definition of resilience in the academic literature, it is imperative to state the definition of resilience employed in this study right at the onset. The term "resilience" tends to have different interpretations for different areas of study. The more traditional definition, known as *engineering resilience,* refers to a system or component's resistance to disruption and the speed of its return to an equilibrium state [26]. However, *ecological resilience* is quantified by the magnitude of disruption that can be endured by the systems before a change in its equilibrium state is noted [19, 26]. Since it is extremely difficult to accurately predict the direct and indirect consequences of a disruption on a complex, large-scale system, quantifying resilience in terms of the recovery time required for a system to return to its equilibrium state is even more difficult. For this reason the definition used in this study is a reworking of ecological resilience for industrial and infrastructure systems [32]. Henceforth, resilience in this paper refers to *the ability of a system to maintain its structure and function in the face of perturbations*.

### 5.1.1 Construction of the London Metro System Model

Metro systems are modeled as networks for studying the topological properties and local vulnerabilities, where metro stations are considered nodes and rail connections between them are edges. London metro system data on passenger flow and station connectivity is converted into networks by creating *adjacency matrices*. An adjacency matrix is a '$n$ x $n$' matrix (in this case

$n = 268$) whose $(i, j)$ entry is 1 if the *ith* and *jth* node are connected to the each other, and 0 if they are not, for a network with n number of nodes. Such a matrix would represent an unweighted and undirected network, which can be converted to a weighted-directed network if magnitude and direction of the flow between *ith* and *jth* nodes is known. The London metro system is modeled as both an *unweighted-undirected* ($UW_{ud}$) network based on the station connections, and a *weighted-directed* ($W_d$) network based on the passenger flow information available from RODS.

## 5.2 METHODS

The methodology adopted to examine network properties and vulnerabilities of the London metro system for understanding the implications on resilience is described next.

### 5.2.1 Topological analyses of the London Metro networks

In real-world large-scale networks, there are a number of common recurring patterns of connections that have a profound effect on the way these complex systems behave. The procedure for analyzing the topology of the London metro system by separately examining the $UW_{ud}$ and $W_d$ networks is discussed below. Topological analyses of both these configurations provide unique insights on the resilience of the London metro system.

For topological analysis of the $UW_{ud}$ London metro network, the first step is to examine whether the network exhibits a small-world effect. Watts and Strogatz introduced the concept of *small-world* effect in networks, characterized by a small characteristic path length- the average shortest path length for the network, and a high clustering coefficient- a measure of clustering in the network [51]. For this reason, nodes in a small world network are not connected directly to each other but most nodes can be reached indirectly from all other nodes by a small number of steps [50]. In addition to the methodology proposed by Watts and Strogatz, other methodologies are also employed from the literature to determine small-world properties for real networks. Expanding the Watts and Strogatz approach to real world networks, Latora and Marchiori asserted that in physical terms the flow of information in a small world network is extremely efficient [54]. For this reason, efficiency of information propagation is computed at both global (network) and local (node) levels as a second methodology for small world detection. A high value for these measures will suggest a small-world topology. Global efficiency refers to the overall network efficiency, while local efficiency is the average efficiency of each node's sub-graph comprised of its neighbors. The third method used to detect small world effect in the $UW_{ud}$ London metro network also uses the network metrics considered by Watts and Strogatz. In this approach, the characteristic path length and the clustering coefficient for the $UW_{ud}$ London metro network is compared with those of a synthetically generated small network with the same edge density. If the values for characteristic path length and clustering coefficient of both the networks are notably similar, then one can conclude that the $UW_{ud}$ London metro network may exhibit small-world tendencies. The mathematical details for each of the metrics used by the three approaches are described in Appendix C (Table 14).

The network topology of the $W_d$ London metro network is analyzed by constructing probability distributions *p(s)* of passenger strength for each station. By constructing these strength distributions for the networks, the spread of passenger flow for all stations in the London metro network is characterized. Strength distributions for the three time snapshots (am peak, mid-day and pm peak) are examined to check whether they follow a power law. If strength distributions follows a power law of the form $p(s) \propto s^{-\varepsilon}$, where ε is a constant parameter of the distribution known as the scaling factor, then it would suggest that there are a handful of critical stations that contribute a large fraction of passenger flow, while the majority of stations serves a far smaller percentage of the passengers. In order to verify whether the strength data follows a power-law, a statistical framework is adopted that estimates the scaling factor, ε, by using MLE in tail region of the distribution (above some lower bound $s_{min}$). The scaling factor, ε, for power-law distributions mostly lies in the range of $2 < \varepsilon < 3$, however this is not a rule [165]. The mathematical formulations behind this comprehensive power-law detection methodology are discussed in detail in Appendix C.

### 5.2.2 Robustness analysis of the London metro network

Robustness analysis is useful to understand the network topology on the basis of node removal. It also allows us to observe the inherent vulnerability of the system due to connectivity pattern of the nodes. The robustness of London metro $W_d$ network is investigated by determining the impact of systematic targeted and random disruptions of stations on overall connectivity and passenger flow of the network. The impact of systematic node removal on the network is measured using network level graph theory metrics. The degradation in total passenger strength of the London metro network caused due to targeted and random removal of stations is specifically measured. As an example, targeted removals may signify terrorist attacks affecting the most influential stations, and random removals represent natural disasters, track failures, or regular maintenance work in the metro system.

### 5.2.3 Graph theory based metrics developed to analyze vulnerabilities

A geospatial model of the London metro network is developed that incorporates the station connectivity and the passenger traffic data with the geographical location.

Disruption scenarios are created for identifying nodes that are sources of functional vulnerability for the metro network. The geospatial model of the London metro is used to identify vulnerability of a station in terms of its capability to displace passengers to neighboring stations within a set radius of 1.6 km after its disruption. Studies have claimed that commuters are comfortable walking 400 meters to access public transportation, and do not prefer using public transportation if they have to walk more than 400 to reach the transit access point, be it a metro station or a bus stop [231]. For this particular reason, a linear function is used to determine the percentage of people displaced, where the inherent understanding is that the closer the proximity, the higher the passenger displacement. In order to determine the distribution of passenger displacement between the neighboring stations, a closeness index was developed for each of the neighboring stations based on their distance from the disrupted station. In this way, the station inoperability that measures the percentage of passenger flow degraded due to failure of each station is computed. The derivation for the equation used to calculate station inoperability is provided in the Appendix C.

Edges that are a source of structural and functional vulnerability are also identified within the London metro network. To measure the structural vulnerability, a metric called the redundancy, $r$, is created which measures the change in the number of connected node pairs after an edge failure in the network. Breadth first search algorithm is used for counting the number of connected node pairs in the network, and the number of connected node pairs in the network is calculated after disruption of each edge. This metric is calculated for the $UW_{ud}$ London metro network. Edge failure that results in a low redundancy indicates the system's low resilience to shocks on that particular edge. Redundancy, *r*, is defined as

$$r = \frac{p_{G|g}}{p_G} \tag{10}$$

$P_G$ represents the number of connected node pairs in graph G, which is *n(n-1)/2* for a connected undirected network where n is the number of nodes. While $P_{G|g}$ is the number of connected node pairs remaining in graph G after removal of an edge, g.

Similarly, a metric called the fracture coefficient, $f_c$, is created to determine the functional vulnerability of an edge in terms of the extent of fracture caused by its removal. This metric is an extension of the fragmentation metric developed by Borgatti [232]. While Borgatti's fragmentation metric was created for identifying key nodes in a social network, the fracture coefficient uses the same concept to identify edges that are points of vulnerability for the rest of the metro network. Unlike the redundancy metric used for determining structural vulnerability, the $W_d$ London metro network with data on passenger flow between metro stations is used to identify the functional vulnerabilities in the context of urban dynamics. Fraction coefficient, $f_c$, is defined as follows,

$$f_c = 1 - \left( \frac{|S_{C1} - S_{C2}|}{S_T} \right) \tag{11}$$

$S_{C1}$ signifies the total strength of nodes in component 1, $S_{C2}$ is the total strength of nodes in component 2 and $S_T$ is the total strength of all nodes in the London metro network. An edge with a high fraction coefficient signifies that its removal will result in two large components, and cause a high reduction in passenger flow due to the disruption. Thus, high fracture coefficient for an edge signifies that system is functionally vulnerable to its disruption, which suggests low resilience.

### 5.2.4 Community detection within London Metro network

By further understanding the pattern of passenger commutes, insights regarding the station dependencies are derived that can help assess the cascading impacts throughout the system resulting from disruptions. For this reason, sub-communities comprising of stations are detected within the $W_d$ London metro system. The modularity optimization method developed by Leicht and Newman for $W_d$ networks is used to identify sub-communities [179]. Modularity based community detection identifies sub-communities by maximizing the modularity function, Q, is defined as follows

*Q= (fraction of intra-community edges) – (expected fraction of such edges).*

It works on the premise that connections will be denser within a community and sparser between communities. A high modularity value for a community translates into a valid community division indicating there are more connections inside a community than what one would expect by chance for a random network. Specifically, the spectral optimization technique is used to maximize the modularity for community detection [179]. In addition, the repeated bisection graph-partitioning algorithm is employed to identify natural groupings of nodes in the network. This method starts by dividing the network in two, and then repeating the division while optimizing for maximum modularity of the communities. A good division of a network results in a high modularity score, thus Q is maximized over all possible divisions of the economic network to identify communities of industrial sectors. Mathematical details of the spectral optimization algorithm and the underlying equations are in the Appendix C.

## 5.3 RESULTS

### 5.3.1 Topological analyses of the London Metro networks

**Table 5. Results for small-world detection in the *UWud* London Metro system using three methodologies.** C and L refer to clustering coefficient and characteristic path length respectively. Subscript *real* refers to the $UW_{ud}$ London Metro network, *ER* (Erdős–Rényi model) refers to a random network, and *SW* refers to a synthetically generated small-world network. $E_{Global}$ and $E_{Local}$ refer to global efficiency and local efficiency of the $UW_{ud}$ London Metro network respectively.

| Methods | Criteria | Results | Conclusion |
|---|---|---|---|
| 1 | $C_{real} \approx C_{sw}$ & $L_{real} \approx L_{sw}$ | $C_{real} = 0.035$; $C_{sw} = 0.667$<br>$L_{real} = 18.426$; $L_{sw} = 13.854$ | Not Small-World |
| 2 | $L_{real}$ must be slightly larger than $L_{ER}$<br>&$C_{real}$ must be much larger than $C_{ER}$ | $C_{real} = 0.035$; $C_{ER} = 0.002$<br>$L_{real} = 18.426$; $L_{ER} = 9.259$ | Not Small-World |
| 3 | $E_{Global}$ & $E_{Local}$ must be large<br>($0 \leq E_{Global}$ , $E_{Local} \geq 1$) | $E_{Local} = 0.098$ ; $E_{local} = 0.007$ | Not Small-World |

Network topology, the structural organization or the overall pattern of connectedness of system components (nodes and edges), of the London metro system is examined to understand its implication on the resilience of the entire system. The results for the three approaches used to detect whether the $UW_{ud}$ London metro network exhibits small-world properties are presented in Table 5. All three approaches suggest that the $UW_{ud}$ version of the London metro is not a small-world network. Small-world transportation networks have high connectivity and redundancy that allows them to be fault-tolerant, like the air transportation networks. However, the topology of the London metro network does not allow it to be robust to disruptions that would result in negligible impacts for small world transportation networks.

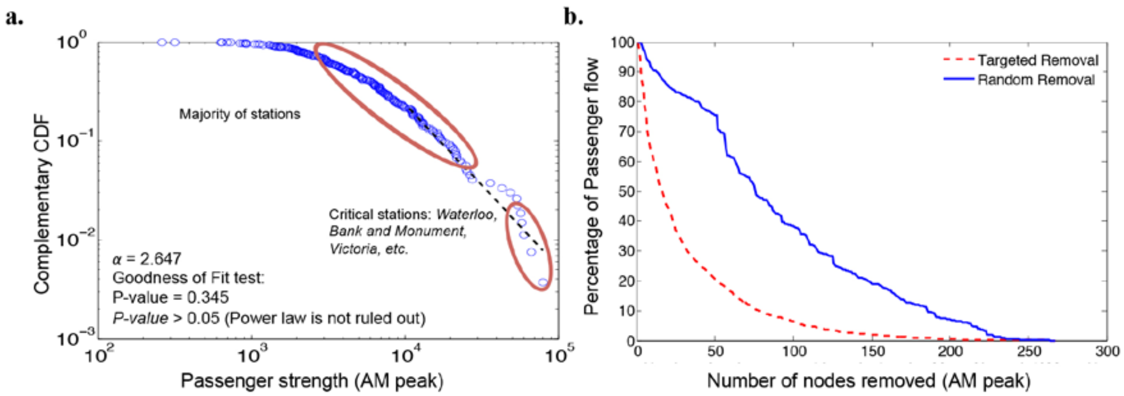



**Figure 17. (a.) Total passenger strength distribution for am peak snapshot; and (b.) Robustness analysis for the London metro system.**

Topological analysis of the $W_d$ London metro network based on probability distributions *p(s)* of passenger strength for each station determines whether the distribution follows a power law. Result for power law detection using statistical tests including maximum likelihood estimation and goodness-of-fit (GOF) for strength distribution at am peak is presented in Figure 17.a. The total passenger strength distribution for the am peak snapshot follows a power law, and similar results are noted for passenger strength distributions during pm and mid-day snapshots that are presented in the Appendix C (Figure 37). Power law for the passenger strength distribution for different time periods in the day indicates that while a relatively small number of passengers depend on majority of the metro stations, an extremely small number of stations are responsible for a large part of the passenger traffic. These critical stations are a primary source of vulnerability, and shocks on them may render the London metro system dysfunctional.

### 5.3.2 Robustness analysis of the London metro network

In order to verify the robustness of the London metro network to shocks on these critical stations, the impact on the overall passenger strength is measured due to systematic, targeted and random, removal of stations. The result of robustness analysis for the $W_d$ London metro network is presented in Figure 17.b. This result suggests high vulnerability of the London metro network as indicated by the sharp degradation in the total passenger strength of the network to targeted removal of stations responsible for the highest passenger traffic, compared to removal of sectors that are randomly chosen. While the system is extremely vulnerable to shocks on a few key stations, the London metro network does exhibit robustness to shocks on most other nodes because of their low importance in terms of passenger traffic.

### 5.3.3 Graph theory based metrics developed to analyze vulnerabilities

After understanding the implications of the London metro network topology on its resilience, specific nodes and edges are identified that are sources of structural and functional vulnerabilities in the metro network. Through the use of disruptive scenarios, the resilience of the network is assessed in terms of its vulnerability to removal of specific nodes, and edges. These disruptions in our scenarios do not cause a complete shutdown of the metro line that they are a part of.

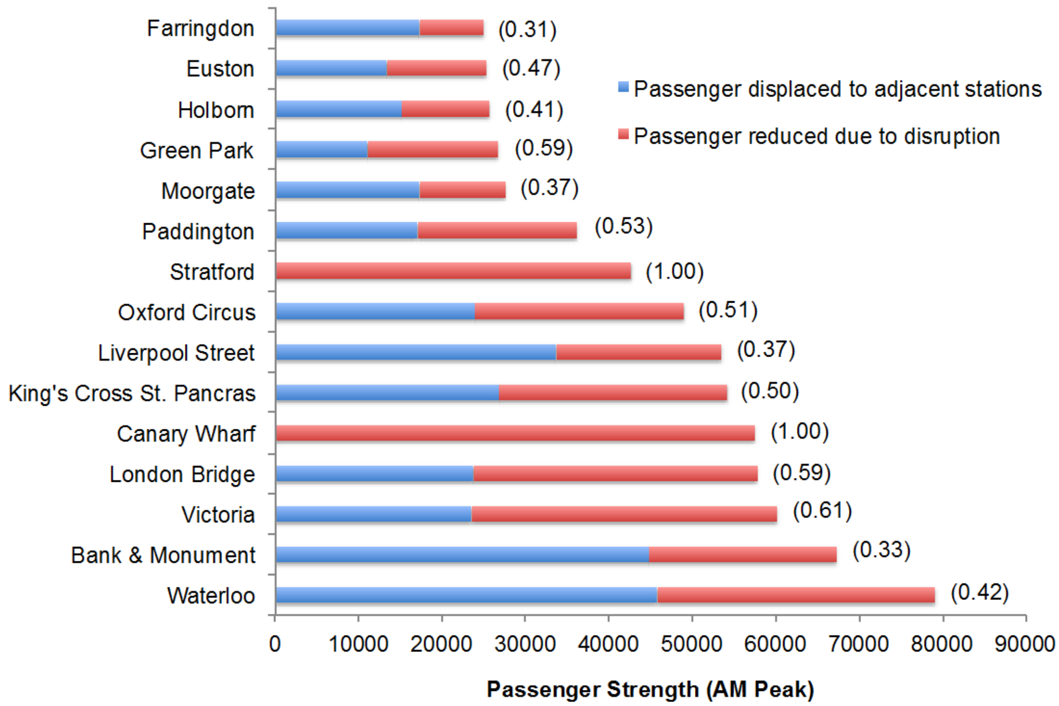
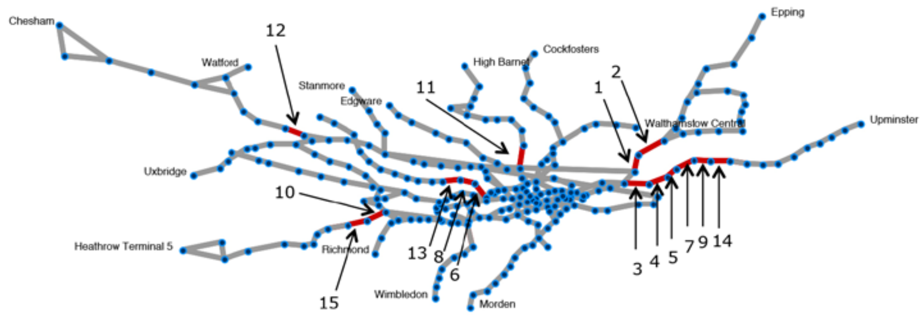



**Figure 18. Functional vulnerability of 15 most critical stations from the London Metro System.**

The distance within which passengers displace to adjacent stations is 1.6 km, and the number in the bracket refers to the respective station inoperability.

The functional vulnerability of nodes in the metro system is calculated in terms of its functional flexibility, ability of the commuters to reach their destination even after node failure. Figure 18 presents station inoperability, the reduction in percentage of commuters using the metro system after disruption of a specific node, for the fifteen most critical stations, which is calculated based on the number of passengers displaced to stations within a 1.6 km radius during am peak. It is evident that the critical stations (stations responsible for high passenger flow) are able to mitigate the vulnerability to an extent by displacing passengers to stations nearby. However, there is room for improvement in this regard as the station inoperability is high (close to 1) for critical stations like *Canary Wharf, Stratford etc.* Similar results are observed for other time snapshots as well.

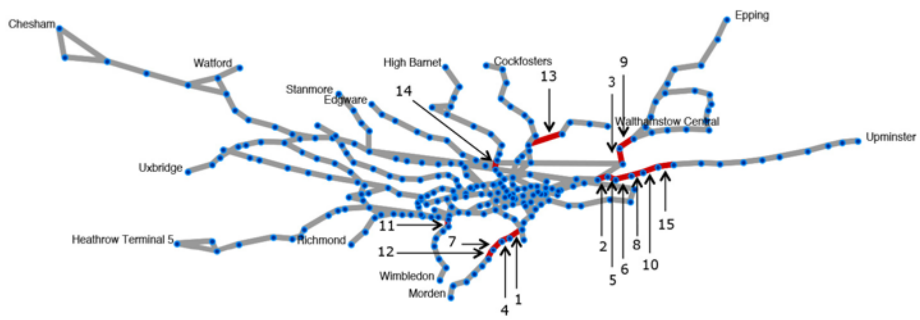



| Ranking | Edge between station *s* and station *t* | Redundancy, *r* |
|---|---|---|
| 1 | *Stratford* and *Leyton* | 0.861 |
| 2 | *Leyton* and *Leytonstone* | 0.868 |
| 3 | *Mile End* and *Bow Road* | 0.894 |
| 4 | *Bow Road* and *Bromley-by-Bow* | 0.901 |
| 5 | *Bromley-by-Bow* and *West Ham* | 0.907 |
| 6 | *Paddington* and *Warwick Avenue* | 0.907 |
| 7 | *Plaistow* and *West Ham* | 0.914 |
| 8 | *Maida Vale* and *Warwick Avenue* | 0.914 |
| 9 | *Plaistow* and *Upton Park* | 0.921 |
| 10 | *Acton Town* and *South Ealing* | 0.921 |
| 11 | *Camden Town* and *Kentish Town* | 0.921 |
| 12 | *North Harrow* and *Pinner* | 0.921 |
| 13 | *Kilburn Park* and *Maida Vale* | 0.921 |
| 14 | *East Ham* and *Upton Park* | 0.928 |
| 15 | Northfields and South Ealing | 0.928 |

**Figure 19. Structural vulnerabilities of edge failure are identified based on redundancy, *r*.**

The number suggests the ranking of the vulnerable edges.

In addition to finding specific nodes that are a source of vulnerability, edges that are a source of structural and functional vulnerability are identified in the London metro network. Figure 19 ranks the top 15 edges that are sources of structural vulnerability in the $UW_{ud}$ London metro network based on the redundancy metric, $r$. It is important to note that edges with lower redundancy are larger sources of vulnerability for the system. Figure 19 demonstrates that edges in peripheral lines that have no loops tend to be large sources of structural vulnerability.



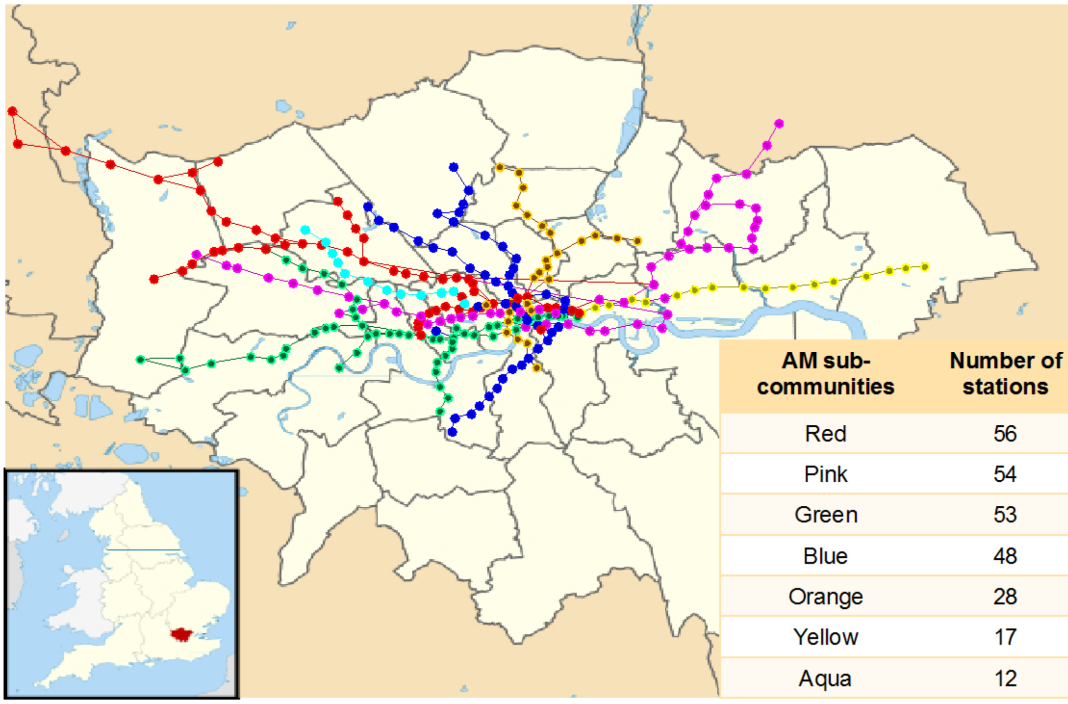

| Ranking | Edge between station *s* and station *t* | Fracture Coefficient, $f_c$ |
|---|---|---|
| 1 | *Stockwell* and *Clapham North* | 0.059 |
| 2 | *Mile End* and *Bow Road* | 0.059 |
| 3 | *Stratford* and *Leyton* | 0.056 |
| 4 | *Clapham North* and *Clapham Common* | 0.056 |
| 5 | *Bow Road* and *Bromley-by-Bow* | 0.054 |
| 6 | *Bromley-by-Bow* and *West Ham* | 0.052 |
| 7 | *Clapham Common* and *Clapham South* | 0.049 |
| 8 | *West Ham* and *Plaistow* | 0.048 |
| 9 | *Leyton and Leytonstone* | 0.048 |
| 10 | *Plaistow* and *Upton Park* | 0.044 |
| 11 | *Fulham Broadway* and *West Brompton* | 0.042 |
| 12 | *Clapham South* and *Balham* | 0.042 |
| 13 | *Finsbury Parl* and *Seven Sisters* | 0.039 |
| 14 | *Camden Town* and *Kentish Town* | 0.037 |
| 15 | *Upton Park* and *East Ham* | 0.037 |

**Figure 20. Functional vulnerabilities of edge failure are identified based on fracture coefficient, $f_c$.**

The number suggests the ranking of the vulnerable edges.

Similarly, to identify edges that are sources of functional vulnerability, fracture coefficient, $f_c$, for each edge in the $W_d$ London metro network is computed. Figure 20 identifies top 15 edges with the highest $f_c$ for the London metro system in the am peak hours. Again, it is noted that edges with functional vulnerability (with high $f_c$) are on lines with no loops; however since $f_c$ considers passenger flow data as well, the ranking for the most vulnerable edges differ. Removal of an edge with either low r or high $f_c$ results in the fragmentation of the London Metro system into two sub-networks. Thus, these edges are a source of vulnerability for the metro system as their removal has the highest impact. Additional $f_c$ results for pm peak and mid-day $W_d$ London metro network snapshots are presented in the Appendix C. Ranking of structural vulnerability, in terms of *r*, and functional vulnerability, in terms of $f_c$, for all edges are also presented in the Appendix C.

### 5.3.4 Community detection within London Metro network



| AM sub-communities | Number of stations |
|---|---|
| Red | 56 |
| Pink | 54 |
| Green | 53 |
| Blue | 48 |
| Orange | 28 |
| Yellow | 17 |
| Aqua | 12 |

**Figure 21. Result for community detection in the London metro system for AM peak hours.**

Using the modularity-based community detection approach, sub-communities are identified within the $W_d$ London metro network. The result for community detection for the am peak snapshot is presented in Figure 21, while results for mid-day and pm peak can be found in the Appendix C (Figure 38). The results suggest that sub-communities spread across metro lines and regional boundaries. Also it is interesting that the number of sub-communities and their composition varies for different snapshots. There are seven sub-communities for am peak snapshot, eight sub-communities for mid-day snapshot, and just five sub-communities for pm peak snapshot of the London metro system. Insights from community detection enable us to identify stations that are most likely to be impacted due to a disruption on the London metro system. If a station is disrupted, passenger flow between stations within its community will be affected.

## 5.4 DISCUSSION

A comprehensive, multi-pronged approach was applied to analyze the network structure, spatial locations and passenger flow for understanding London metro's resilience. This approach has been able to understand the influence of both global properties, such as understanding the topology and identifying communities, and local properties, such as identifying and ranking most vulnerable nodes and edges, on its resilience. Unlike previous studies that have compared various metro systems from across the globe to explore their robustness and resilience [148, 151], this study aims to provide a more in depth examination of potential patterns of vulnerability within the London metro.

Topological analysis of the London metro system indicates that the Tube is bereft of high levels of fault-tolerance, a property of small-world transportation networks like air transportation networks[44]. While the engineering and design of a metro system does not allow for small-world topology, which has been suggested by previous studies as well, relatively more small-world metro systems with higher connectedness will result in an improvement in its resilience. Additionally, analysis of passenger strength distribution for power-law, and subsequent robustness analysis based on targeted attacks and random failures establish the disproportionate vulnerability of the London metro to disruption of certain stations that behave like hubs. Polycentric patterns of movement within London render the functionality of the network highly reliant on a few critical stations that account for large amounts of passenger flow and hardly reliant on an overwhelming majority of smaller stations. Considering the potential impact of shocks on these critical stations on the metro systems functionality, it is undesirable to have such an imbalance among the vulnerability of stations from a resilience perspective.

In order to amend the topology of the London metro for building resilience, it is essential to identify critical stations (nodes) and the rail connections between them (edges) that are a source of vulnerability, and subsequently securing them. Shocks on nodes and edges that cause the largest reduction in the functionality, i.e. number of commuters, are the largest sources of vulnerability for the system. These critical stations can mitigate vulnerability by displacing passengers to other stations in their vicinity, and in turn having low station inoperability. In the case of the London metro system, a few critical stations are able to relatively mitigate their vulnerability to other stations. Our analysis also identifies critical stations with high station inoperability, whose vulnerability needs to be further reduced, for instance by connecting these stations with feeder buses.

Additionally, edges that are largest sources of functional and structural vulnerabilities were identified based on the two metrics developed in this study- fracture coefficient and redundancy respectively. While both methods indicate that edges on metro lines with no loops are significantly more vulnerable, edges with high structural vulnerability differ from those with high functional vulnerability. This information allows transportation planners to prioritize modifications to the metro system for reducing edge vulnerability. Edges with high structural vulnerability should be the focus of the network structure improvements if the intra-urban movement patterns evolve rapidly, whereas to improve resilience in the short term edges with high functional vulnerability must be targeted. Moreover, the ranking provided for both nodes and edges that are points of vulnerability for the London metro system helps develop a blueprint for building resilience based on the available resources and budget of the transport authority.

The results of modularity-based community detection for the London metro system showed a pattern of interdependence that is counter-intuitive as communities of stations spread across regional boundaries and station lines. Community detection provides an understanding of interdependence that isn't purely constrained by a spatial or anecdotal conceptualization of the network. This allows for a more quantified estimation of the impact of station disruption on the network at different times of the day, therefore allowing improved disaster preparedness and relief. Without this information, responders could be misinformed about which stations may be affected, subsequently delaying the recovery process of the network.

The insights from our novel networks framework assists transport planners and urban policymakers in their efforts to improve resilience of metro system. Developing resilience strategies for metro systems require additional assessment of system specific variables and challenges. For this reason, this article does not compile a list of specific alterations for a more resilient London metro system. As such, the analysis is tempered with the intention of providing policymakers with resources to make vital decision. However, future extrapolation of this work depends on open distribution of infrastructure data similar to RODS by Transport for London. Subject to availability of data, further examination of the overall multi-modal transportation system of London can provide additional insights for developing resilient urban transportation infrastructure for cities with polycentric spatial organization. In addition, similar 'systems' approaches are necessary for improving the organization of critical infrastructure assets in order to continually maintain their structure and function in the face of disruptions.

# 6.0 CONCLUSIONS

Resilience as a concept has been gaining popularity in the recent past, but fundamental network properties that contribute towards resilience of complex systems are still not well understood. This works demonstrates it is imperative to recognize the overall network structure of connections and dependencies, identify sources of vulnerability, and develop specific strategies to make them more resilient and functional after a disaster. Garnering this information about a complex system is not a trivial task, and a systems approach is vital for assessing the resilience of large-scale complex engineered systems.

The graph theoretic framework developed and presented here is a useful approach to design strategies that improve resilience and reduce inherent vulnerability of both new and existing large-scale complex system of different sizes and spanning different spatial scales. The framework has been applied to study the resilience of an individual infrastructure system in an urban setting, a network of distinct industries representing different infrastructure sectors at a regional level, and a national economy in terms of its network of critical infrastructure sectors. While three case studies have been used to describe the utility of this model, it can be further integrated with alternate modeling techniques to quantify resilience of other infrastructure systems, in the same way IO models were incorporated.

Another major accomplishment of this approach is that it equips policy makers with essential information necessary to go beyond risk management, and explore avenues to incorporate risk adaptation in these complex systems. A segment of the literature emphasizes the use of decision analytic approaches to improve resilience of infrastructure systems. However, designing resilience building strategies based on expert judgment can only enable the creation of fail-safe infrastructure systems. In order to design safe to fail infrastructure systems, one needs to exploit the capability of data driven analytics for creating safe-to-fail complex systems. The graph theoretic approaches discussed here significantly rely on availability of data regarding complex systems that is expected to grow remarkably in the future. Utilizing data analytics to identify points of vulnerability and ranking risks in complex systems is more reliable for decision making, rather than depending on subjective methods that do not take into account the complex dependencies into account. Insights from this methodology can help prioritize and systematize resilience-building strategies depending on the type and extent of disruption caused due to an extreme event.

## 6.1 RESILIENCE INSIGHTS

Results from application of the graph theoretic framework on the three distinct case studies suggest that resilience strategies may not be generalized across complex systems. For instance, on one hand, this work highlighted that greater interdependence and interconnectedness between critical infrastructures sectors negatively impacts the resilience of the U.S. economy. On the other hand, research exploring the resilience of Kalundborg Industrial Symbiosis network suggests that increasing complexity by adding more industries and commodities being exchanged can benefit its ability to cope with stress. Another example of this fact is while network structure of an EIO network and a transportation system may exhibit small world properties, the topological property does not have the same implication for their resilience. Small world property of the EIO network has a negative impact on its resilience, as it tends to have large cascading impacts, on the other hand, the same topological property for a transportation system, like aviation system, has a positive impact on its resilience as it increases fault-tolerance as a result of high redundancy and interconnectivity.

Strategies and recommendations to build resilience might even differ among similar types of systems. For instance, the insights for improving resilience of the London Metro system may not be applicable to metro systems with a different network structure and passenger flows from cities with contrasting spatial organizations. However, results from a metro system in a polycentric city can loosely be applied to metro systems from other polycentric cities if detailed data on passenger flow is not available. However, for accurate results and creating effective data-driven tactics to build resilience, it is beneficial to apply this framework to complex systems separately.

While it is clear that each of these systems require a unique strategy for building resilience, testing for power laws and applying metrics to identify for points of vulnerability in the system provide similar insights for different systems. The strength distribution of economic size of industries in the U.S. EIO network and the strength distribution of passengers flow at different stations in the London metro network follow a power law, which suggests that a few nodes are extremely critical for these system in comparison to other nodes. This insight is common for both systems, and can inform creation of plans for protecting specific points of vulnerability for the system. Table 6 provides a synthesis for the network properties and their implications for resilience for the three case studies.

**Table 6. Synthesis of insights for improving resilience of each of the three complex systems explored as case studies.**

Here *n* refers to the number of nodes in the network, *L* refers to its characteristic path length and *C* refers to its clustering coefficient.

| Case Studies | Network Statistics | | | Network topology | | Insights for improving resilience |
|---|---|---|---|---|---|---|
| | ***n*** | ***L*** | ***C*** | ***Weighted network*** Power-law strength distribution | ***Unweighted network*** Small-World network | |
| ***1.*** *CIS in 2007 U.S. EIO network* | **389** | **1.212** | **0.790** | **Yes** | **Yes** | Reduce coupling between industrial sectors with high interdependency in order to alleviate cascading impacts |
| ***2.*** *IS network at Kalundborg, Denmark* | **9** | **1.911** | **0.444** | **Not Applicable** since network is small | **Not Applicable** since network is small | Increase diversity in types of participating industries, increase redundancy of resource exchanges, and build multifunctionality of the system |
| ***3.*** *London Metro-rail network* | **268** | **18.426** | **0.035** | **Yes** | **No** | Reduce sources of node (stations) and edge (the connections between stations) structural and functional vulnerabilities through strategic interventions |

## 6.2 FUTURE WORKS

The quantitative framework described here for assessing resilience of complex systems is not computationally challenging to implement, and should be applied to study other complex systems. The scope of this approach for assessing resilience of infrastructure and other engineered complex systems is tremendous since the topic is heavily under-researched, relative to its significance.

This work is not only useful for understanding and quantifying resilience of infrastructure, but also applicable for enhancing community resilience to reduce impacts of disasters. The level of disaster preparedness of a community can be assessed in terms of resilience of the infrastructure that it depends on. Additionally, this framework can be adapted and utilized to complement traditional methodologies used in research areas like disaster management and adaptation to global environmental change. Out of prevention, mitigation, preparedness, response and recovery issues within disaster management, majority of the efforts have been focused on post disaster response and recovery. However, over the past few years, concerted effort has been made to strengthen pre-disaster prevention, mitigation and preparedness. The graph theoretic framework presented here can be utilized for the development of a systematic and comprehensive risk management process for disaster risk reduction.

There are a number of avenues to extend this work in the future. The work on understanding the implications of high coupling between CIS in the U.S. EIO network on its resilience (Chapter 3) should be extended to study other economic networks, like the Indian EIO network, for understanding whether insights from one economic system is translatable to others. Additionally, application of this methodology to regional EIO networks of specific states would provide additional useful information for regional policy makers. Also, disaggregating industrial sectors in the EIO tables, like the electricity generation sector into electricity production from different energy sources, can result in greater resolution data, which may provide more practical insights for resilience building.

The industrial symbiosis work described in the networks presented in Chapter 4 can be extended to study other emerging industrial symbiosis parks from across the world. With increasing adoption of IS and availability of empirical data, the aim is to further expand the theoretical framework for design of IS resiliency. Application of this model to other systems will not only validate the resilience building strategies identified in the study, it will also help identify other strategies that due to regional variation, or the types of industries involved.

The work on understanding resilience of the London metro system has immense potential for being extended to study other urban single and multi-modal transportation systems, but also study resilience of other urban infrastructure systems like water and energy distribution systems. The approach and metrics developed to understand and improve resilience of the London metro system must be further applied to metro systems from other parts of the world. Since London is a polycentric city, it will be interesting to apply this methodology to a monocentric city and understand how the recommendations for building resilience change. Also, the next logical step is to investigate the resilience of London's multi-modal transportation system, which includes various modes of public transportation available like the metro, bus light rail and tram systems overlapped on one another. Also, application of this methodology to investigate other urban infrastructure systems can inform urban planners regarding resilience building.

Overall, there is plenty of scope for extending the graph theoretic approach presented in this thesis to other complex systems. It will be particularly interesting to investigate the network attributes that contribute towards resilience of national and international aviation and trade networks, among others. Since this approach can be applied to systems across spatial scales, this methodology is particularly suited and useful for developing a generic resilience assessment tool that can be used to model different complex systems, and explore their resilience to disruptions, natural or otherwise.

# APPENDIX A

## SUPPORTING INFORMATION FOR CASE STUDY 1: CRITICAL INFRASTRUCTURE SECTORS IN THE U.S. ECONOMIC NETWORK

### A.1 CRITICAL INFRASTRUCTURE SECTORS

U.S. Presidential Policy Directive [223] on *Critical Infrastructure Security and Resilience* establishes a national policy to manage risk and develop resilience (the capability to absorb disruptions while maintaining structure and function) of critical infrastructure sectors [30]. This directive lists 16 CIS similar to the one whose incapacity due to hazards, ranging from natural disasters to cyber-attacks, would have a debilitating impact on the nation's security, economy, health and safety.

**Table 7. 16 CIS and their respective sector specific agencies as per the PPD.**

| Critical Infrastructure Sectors | Sector-Specific Agency |
|---|---|
| Chemical | Department of Homeland Security |
| Commercial Facilities | Department of Homeland Security |
| Communications | Department of Homeland Security |
| Critical Manufacturing | Department of Homeland Security |
| Dams | Department of Homeland Security |
| Defense Industrial Base | Department of Defense |
| Emergency Services | Department of Homeland Security |
| Energy | Department of Energy |
| Financial Services | Department of the Treasury |
| Food and Agriculture | U.S. Department of Agriculture |
| | Department of Health and Human Services |
| Government Facilities | Department of Homeland Security |
| | General Services Administration |
| Healthcare and Public Health | Department of Health and Human Services |
| Information Technology | Department of Homeland Security |
| Nuclear Reactors, Materials, and Waste | Department of Homeland Security |
| Transportation Systems | Department of Homeland Security |
| | Department of Transportation |
| Water and Wastewater Systems | Environmental Protection Agency |

Since CIS like *Emergency services sector*, *Defense Industrial Base sector* and *Government Facilities sector* are very broadly defined and cannot be identified as specific sectors in the economy, the analysis is restricted to seven economically significant CIS. To understand interdependency between CIS the impact of disruptions is examined on each of the IO sectors corresponding to the chosen CIS. IO sectors with the highest throughput are chosen as CIS for further analysis.

**Table 8. IO sectors corresponding to the 7 chosen CIS.**

| IO sectors representing the CIS | Critical Infrastructure Sectors |
|---|---|
| Grain farming | Agriculture CIS |
| Petroleum refineries | Energy CIS |
| Oil and gas extraction | |
| Electric power generation, transmission, and distribution | |
| Air transportation | Transportation CIS |
| Monetary authorities and depository credit intermediation | Finance CIS |
| Data processing hosting and related services | IT CIS |
| Wired telecommunications carriers | Communications CIS |
| Hospitals | Healthcare and Public Health CIS |

## A.2 INPUT-OUTPUT TABLES

The 2007 version of the Input Output tables for the US economy available from Bureau of Economic Analysis in the form of make (*industry-by-commodity*) and (*commodity-by-industry*) use tables are used. Using this data the [*389 X 389*] industry-by-industry matrix is prepared that allows us to visualize economic systems as graphs. This industry-by-industry square matrix can be perceived as an adjacency matrix. By considering the industrial sectors as nodes and the monetary transactions between them as edges, a complex weighted-directed network for further analysis of the US economy is constructed. Unweighted-directed network is also constructed by disregarding the weights of the flows between the nodes to analyze the connectivity of sectors.

### A.2.1 Network Topology of the U.S. EIO network

Insights on the overall topological interconnectedness of the US economy using frequency distribution based on in and out degree of both unweighted and weighted U.S. economic network. Moreover, a principled statistical framework is applied that combines maximum likelihood estimation with goodness-of-fit tests based on the KS statistic for power-law detection in weighted-directed US economic network for the year 2007.

a. b. c.

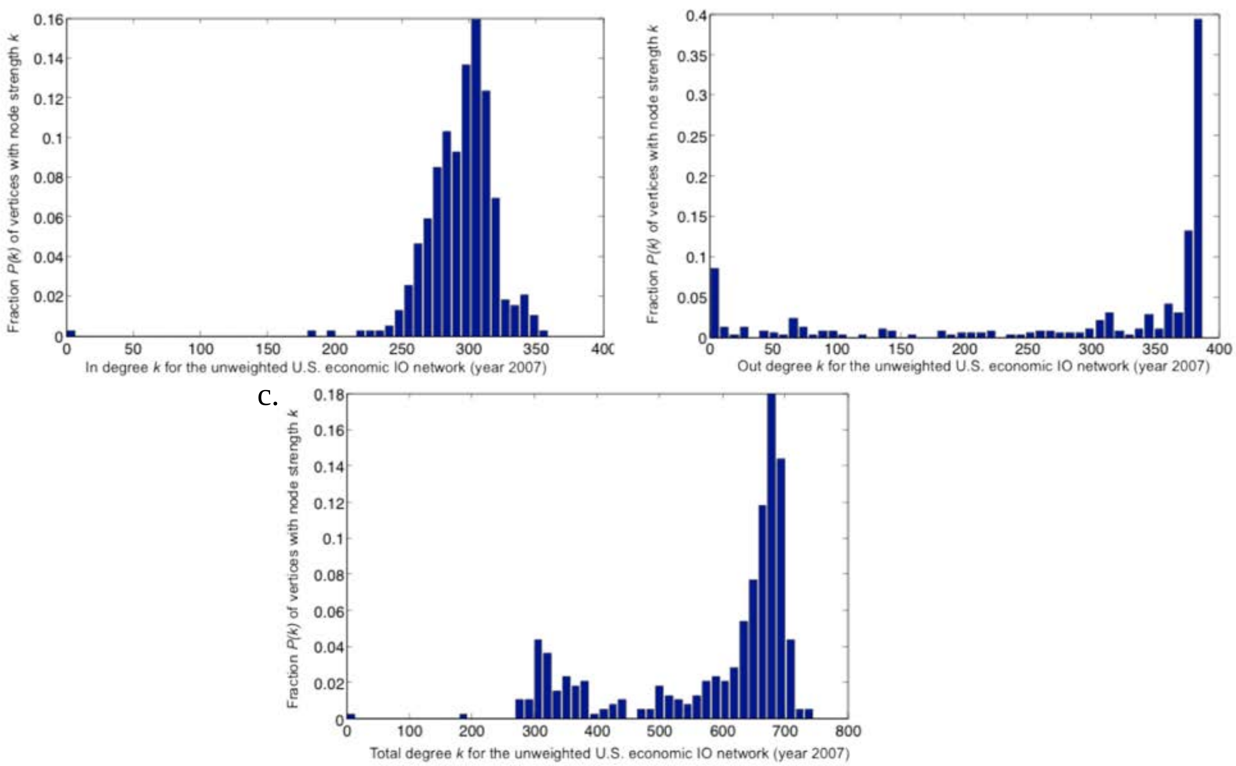



**Figure 22. Frequency distribution of unweighted *a. Total-degree b. Out-degree and c. In-degree* for the 2007 U.S. Economic IO network.**

The histogram suggests that majority of the industrial sectors are involved in monetary exchange of some sort with most other sectors in the economy.

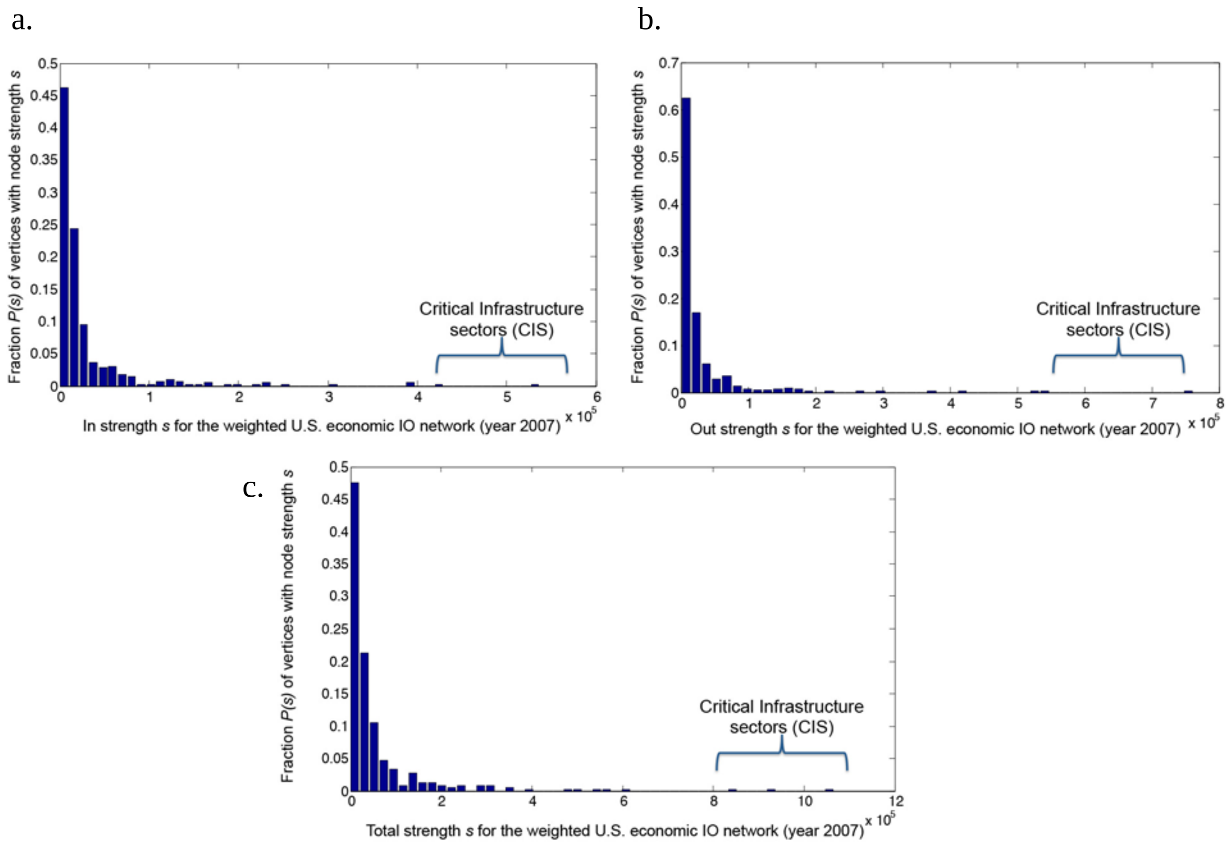
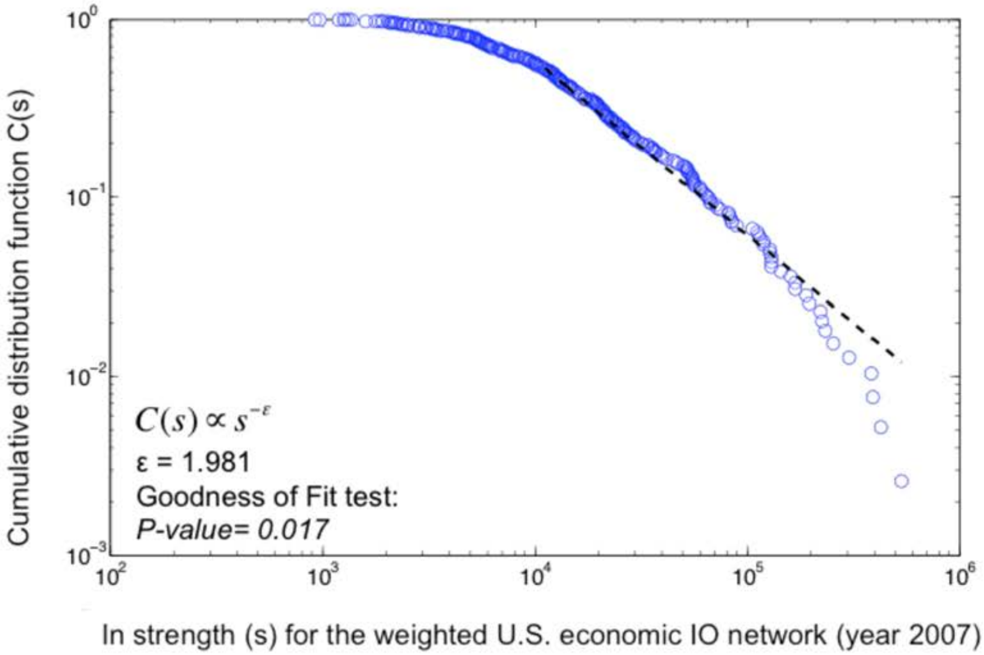



**Figure 23. Frequency distribution of *a. Total strength b. Out strength and c. In strength* for the weighted 2007 US EIO network.**

The histogram suggests that while most industrial sectors are involved in negligible amounts of monetary transaction, only a small number of industrial sectors are involved in extremely large amounts of inter-industrial financial exchanges.

a.




b.

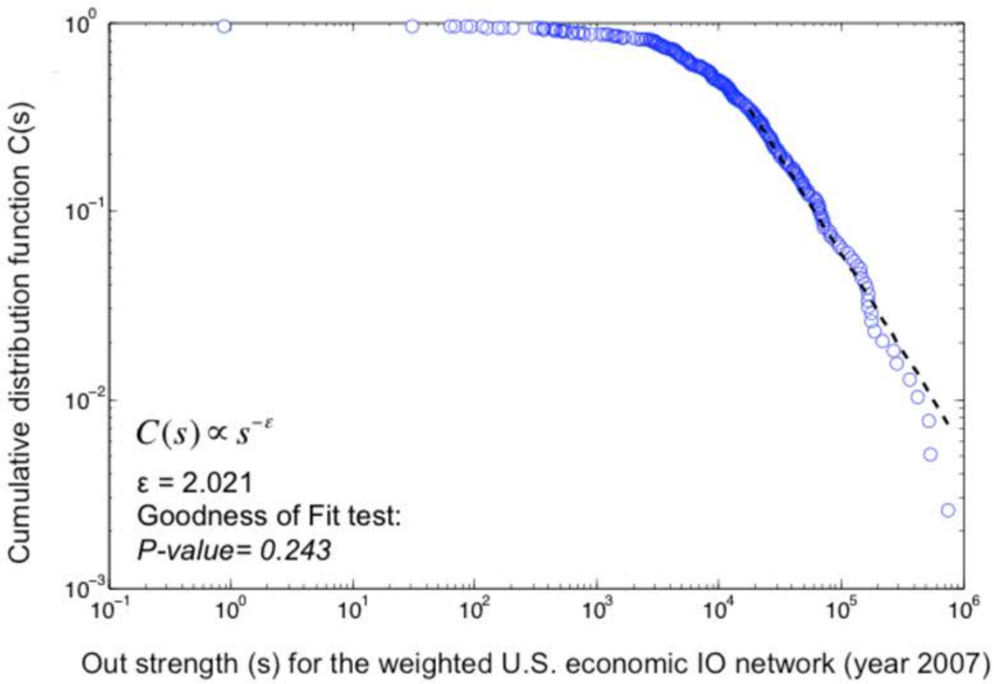



**Figure 24. Cumulative Distribution function of *a.* In strength and *b.* Out strength, and the maximum likelihood power-law fit for 2007 US Economic IO weighted network.**

Power law is ruled out as a good fit.

## A.3 TOPOLOGICAL ANALYSIS

### A.3.1 Detecting Small-world behavior

Global efficiency and local efficiency is used to determine whether the network at hand exhibits small-world behavior. Latora and Marchiori developed this framework to detect small-world phenomena [54].

Global efficiency, $E_{Global}$, of a network, $G$, refers to the overall network efficiency, which is computed based on the following formula,

$$E_{Global} = \frac{1}{N(N-1)} \sum_{i \neq j \in G} \frac{1}{d_{ij}} \tag{12}$$

where $d_{ij}$ is shortest path lengths between all nodes pairs $i$ and $j$, and $N$ is the number of nodes in the network.

Local efficiency, $E_{Local}$, refers to the average efficiency of each node's sub-graph, $G_i$, comprised of its neighbors. It is computed by making a slight modification to the global efficiency formula as follows,

$$E_{Local} = \frac{1}{N} \sum_{i \in G} E_{Global}(G_i) \tag{13}$$

where $G_i$ is the sub-graph of the neighbors of node $i$.

### A.3.2 Analysis of Power-law distributions

The following steps are used to analyze power-law distribution in U.S. economic IO network [165]:

Estimate the parameters $k_{min}$ and ε for the degree distribution. To estimate the scaling factor ε accurately, $k_{min}$ needs to be accurately estimated. In most cases, empirical data that tends to follow a power-law distribution does so only for values of k greater than a lower bound $k_{min}$; therefore, all values below the $k_{min}$ are discarded.  If a very low or a very high $k_{min}$ is chosen, the estimate for the scaling factor ε will be biased. To estimate the $k_{min}$ accurately, the Kolmogorov-Smirnov (KS) statistic is chosen. Using the KS test the value of $k_{min}$ is estimated that makes the degree distribution of U.S. economic network fit best to the power law model. The KS statistic is used to quantify the maximum distance *D* between cumulative distribution functions of two non-normal distributions as follows:

$$D = \max_{k \geq k_{\min}} \left| s(k) - p(k) \right| \tag{14}$$

Here *s(k)* is the CDF of the node degrees for the U.S. economic network with the smallest $k_{min}$, and *p(k)* is the CDF for the power law model that best fits the data in the region $k \geq k_{min}$. A value of $k_{min}$ is picked that minimizes the value of D, the distance, between the empirical and the synthetic distributions.

The method of maximum likelihood estimation (MLE) is used to estimate the scaling factor ε for the known lower bound estimate. Maximum likelihood estimation is an estimation technique for finding model parameters that are most consistent with the observed data [233]. The following maximum likelihood estimator of the scaling factor is derived for continuous distributions [165]:

$$\varepsilon = 1 + n\left[\sum_{i=1}^{n} \ln \frac{k_i}{k_{\min}}\right]^{-1}, \tag{15}$$

where $k_i$ is the degree of nodes that have $k_i \geq k_{min}$, and *n* is the number of such nodes.

Compute the goodness-of-fit between the data and the power law using the Kolmogorov-Smirnov test. A goodness-of-fit test is used to test the hypothesis that the strength distribution for U.S. EIO network fits power law distribution. To begin with, the degree distribution is fit to the power law and calculate the KS statistic mentioned above in step 1. Then, synthetic data sets that follow power law are generated with scaling factor and lower bound parameters that are equal to those found for the concerned economic networks. The KS statistic is calculated for each of the synthetic data sets relative to its power law model. The fraction of instances when the resulting KS statistic is greater than the KS statistic for the U.S. economic network represents the p-value. If the resulting p-value is greater than the user specified $\alpha$ ($\alpha = 0.1$), the power law is a plausible hypothesis for the data, otherwise it is rejected. However, one should not depend on the *p-value* alone to decide whether the distribution follows a power law, since there might be other alternate distributions that might fit the degree distribution for the U.S economic IO networks better.

Use likelihood ratio test to compare whether other alternate distributions fit the U.S. economic network data better than power law. Likelihood ratio test computes the likelihood of data under the alternate distribution against the likelihood of the data under the null distribution (i.e. power law), and a greater likelihood signifies a better fit with the alternate distribution. Thus, the sign of the log-likelihood ratio serves as an indication whether or not the alternative is favored over the power-law model. Vuong's method is used to decide whether the likelihood ratio is considerably far from zero [234]. This method also provides a *p-value* indicating whether the likelihood ratio is statistically significant or not. If the *p-value* is considerably small ($p < 0.1$) then the sign of log-likelihood ratio is not a matter of chance, and can be relied upon.

## A.4 DISRUPTIVE SCENARIOS APPLIED ON CIS

To understand interdependency between CIS, the impact of hypothetical disruption in the form of reduction in throughput of CIS by $10 million is examined.


**Figure 25. Industrial sectors experiencing greatest cascading impacts in $ millions due to disruption.**

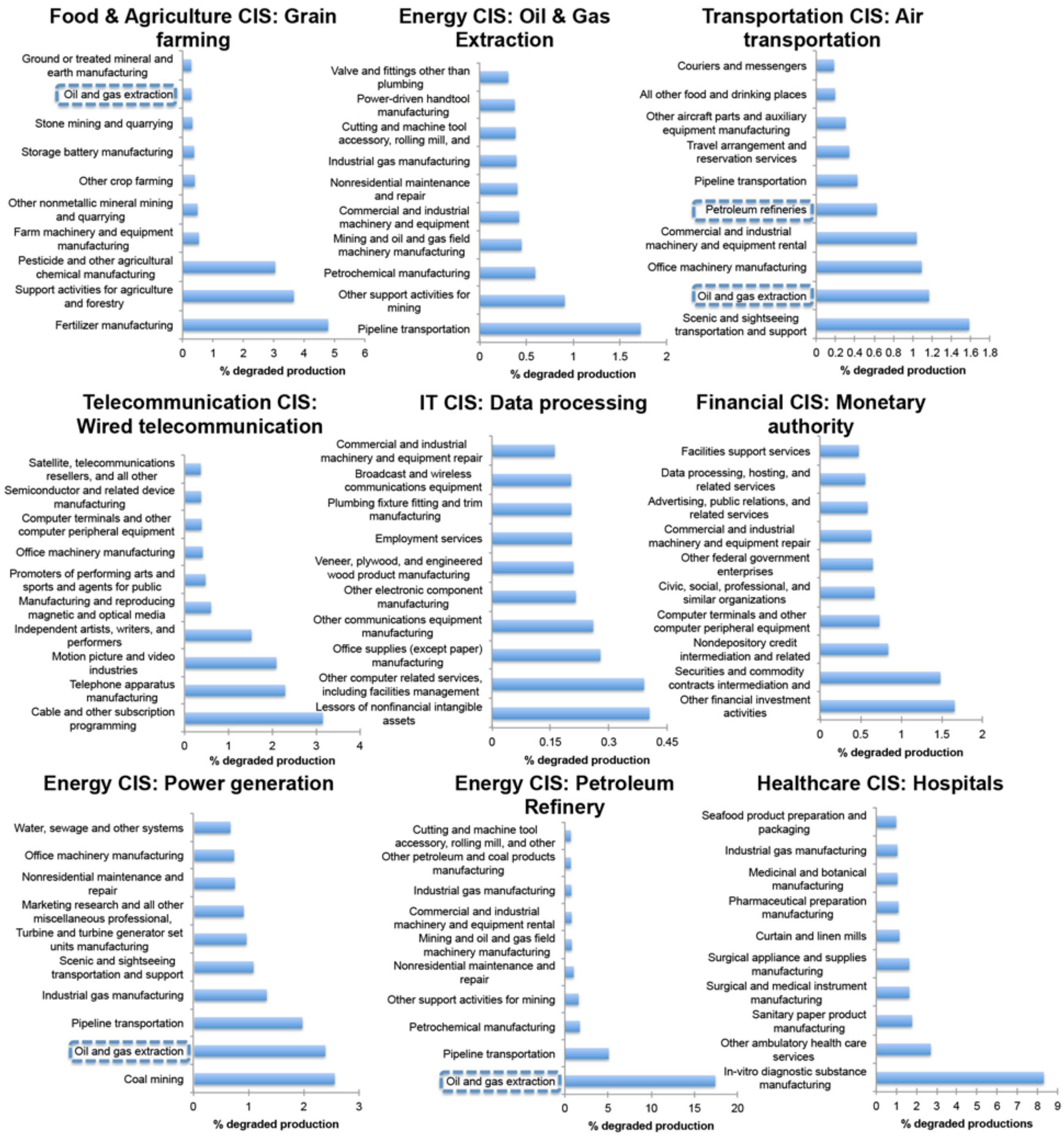



**Figure 26. Industrial sectors experiencing greatest inoperability, calculated in terms of percentage-degraded production, due to reduction of throughput for each CIS by 10%.**

CIS sectors are highlighted.

## A.5 COMMUNITY STRUCTURE OF THE U.S. EIO NETWORK

**Table 9. List of industrial sectors comprising the communities found using the modularity based community detection methodology.**

| Community 1: **Service sectors** |
|---|
| Telephone apparatus manufacturing |
| Manufacturing and reproducing magnetic and optical media |
| Dental equipment and supplies manufacturing |
| Dental laboratories |
| Printing |
| Support activities for printing |
| Medicinal and botanical manufacturing |
| Pharmaceutical preparation manufacturing |
| Biological product (except diagnostic) manufacturing |
| Newspaper publishers |
| Periodical Publishers |
| Book publishers |
| Directory, mailing list, and other publishers |
| Software publishers |
| Motion picture and video industries |
| Sound recording industries |
| Radio and television broadcasting |
| Cable and other subscription programming |
| Wired telecommunications carriers |
| Wireless telecommunications carriers (except satellite) |
| Satellite, telecommunications resellers, and all other telecommunications |
| Data processing, hosting, and related services |
| Internet publishing and broadcasting and Web search portals |
| Real estate |
| Automotive equipment rental and leasing |
| Consumer goods and general rental centers |
| Lessors of nonfinancial intangible assets |
| Legal services |

Table 9 (continued)

| |
|---|
| Custom computer programming services |
| Other computer related services, including facilities management |
| Accounting, tax preparation, bookkeeping, and payroll services |
| Management consulting services |
| Environmental and other technical consulting services |
| Scientific research and development services |
| Advertising, public relations, and related services |
| Marketing research and all other miscellaneous professional, scientific, and technical services |
| Photographic services |
| Veterinary services |
| Management of companies and enterprises |
| Office administrative services |
| Facilities support services |
| Business support services |
| Investigation and security services |
| Other support services |
| Employment services |
| Travel arrangement and reservation services |
| Elementary and secondary schools |
| Junior colleges, colleges, universities, and professional schools |
| Other educational services |
| Offices of physicians |
| Offices of dentists |
| Offices of other health practitioners |
| Outpatient care centers |
| Medical and diagnostic laboratories |
| Home health care services |
| Nursing and community care facilities |
| Residential mental retardation, mental health, substance abuse and other facilities |
| Individual and family services |
| Child day care services |
| Performing arts companies |
| Spectator sports |
| Promoters of performing arts and sports and agents for public figures |
| Independent artists, writers, and performers |

Table 9 (continued)

| |
|---|
| Museums, historical sites, zoos, and parks |
| Amusement parks and arcades |
| Gambling industries (except casino hotels) |
| Other amusement and recreation industries |
| Accommodation |
| Full-service restaurants |
| Commercial and industrial machinery and equipment repair and maintenance |
| Personal and household goods repair and maintenance |
| Personal care services |
| Dry-cleaning and laundry services |
| Other personal services |
| Community 2: **Energy and Petroleum related sectors** |
| Greenhouse, nursery, and floriculture production |
| Oil and gas extraction |
| Coal mining |
| Drilling oil and gas wells |
| Other support activities for mining |
| Electric power generation, transmission, and distribution |
| Natural gas distribution |
| Water, sewage and other systems |
| Nonresidential maintenance and repair |
| Office machinery manufacturing |
| Electric lamp bulb and part manufacturing |
| Doll, toy, and game manufacturing |
| Office supplies (except paper) manufacturing |
| Stationery product manufacturing |
| Petroleum refineries |
| Asphalt paving mixture and block manufacturing |
| Other petroleum and coal products manufacturing |
| Petrochemical manufacturing |
| Industrial gas manufacturing |
| Other basic inorganic chemical manufacturing |
| Other basic organic chemical manufacturing |
| Plastics material and resin manufacturing |
| Soap and cleaning compound manufacturing |
| Toilet preparation manufacturing |

Table 9 (continued)

| |
|---|
| All other chemical product and preparation manufacturing |
| Plastics pipe, pipe fitting, and unlaminated profile shape manufacturing |
| Polystyrene foam product manufacturing |
| Food and beverage stores |
| Air transportation |
| Rail transportation |
| Water transportation |
| Pipeline transportation |
| Scenic and sightseeing transportation and support activities for transportation |
| News syndicates, libraries, archives and all other information services |
| Commercial and industrial machinery and equipment rental and leasing |
| Computer systems design services |
| Waste management and remediation services |
| Electronic and precision equipment repair and maintenance |
| Private households |
| Federal general government (nondefense) |
| Federal electric utilities |
| State and local general government |
| State and local government passenger transit |
| State and local government electric utilities |
| Other state and local government enterprises |
| Community 3: **Manufacturing and Resource extraction sectors** |
| Forestry and logging |
| Iron, gold, silver, and other metal ore mining |
| Copper, nickel, lead, and zinc mining |
| Stone mining and quarrying |
| Other nonmetallic mineral mining and quarrying |
| Health care structures |
| Manufacturing structures |
| Power and communication structures |
| Educational and vocational structures |
| Highways and streets |
| Commercial structures, including farm structures |
| Other nonresidential structures |

Table 9 (continued)

| |
|---|
| Single-family residential structures |
| Multifamily residential structures |
| Other residential structures |
| Sawmills and wood preservation |
| Veneer, plywood, and engineered wood product manufacturing |
| Millwork |
| All other wood product manufacturing |
| Clay product and refractory manufacturing |
| Glass and glass product manufacturing |
| Cement manufacturing |
| Ready-mix concrete manufacturing |
| Concrete pipe, brick, and block manufacturing |
| Other concrete product manufacturing |
| Lime and gypsum product manufacturing |
| Abrasive product manufacturing |
| Cut stone and stone product manufacturing |
| Ground or treated mineral and earth manufacturing |
| Mineral wool manufacturing |
| Miscellaneous nonmetallic mineral products |
| Iron and steel mills and ferroalloy manufacturing |
| Steel product manufacturing from purchased steel |
| Alumina refining and primary aluminum production |
| Secondary smelting and alloying of aluminum |
| Aluminum product manufacturing from purchased aluminum |
| Primary smelting and refining of copper |
| Primary smelting and refining of nonferrous metal (except copper and aluminum) |
| Copper rolling, drawing, extruding and alloying |
| Nonferrous metal (except copper and aluminum) rolling, drawing, extruding and alloying |
| Ferrous metal foundries |
| Nonferrous metal foundries |
| All other forging, stamping, and sintering |
| Custom roll forming |
| Crown and closure manufacturing and metal stamping |
| Cutlery and handtool manufacturing |
| Plate work and fabricated structural product manufacturing |

Table 9 (continued)

| |
|---|
| Ornamental and architectural metal products manufacturing |
| Power boiler and heat exchanger manufacturing |
| Metal tank (heavy gauge) manufacturing |
| Metal can, box, and other metal container (light gauge) manufacturing |
| Hardware manufacturing |
| Spring and wire product manufacturing |
| Machine shops |
| Turned product and screw, nut, and bolt manufacturing |
| Coating, engraving, heat treating and allied activities |
| Valve and fittings other than plumbing |
| Plumbing fixture fitting and trim manufacturing |
| Ball and roller bearing manufacturing |
| Ammunition, arms, ordnance, and accessories manufacturing |
| Fabricated pipe and pipe fitting manufacturing |
| Other fabricated metal manufacturing |
| Farm machinery and equipment manufacturing |
| Lawn and garden equipment manufacturing |
| Construction machinery manufacturing |
| Mining and oil and gas field machinery manufacturing |
| Other industrial machinery manufacturing |
| Plastics and rubber industry machinery manufacturing |
| Semiconductor machinery manufacturing |
| Vending, commercial laundry, and other commercial and service industry machinery manufacturing |
| Optical instrument and lens manufacturing |
| Photographic and photocopying equipment manufacturing |
| Air purification and ventilation equipment manufacturing |
| Heating equipment (except warm air furnaces) manufacturing |
| Air conditioning, refrigeration, and warm air heating equipment manufacturing |
| Industrial mold manufacturing |
| Metal cutting and forming machine tool manufacturing |
| Special tool, die, jig, and fixture manufacturing |
| Cutting and machine tool accessory, rolling mill, and other metalworking machinery manufacturing |
| Turbine and turbine generator set units manufacturing |
| Speed changer, industrial high-speed drive, and gear manufacturing |

Table 9 (continued)

| |
|---|
| Mechanical power transmission equipment manufacturing |
| Other engine equipment manufacturing |
| Pump and pumping equipment manufacturing |
| Air and gas compressor manufacturing |
| Material handling equipment manufacturing |
| Power-driven handtool manufacturing |
| Other general purpose machinery manufacturing |
| Packaging machinery manufacturing |
| Industrial process furnace and oven manufacturing |
| Fluid power process machinery |
| Electronic computer manufacturing |
| Computer storage device manufacturing |
| Computer terminals and other computer peripheral equipment manufacturing |
| Broadcast and wireless communications equipment |
| Other communications equipment manufacturing |
| Audio and video equipment manufacturing |
| Other electronic component manufacturing |
| Semiconductor and related device manufacturing |
| Printed circuit assembly (electronic assembly) manufacturing |
| Electromedical and electrotherapeutic apparatus manufacturing |
| Search, detection, and navigation instruments manufacturing |
| Automatic environmental control manufacturing |
| Industrial process variable instruments manufacturing |
| Totalizing fluid meter and counting device manufacturing |
| Electricity and signal testing instruments manufacturing |
| Analytical laboratory instrument manufacturing |
| Irradiation apparatus manufacturing |
| Watch, clock, and other measuring and controlling device manufacturing |
| Lighting fixture manufacturing |
| Small electrical appliance manufacturing |
| Household cooking appliance manufacturing |
| Household refrigerator and home freezer manufacturing |
| Household laundry equipment manufacturing |
| Other major household appliance manufacturing |
| Power, distribution, and specialty transformer manufacturing |

Table 9 (continued)

| |
|---|
| Motor and generator manufacturing |
| Switchgear and switchboard apparatus manufacturing |
| Relay and industrial control manufacturing |
| Storage battery manufacturing |
| Primary battery manufacturing |
| Communication and energy wire and cable manufacturing |
| Wiring device manufacturing |
| Carbon and graphite product manufacturing |
| All other miscellaneous electrical equipment and component manufacturing |
| Automobile manufacturing |
| Light truck and utility vehicle manufacturing |
| Heavy duty truck manufacturing |
| Motor vehicle body manufacturing |
| Truck trailer manufacturing |
| Motor home manufacturing |
| Travel trailer and camper manufacturing |
| Motor vehicle gasoline engine and engine parts manufacturing |
| Motor vehicle electrical and electronic equipment manufacturing |
| Motor vehicle steering, suspension component (except spring), and brake systems manufacturing |
| Motor vehicle transmission and power train parts manufacturing |
| Motor vehicle seating and interior trim manufacturing |
| Motor vehicle metal stamping |
| Other motor vehicle parts manufacturing |
| Aircraft manufacturing |
| Aircraft engine and engine parts manufacturing |
| Other aircraft parts and auxiliary equipment manufacturing |
| Guided missile and space vehicle manufacturing |
| Propulsion units and parts for space vehicles and guided missiles |
| Railroad rolling stock manufacturing |
| Ship building and repairing |
| Boat building |
| Motorcycle, bicycle, and parts manufacturing |
| Military armored vehicle, tank, and tank component manufacturing |
| All other transportation equipment manufacturing |
| Wood kitchen cabinet and countertop manufacturing |

Table 9 (continued)

| |
|---|
| Upholstered household furniture manufacturing |
| Nonupholstered wood household furniture manufacturing |
| Other household nonupholstered furniture |
| Institutional furniture manufacturing |
| Office furniture and custom architectural woodwork and millwork manufacturing |
| Showcase, partition, shelving, and locker manufacturing |
| Other furniture related product manufacturing |
| Ophthalmic goods manufacturing |
| Jewelry and silverware manufacturing |
| Sporting and athletic goods manufacturing |
| Sign manufacturing |
| All other miscellaneous manufacturing |
| Breweries |
| Tobacco product manufacturing |
| Fiber, yarn, and thread mills |
| Fabric mills |
| Textile and fabric finishing and fabric coating mills |
| Carpet and rug mills |
| Curtain and linen mills |
| Other textile product mills |
| Apparel manufacturing |
| Leather and allied product manufacturing |
| Pulp mills |
| Paper mills |
| Paperboard mills |
| Paperboard container manufacturing |
| Paper bag and coated and treated paper manufacturing |
| Sanitary paper product manufacturing |
| All other converted paper product manufacturing |
| Asphalt shingle and coating materials manufacturing |
| Synthetic dye and pigment manufacturing |
| Synthetic rubber and artificial and synthetic fibers and filaments manufacturing |
| Paint and coating manufacturing |
| Adhesive manufacturing |
| Printing ink manufacturing |

Table 9 (continued)

| |
|---|
| Plastics packaging materials and unlaminated film and sheet manufacturing |
| Laminated plastics plate, sheet (except packaging), and shape manufacturing |
| Urethane and other foam product (except polystyrene) manufacturing |
| Other plastics product manufacturing |
| Tire manufacturing |
| Rubber and plastics hoses and belting manufacturing |
| Other rubber product manufacturing |
| Wholesale trade |
| Motor vehicle and parts dealers |
| General merchandise stores |
| Other retail |
| Truck transportation |
| Couriers and messengers |
| Warehousing and storage |
| Architectural, engineering, and related services |
| Specialized design services |
| Automotive repair and maintenance |
| Death care services |
| Federal general government (defense) |
| Postal service |
| Community 4: **Financial and Healthcare sectors** |
| Residential maintenance and repair |
| Surgical and medical instrument manufacturing |
| Surgical appliance and supplies manufacturing |
| In-vitro diagnostic substance manufacturing |
| Transit and ground passenger transportation |
| Monetary authorities and depository credit intermediation |
| Nondepository credit intermediation and related activities |
| Securities and commodity contracts intermediation and brokerage |
| Other financial investment activities |
| Insurance carriers |
| Insurance agencies, brokerages, and related activities |
| Funds, trusts, and other financial vehicles |
| Owner-occupied dwellings |

Table 9 (continued)

| |
|---|
| Services to buildings and dwellings |
| Other ambulatory health care services |
| Hospitals |
| Community food, housing, and other relief services, including rehabilitation services |
| Religious organizations |
| Grantmaking, giving, and social advocacy organizations |
| Civic, social, professional, and similar organizations |
| Other federal government enterprises |
| Community 5: **Agriculture and agriculture related sectors** |
| Oilseed farming |
| Grain farming |
| Vegetable and melon farming |
| Fruit and tree nut farming |
| Other crop farming |
| Beef cattle ranching and farming, including feedlots and dual-purpose ranching and farming |
| Dairy cattle and milk production |
| Animal production, except cattle and poultry and eggs |
| Poultry and egg production |
| Fishing, hunting and trapping |
| Support activities for agriculture and forestry |
| Dog and cat food manufacturing |
| Other animal food manufacturing |
| Flour milling and malt manufacturing |
| Wet corn milling |
| Soybean and other oilseed processing |
| Fats and oils refining and blending |
| Breakfast cereal manufacturing |
| Sugar and confectionery product manufacturing |
| Frozen food manufacturing |
| Fruit and vegetable canning, pickling, and drying |
| Fluid milk and butter manufacturing |
| Cheese manufacturing |
| Dry, condensed, and evaporated dairy product manufacturing |
| Ice cream and frozen dessert manufacturing |
| Animal (except poultry) slaughtering, rendering, and processing |

Table 9 (continued)

| |
|---|
| Poultry processing |
| Seafood product preparation and packaging |
| Bread and bakery product manufacturing |
| Cookie, cracker, pasta, and tortilla manufacturing |
| Snack food manufacturing |
| Coffee and tea manufacturing |
| Flavoring syrup and concentrate manufacturing |
| Seasoning and dressing manufacturing |
| All other food manufacturing |
| Soft drink and ice manufacturing |
| Wineries |
| Distilleries |
| Fertilizer manufacturing |
| Pesticide and other agricultural chemical manufacturing |
| Plastics bottle manufacturing |
| Limited-service restaurants |
| All other food and drinking places |

# APPENDIX B

## SUPPORTING INFORMATION FOR CASE STUDY 2: RESILIENCE OF INDUSTRIAL SYMBIOSIS NETWORKS

The goal of our study to understand resilience of Industrial Symbiotic networks by applying a networks approach, and provide strategies to design sustainable IS networks.

### B.1 METHODOLOGY

The famous Industrial Symbiosis at Kalundborg is used as a case study. Kalundborg Industrial Symbiosis (KIS) encompasses exchange of several by-product synergies like gypsum, fly ash, etc. among various industries. The 2002 snapshot of the water synergy network at Kalundborg is used exclusively because of the unavailability of physical flow data for other by-products. With all the interactions known between the industries, an IS can be considered a network where symbiotic water exchanges are depicted as edges and industries and sources of water are considered as nodes of the water network. To visualize and analyze the KIS water network, [n x n] matrix is constructed whose (i, j) entry is 1 if the ith node is connected to the jth node, and 0 if they are not, for a network with n number of nodes. This matrix is known as the adjacency matrix for an un-weighted graph, which can be converted to a weighted graph if the magnitude of the flows between ith and jth node is known. The adjacency matrix for the 2002-snapshot of the KIS- water synergy network is provided in the figure below.

A weighted and directed adjacency matrix is constructed from the quantified flows of water between the industries for the network analysis. On the other hand, un-weighted directed graphs are used to determine the evolution of the structure of the network, and in turn, determine the trend in resilience of the system over time.

| | Asnaes Power plant | Statoil Refinery | Novo Group | Fish pond | Buffer | Lake Tisso | Ground Water | Sea | Municipality |
|---|---|---|---|---|---|---|---|---|---|
| Asnaes Power plant | 0 | 6206250 | 25906250 | 23000000 | 200000 | 0 | 0 | 855610250 | 26406250 |
| Statoil ref | 492000 | 0 | 0 | 0 | 0 | 0 | 0 | 1200000 | 0 |
| Novo Group | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2300000 |
| Fish pond | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23000000 | 0 |
| Buffer | 100000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 66000 |
| Lake Tisso | 686000 | 1600000 | 491000 | 0 | 0 | 0 | 0 | 0 | 0 |
| Ground Water | 51000 | 20000 | 1900000 | 0 | 0 | 0 | 0 | 0 | 0 |
| Sea | 936000000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Municipality | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2366000 | 0 |

**Figure 27. Adjacency matrix for the weighted-directed 2002 water synergy network at Kalundborg.**

The exchange of water between industries is presented in $m^3$.

### B.1.1 Network Efficiency Metric

The Latora and Marchiori (LM) network measure is defined as

$$E = E(G) = \frac{1}{n(n-1)} \sum_{i \neq j \in G} \frac{1}{d_{ij}} \qquad (16)$$

where $E$ is the measure of efficiency of the network, $n$ is the number of nodes present in the network $G$ and $d_{ij}$ represents the geodesic distance between the nodes $i$ and $j$ [211, 212], This measure was developed to determine the efficiency of information exchange on the basis of network topology.

Another network efficiency measure, developed from the LM measure, is the Nagurney and Qiang [235] measure that considers flow of information between the components to determine the efficiency of networks like transportation, power grid, internet and supply chain networks. It is defined as

$$\varepsilon = \varepsilon(G, d) = \frac{\sum \omega \in W \frac{d_\omega}{\lambda_\omega}}{\eta_W} \tag{17}$$

where ε measures the network efficiency or performance of a network with a topology *G* and the demand vector *d*. In addition, $\eta_W$ is the number of O/D pairs in the network, and $d_\omega$ and $\lambda_\omega$ represent the final demand/flow and equilibrium disutility for the O/D pair $\omega \in W$, respectively [235].

Building upon the LM and NQ network efficiency measures, a measure suitable to compute the efficiency of an IS network is derived.

Under certain assumptions, LM and NQ measures are equitable as shown in the following expression

$$E = E(G) = \frac{1}{n(n-1)} \sum_{i \neq j \in G} \frac{1}{d_{ij}} = \frac{\sum_{i \neq j \in G} \frac{1}{d_{ij}}}{\eta_W} = \frac{\sum \omega \in W \frac{d_\omega}{\lambda_\omega}}{\eta_W} = \varepsilon \tag{18}$$

Since our system satisfies the assumption that there exists a positive demand for water in the 2006 KIS Water Network, the above equation is used to adapt the network efficiency measure to our system. The $d_\omega$ is equated to 1 to denote that all nodes in the system have beneficial interactions, which is true in the case of IS networks. This alleviates the problem caused by equilibrium disutility in our system by estimating the equilibrium disutility term $\lambda_\omega$ from NQ as $d_{ij}$ from the LM measure as both are inherently defined as shortest-paths in the system [235]. Moreover, the term $\eta_W$ is used as the divisor in our efficiency measure because including all O/D pairs is computationally meaningless for calculating network efficiency since some of the O/D pairs might be not be a part of the network after removal of a node.

However, the derived network efficiency measure (equation 4) expects a network with smaller weights to have a higher efficiency, which is not true for a network like ours. Unlike a transport network where shorter weights in the form of distance or time taken to travel between nodes means higher network efficiency, in an IS network greater synergetic flows between industries are more appropriate for achieving greater network efficiency. For this reason the reciprocal term (*1/*$d_{ij}$) is used in the following expression for computing efficiency of an IS network.

$$E(G) = \frac{\sum_{i \neq j \in G} d_{ij}}{\eta_W} \qquad (19)$$

## B.2 ADDITIONAL RESULTS

### B.2.1 Disruptive Scenarios on the 2002 Water Network

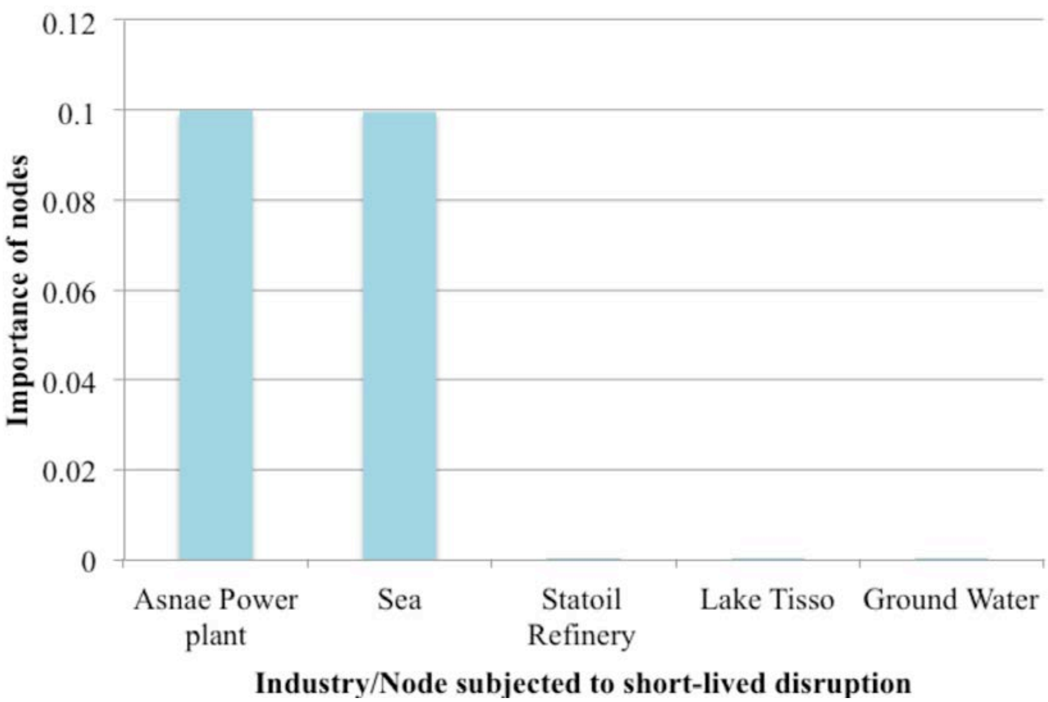
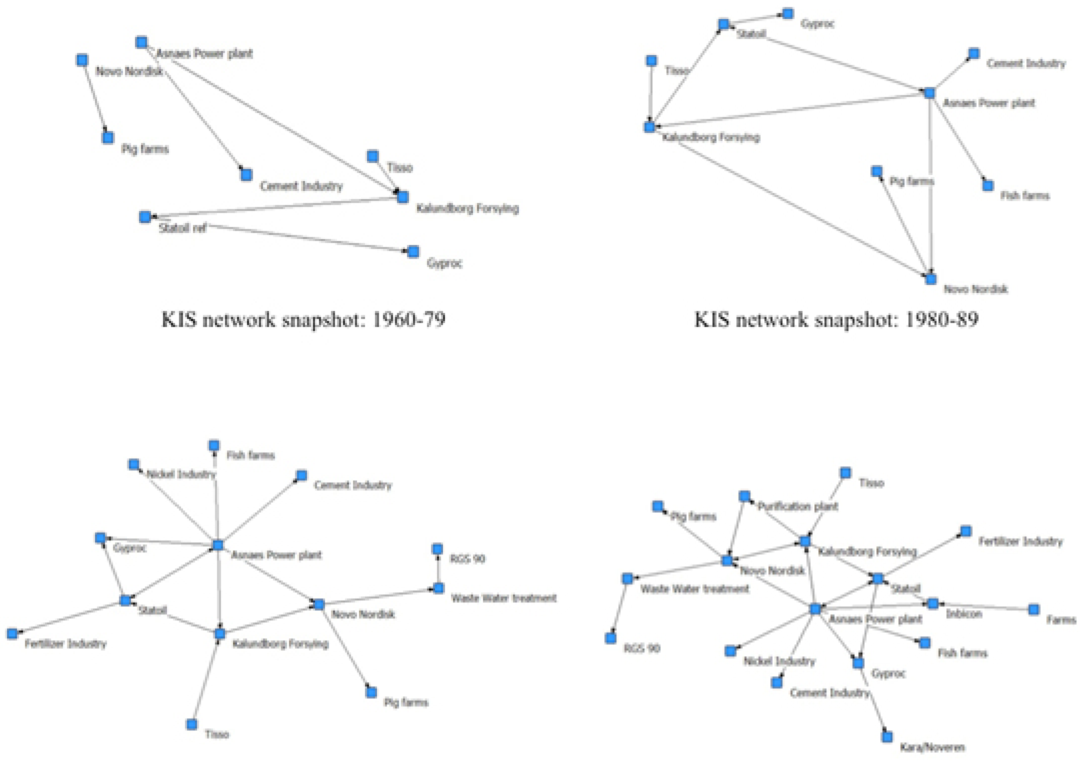



**Figure 28. Importance of nodes based on decrease in network efficiency because of short-lived or partial node disruption scenario.**

These results are similar to permanent disruption scenario discussed in the main paper.

### B.2.2 Evolution of IS network from 1960-2010

The KIS network has evolved over time to include more industries and by-product and waste synergies as seen in the following figures. The complexity of KIS network has increased from 1960 to 2010 with the increase in the number of industries and interactions between them.




KIS network snapshot: 1960-79

KIS network snapshot: 1980-89

KIS network snapshot: 1990-99

KIS network snapshot: 2000-10

**Figure 29. Evolution of IS network from 1960-2010.**

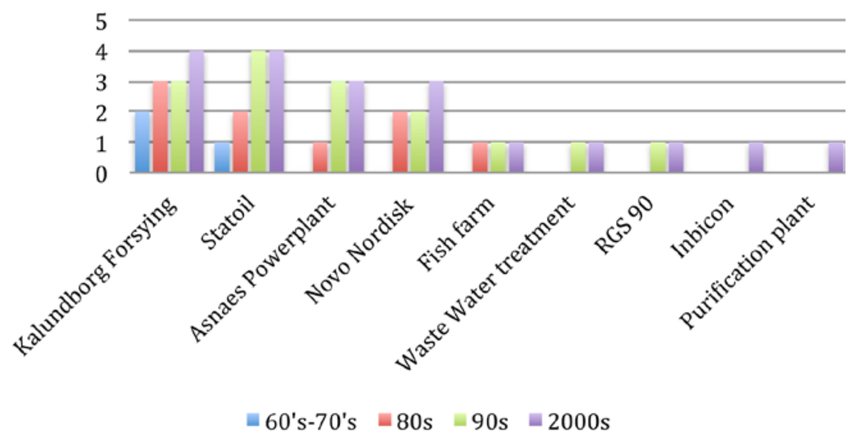



**Figure 30. Evolution of absolute In-degree for the Water synergies.**

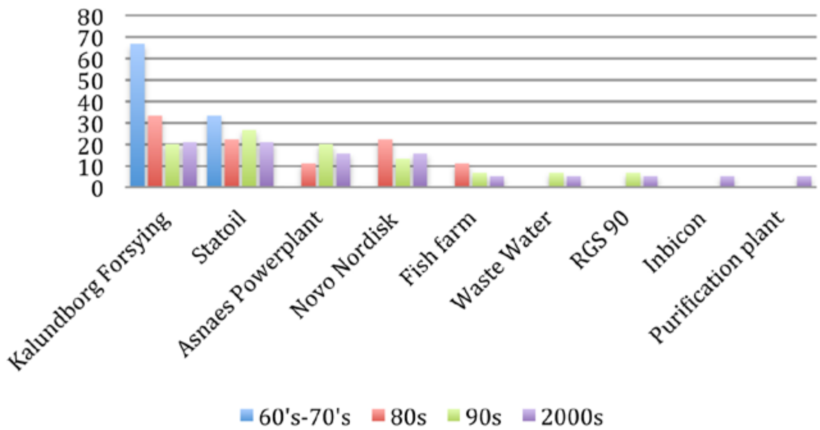



**Figure 31. Evolution of the normalized In-degree for the Water network.**

*Discussion on evolution based on changing in-degree of the network at different time snapshots.* Since the number of nodes and edges has increased over time, an increase in the absolute in-degree and a decrease in the normalized in-degree for all four by-product synergy networks is observed.

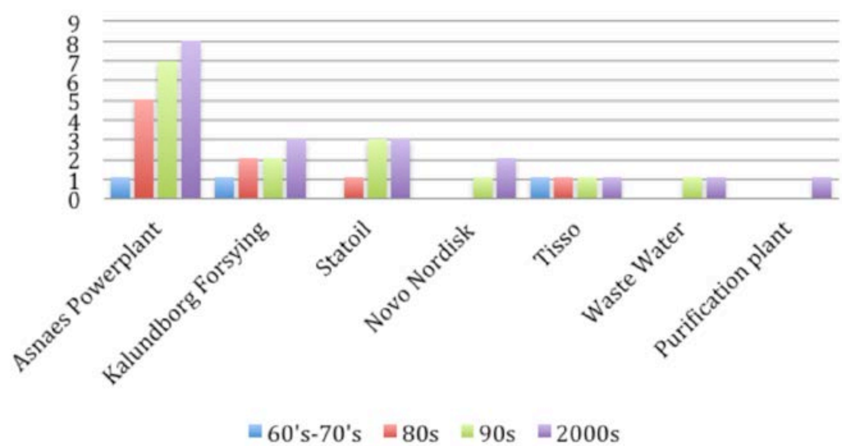



**Figure 32. Evolution of absolute Out-degree for Water synergies.**

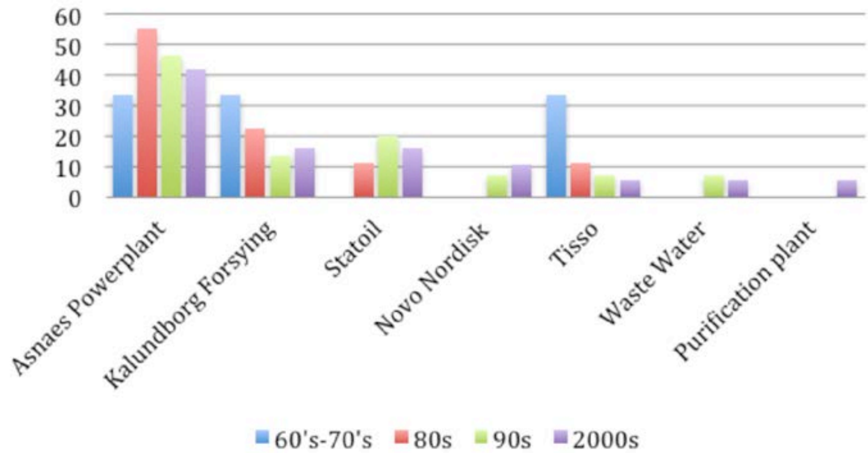



**Figure 33. Evolution of normalized Out-degree for Water synergies.**

*Discussion on evolution based on changing out-degree of the network at different time snapshots.* Similar to trends noted in In-degree of KIS networks over time. Increasing absolute in-degree results in greater diversity and flexibility in the system, and decreasing normalized in-degree suggests reduction in the vulnerability of the nodes over time. Both these traits signify a relative increase in resilience.

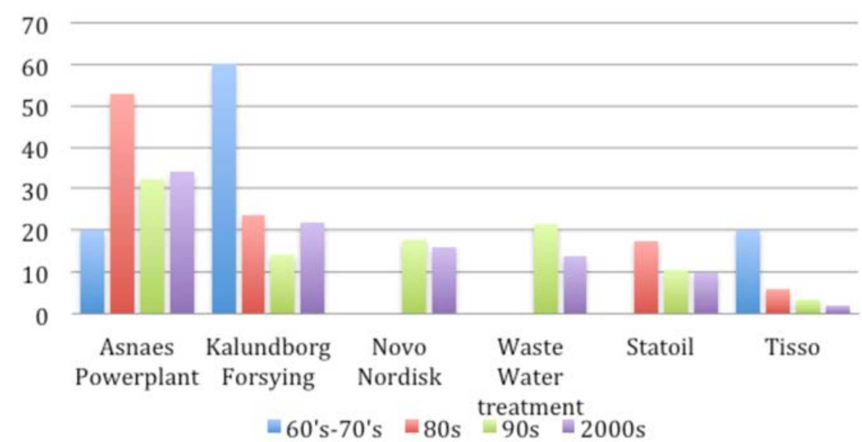



**Figure 34. Evolution of the normalized Stress Centrality for the Water network.**

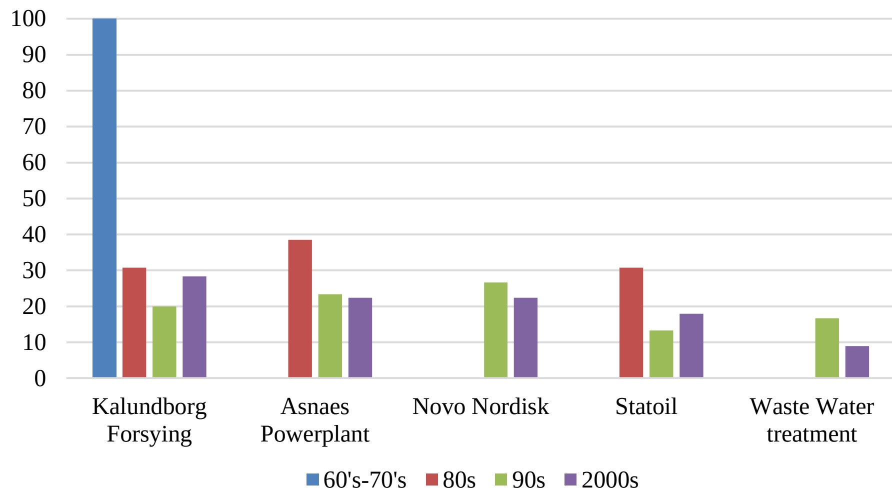



**Figure 35. Evolution of Betweenness Centrality for Water Synergies.**

Both Betweenness and Stress centrality have a decreasing trend for each of the nodes in the systems suggesting that the vulnerability is more equitably distributed over time, and no one node emerges as a critical node that might be responsible for the collapse of the complete system.

### B.2.3 Hypothetical Savings from 1960-2010

**Table 10. Ecological Savings made by each industry in KIS network.**

| Industry | Cost of Virgin natural resource saved in $US |
|---|---|
| Asnae Power plant | 1736077.16 |
| Statoil ref | 4003475.98 |
| Novo Group | 4525064.27 |
| Fish pond | 0 |
| Gyproc | 825440.00 |
| Cement Industry | 745600.00 |
| Farm | 2820694.09 |
| Fertilizer industry | 99000.00 |
| Public works | 3647648.67 |

**Table 11. Industrial Savings made by each industry in KIS network.**

| Industry | Total Savings for each industry in $US |
|---|---|
| Asnae Power plant | 6260705.94 |
| Statoil ref | 3486832.13 |
| Novo Group | 2066234.18 |
| Fish pond | 75000.00 |
| Gyproc | 1823824.34 |
| Cement Industry | 1794100.00 |
| Farm | 372800.00 |
| Fertilizer industry | 49500.00 |
| Public works | 1823824.34 |

**Table 12. Market price for commodities replaced by waste and by-products synergies.**

| Commodities replaced by by-product and waste synergies | Price | Units | Source |
|---|---|---|---|
| Nitrogen | 321.76 | $/ton | USGS [236] |
| Phosphorous | 41.25 | $/ton | USGS [236] |
| Gypsum | 5.36 | $/ton | USGS [236] |
| Clay | 23.3 | $/ton | USGS [236] |
| Vanadium | 11.63 | $/kg | USGS [236] |
| Nickel | 17.91 | $/kg | USGS [236] |
| Soya pills | 231 | $/ton | United Soybean board [237] |
| Sulfur | 33 | $/ton | USGS [236] |
| Fish (Trout) | 2000 | $/ton | FAO [238] |
| Steam (Natural Gas boiler) | 4.31 | $/GJ | US-EIA [239] |

Table 10 and Table 11 are the results for hypothetical industrial and ecological savings by each industry in the network. Table 12 provides the market price for commodities that were replaced by by-products and waste resources for quantifying the monetary value of natural resources avoided through IS.

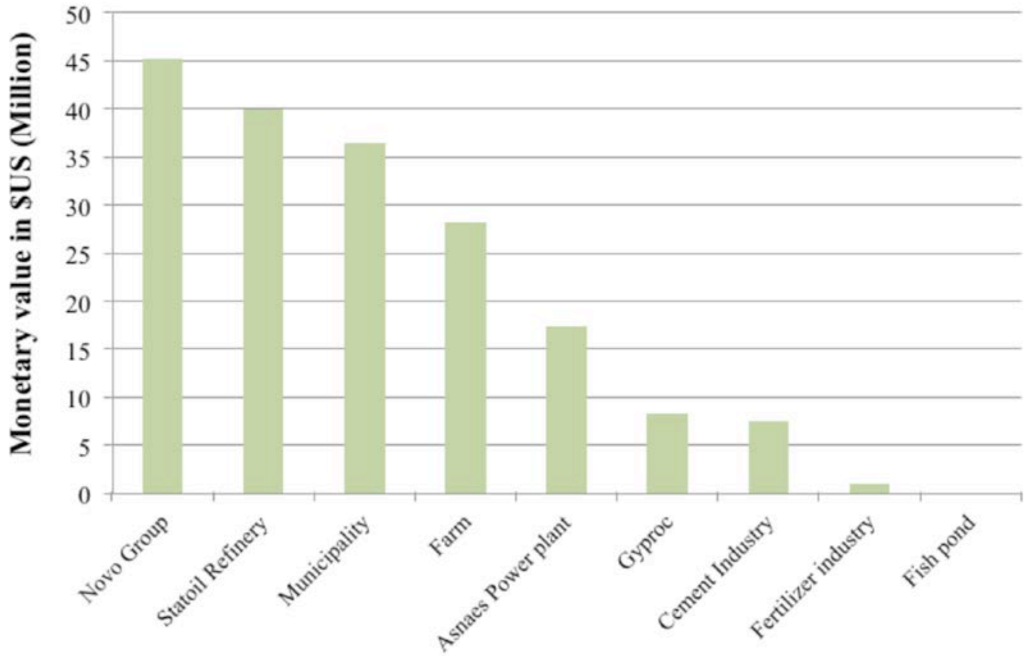



**Figure 36. Value of natural resource preserved by each industry in the KIS 2002 network.**

**Table 13. Resource flow data used for Hypothetical Savings analysis [121].**

| By-product or Waste product synergy | Virgin product substituted | Donor industry | Recipient industry | Physical savings per year (2002) due to synergy | Type of transaction between industries |
|---|---|---|---|---|---|
| **Water based synergies** | | | | | |
| Wastewater | Ground water and Surface water | Statoil Refinery | Asnaes Powerplant | 9,000 $m^3$ | Giveaway |
| Surface water | Groundwater | Lake Tisso | Novo Group<br>Asnaes Powerplant<br>Statoil Refinery | 2,800,000 $m^3$ | Priced on the basis of market price of product substituted |
| Cooling water | Surface water and Sea water | -Statoil Refinery | Asnaes Powerplant | 483,000 $m^3$ | Priced on the basis of market price of product substituted |
| | | Asnaes Powerplant | Fish Farm | 23,587,000 $m^3$ | Giveaway |
| Boiler water | Ground water and Surface water | Asnaes Powerplant | Statoil Refinery | 50,000 $m^3$ | Priced on the basis of market price of product substituted |
| **Material synergies** | | | | | |
| Fly ash | Clay | Asnaes Powerplant | Cement Industry | 32,000 tons of Fly ash | Priced on the basis of market price of product substituted |
| | Vanadium and Nickel | | Asnaes Powerplant | 186Kg of Vanadium<br>41 kg of Nickel | |
| Yeast Slurry | Pig feed | Novo Group | Farms | 10,600 tons | |
| Amino Thiosulphate | Sulphur | Statoil Refinery | Fertilizer Industry | 3,000 tons | |
| Biomass | Nitrogen and Phosphorous in Chemical fertilizers | Novo Group | Fertilizer Industry | 1084 tons of Nitrogen<br>565 tons of Phosphorous | Giveaway |
| **Energy synergies** | | | | | |
| Steam | Natural Gas | Asnaes Powerplant | Statoil Refinery | 197,000 GJ | Priced on the basis of market price of product substituted |
| | | | Novo Group | 829,000 GJ | |
| | | | Municipality | 845,000 GJ | |

# APPENDIX C

# SUPPORTING INFORMATION FOR CASE STUDY 3: RESILIENCE OF LONDON METRO SYSTEM

## C.1 TOPOLOGICAL ANALYSIS OF THE LONDON METRO NETWORK

### C.1.1 Network Metrics used for Small-World detection

**Table 14. Network metrics utilized for the Topological Small-World Analysis of the London Metro Network.**

| Network Metric and Type | Formula | Definition |
|---|---|---|
| **Global Clustering Coefficient** [48] | $C_{WS} = \frac{1}{n}\sum_{i=1}^{n}\frac{R_i}{k_i - 1}$ <br> where, <br> *$n$ = number of nodes in the network* <br> *$k_i$ = the degree of node i* <br> *$R_i$ = redundancy (or average degree of the subgraph of node i, not including node i)* | Global clustering coefficient averages the local clustering coefficient across the network. The local clustering coefficient estimates the propensity of the network to form connected clusters or triangles. |
| **Average Shortest Path Length** <br> [48] | $l = \frac{1}{n^2}\sum_{ij} d_{ij}$ <br> where, <br> *$n$ = number of nodes in the network* <br> *$d_{ij}$ = geodesic path length from nodes i to j* | The average shortest path length averages the average number of edges between every pair of nodes in the network. |

Table 14 (continued)

| | | |
|---|---|---|
| **Local Efficiency** [54] | $E_{loc} = \frac{1}{N(N-1)} * \sum_i (\frac{1}{n_i(n_i-1)1)} * \sum_{jk} \frac{1}{d_{jk}})$ where, $d_{jk}$ = *the geodesic path length from all node pairs within the subgraph of the neighbors of node i* $n_i$ = *the number of nodes within the subgraph of the neighbors of node i* *N = the number of nodes in the network* | Efficiency is the inverse of the geodesic path length between all pairs of nodes of a set group of nodes. Local efficiency evaluates the average efficiency of the subgraph of nodes neighboring a node *i*, and averages it across the network. |
| **Global Efficiency** [54] | $E_{glob} = \frac{1}{N(N-1)} * \sum_{ij} \frac{1}{d_{ij}}$ where, $d_{ij}$ = *the geodesic path length between all pairs of nodes in the network* *N = the number of nodes in the network* | Global efficiency evaluates the average efficiency of all nodes *i* within the network. |

### C.1.2 Analysis of Power-law distributions

The same methodology described in Appendix A.3.1. The following steps to analyze power-law distribution of passenger distribution in the London Metro network [165]:

1. Estimate the parameters $k_{min}$ and ε for the degree distribution. To estimate the scaling factor ε accurately, first estimate the $k_{min}$ accurately. In most cases, empirical data that tends to follow a power-law distribution does so only for values of k greater than a lower bound $k_{min}$; therefore, all values below the $k_{min}$ are discarded. If a very low or a very high $k_{min}$ is chosen, the estimate for the scaling factor ε will be biased. To estimate the $k_{min}$ accurately, the Kolmogorov-Smirnov (KS) statistic is chosen. Using the KS test the value of $k_{min}$ is estimated that makes the degree distribution of U.S. economic network fit best to the power law model. The KS statistic is used to quantify the maximum distance *D* between cumulative distribution functions of two non-normal distributions as follows:

$$D = \max_{k \geq k_{\min}} |s(k) - p(k)| \tag{20}$$

Here $s(k)$ is the CDF of the passenger strength dependent on each station for the London metro network with the smallest $k_{min}$, and $p(k)$ is the CDF for the power law model that best fits the data in the region $k \geq k_{min}$. A value of $k_{min}$ is picked that minimizes the value of D, the distance, between the empirical and the synthetic distributions.

The method of maximum likelihood estimation (MLE) is used to estimate the scaling factor ε for the known lower bound estimate. Maximum likelihood estimation is an estimation technique for finding model parameters that are most consistent with the observed data [233]. The following maximum likelihood estimator of the scaling factor is derived for continuous distributions [165]:

$$\varepsilon = 1 + n\left[\sum_{i=1}^{n} \ln \frac{k_i}{k_{\min}}\right]^{-1}, \tag{21}$$

where $k_i$ is the degree of nodes that have $k_i \geq k_{min}$, and $n$ is the number of such nodes.

2. Compute the goodness-of-fit between the data and the power law using the Kolmogorov-Smirnov test. A goodness-of-fit test is used to test the hypothesis that the passenger strength distribution for London metro fits power law distribution. To begin with, the degree distribution is fit to the power law and calculate the KS statistic mentioned above in step 1. Then, synthetic data sets are generated that follow power law with scaling factor and lower bound parameters that are equal to those found for the concerned economic networks. The KS statistic is calculated for each of the synthetic data sets relative to its power law model. The fraction of instances when the resulting KS statistic is greater than the KS statistic for the passenger flow in the London metro network represents the p-value. If the resulting p-value is greater than the user specified α (consider α= 0.1), the power law is a plausible hypothesis for the data, otherwise it is rejected.

### C.1.3 Results from Topological analysis of the London metro network

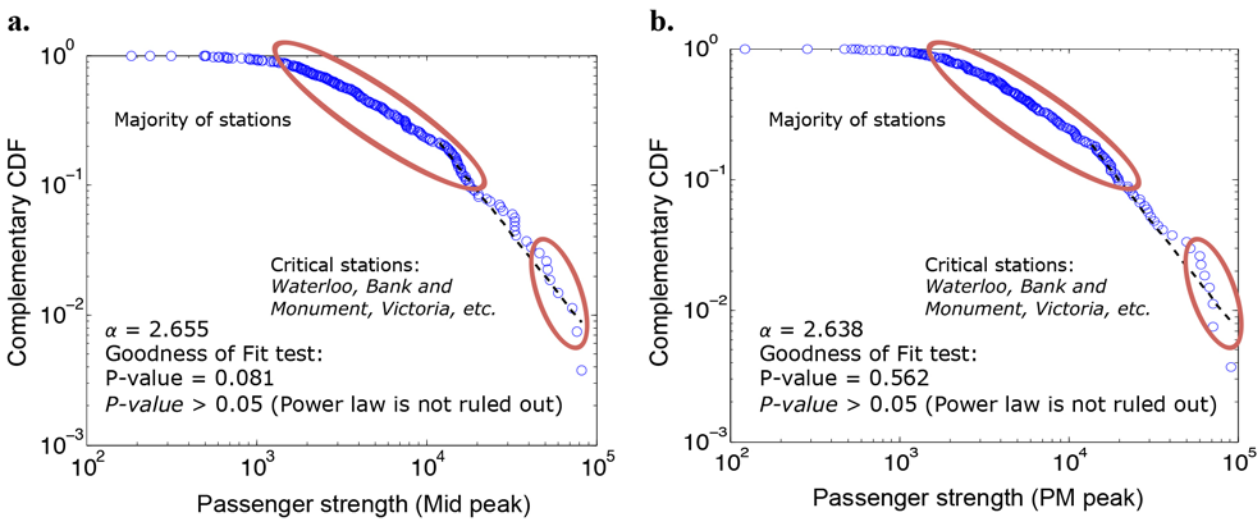



**Figure 37. a. Total passenger strength distribution for mid-day snapshot; and b. Total passenger strength distribution for pm peak snapshot.**

## C.2 MATHEMATICAL DESCRIPTION OF COMMUNITY DETECTION

For determining industrial communities in our study the modularity based clustering approach for directed networks was used. Modularity, Q, for directed-weighted networks is defined as

$$Q = \frac{1}{2m}\sum_{ij}[A_{ij} - \frac{k_i^{in}k_j^{out}}{2m}]\delta_{c_i, c_j} = \frac{1}{2m}\sum_{ij} B_{ij}\delta_{c_i, c_j} \tag{22}$$

where,

$$B_{ij} = A_{ij} - \frac{k_i k_j}{2m} \tag{23}$$

and

- $A_{ij}$ is 1 if there is an edge from node *j* to node *I*, and zero otherwise

- *m* is the edges in the network

- $k_i$ is the in-degree (number of incoming edges) for node i

- $k_j$ is the out-degree (number of outgoing edges) for node j

- $\delta_{ij}$ is the Kronecker delta symbol

- $c_i$ is the community node i is assigned

- $c_j$ is the community node j is assigned

The spectral optimization methodology to find the best division of the economic network by maximizing the value of *Q* [179]. The modularity matrix, *B*, is an *n x n* matrix with elements $B_{ij}$. The algorithm for modularity maximization in simple terms assigns nodes to different communities based on the sign of the eigenvector, corresponding to the largest positive eigenvalue, of the modularity matrix. The above mentioned community detection algorithm of modularity maximization divides the network into exactly 2 communities. In order to identify the natural fault lines in the network by identifying natural groupings of nodes, the repeated bisection graph-partitioning algorithm is applied. This method basically starts by dividing the network in two and then repeating the division while keeping in mind the aim to maximize the modularity for the entire network. A good division of a network results in a high modularity score, thus $Q$ is maximized over all possible divisions of the economy to identify true industrial communities[179].

Using this method, communities within the London Metro network are identified. Results for community at different time periods are presented below.

### C.2.1 Communities Indentified in the London Metro networks

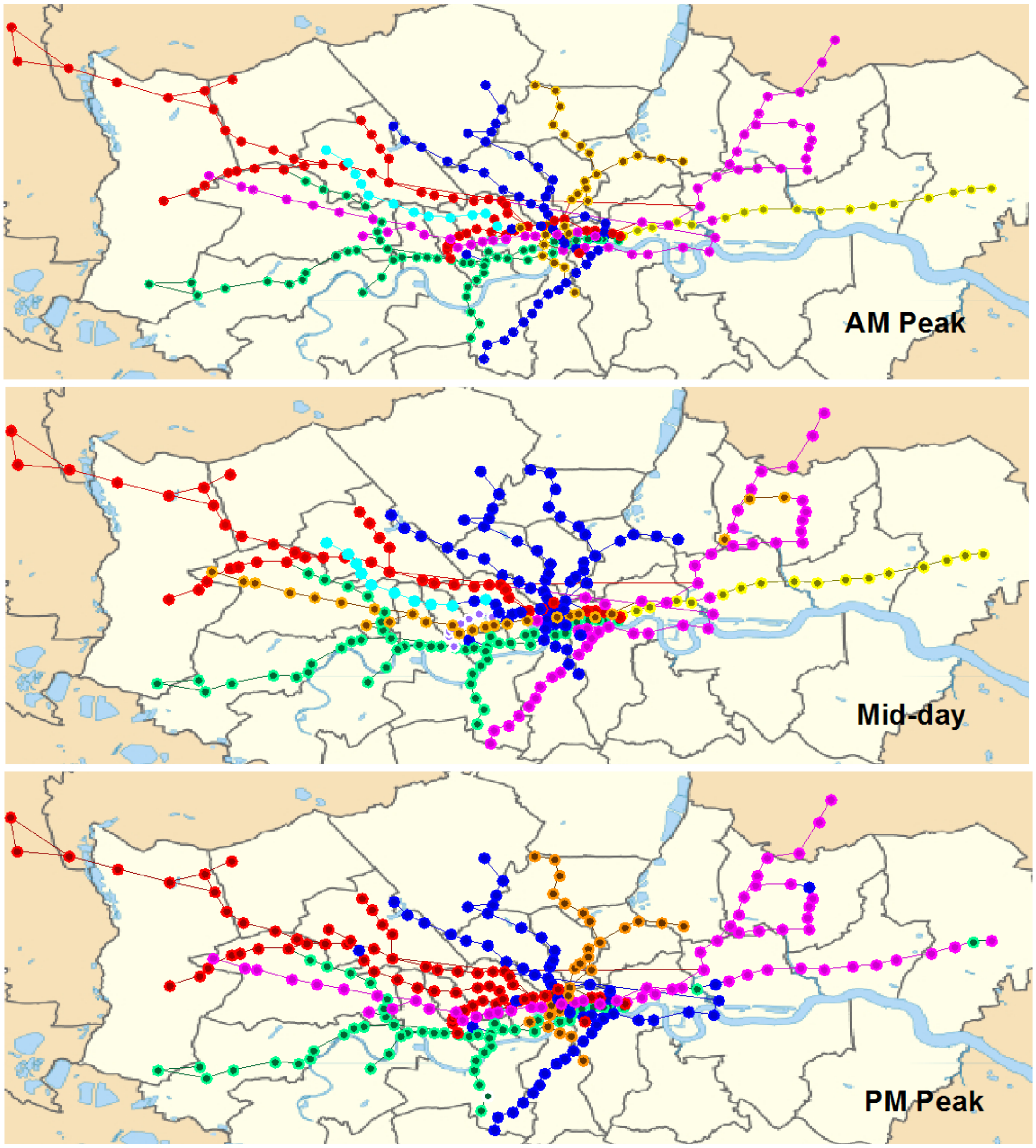



**Figure 38. Sub-communities identified within the London Metro system at different time periods of the day.**

Seven communities identified at AM peak, eight communities identified at PM peak and five communities identified at Mid-day.

## C.3 DERIVATION OF STATION INOPERABILITY

The following outlines our derivation of the station inoperability, which quantifies the fraction of passengers that are not displaced to neighboring stations in light of a malfunction where a station is no longer operating.

$$Relative\ closeness = c_r = l_t/l_i \tag{24}$$

Where:

$l_i$ = length from malfucntioning station to station i (in km)

$l_t$ = total length in km of all neighboring stations j = $\sum_j l_j$

Relative closeness refers to how close neighboring station "i" is to the malfunctioning station compared to the other stations that neighbor the malfunctioning station. If $c_r$ is high, the station is relatively close. If $c_r$ is low, the station is relatively far away.

$$Summed\ closeness = c_t = \sum_i \frac{l_t}{l_i} \tag{25}$$

$$Pecentage\ closeness = c_p = \frac{c_r}{c_t} = \frac{{l_t}/{l_i}}{\sum_i {l_t}/{l_i}} = \frac{1}{l_i * \sum_i {1}/{l_i}} \tag{26}$$

The relative closeness of station i is divided by the summed closeness (the sum of the relative closeness of each station within the sub-graph of the malfunctioning station) to normalize the value between zero and one, called the percentage closeness. If $c_p$ is 1, station i is infinitely close to the malfunctioning station. If the $c_p$ is 0, station i is infinitely far away from the malfunctioning station.

$$Distance\ factor = d_f(l_i) = \begin{cases} \frac{-1}{1.6\ km} * l_i + 1, & l_i < 1.6\ km \\ 0, & l_i \geq 1.6\ km \end{cases} \tag{27}$$

Next, a distance factor is added to predict how far passengers are willing to walk or commute through other means to displace to an alternate station. Literature suggests that most people are willing to walk 400 m to accommodate for public transportation [231]. Assuming that some commuters are already walking distances to reach the malfunctioning station, a conservative estimate that at a 400 m distance, 75% of passengers will be displaced is used. This creates a regression of linear form according the function outlined by $d_f(l_i)$. If $d_f(l_i) = 1$, station i is 0 km away from the malfunctioning station and 100% of passengers will displace to i. If $d_f(l_i) = 0$, station i is 1.6 km or more away from the malfunctioning station and 0% of passengers will displace to i.

$$Percentage\ passenger\ retention = \sum_i \left(c_p * d_f(l_i)\right) \tag{28}$$

The distance factor is multiplied by the percentage closeness to calculate what percentage of passengers will displace to a particular station i. This is then summed across all stations “i” in the sub-graph to find the total percentage of passengers that will displace, which quantifies the percentage passenger retention.

$$Station\ inoperability = 1.00 - \sum_i \left(c_p * d_f(l_i)\right) \tag{29}$$

To find the percentage of passengers that do not displace (inoperability), the percentage passenger retention is subtracted from 1.00.

$$Total\ passenger\ reduction = P_{M.S.} * \left[1 - \sum_i \left(c_p * d_f(l_i)\right)\right] \tag{30}$$

Where:

$P_{M.S.}$ = passenger strength of malfunctioning station

In order to quantify the overall number of passengers that will no longer ride the metro, the inoperability is multiplied by the normal amount of passengers that use the London Metro.

## C.4 RANKING OF EDGES WITH HIGHEST STRUCTURAL AND FUNCTIONAL VULNERABILITY

**Table 15. Redundancy (structural vulnerability) of edges between station *s* and station *t*.**

Edges with r < 1 are listed below.

| **Station *s*** | **Station *t*** | **Redundancy, *r*** |
|---|---|---|
| Stratford | Leyton | 0.861 |
| Leyton | Leytonstone | 0.868 |
| Bow Road | Mile End | 0.894 |
| Bow Road | Bromley-by-Bow | 0.901 |
| Bromley-by-Bow | West Ham | 0.907 |
| Paddington | Warwick Avenue | 0.907 |
| Plaistow | West Ham | 0.914 |
| Maida Vale | Warwick Avenue | 0.914 |
| Plaistow | Upton Park | 0.921 |
| Acton Town | South Ealing | 0.921 |
| Camden Town | Kentish Town | 0.921 |
| North Harrow | Pinner | 0.921 |
| Kilburn Park | Maida Vale | 0.921 |
| East Ham | Upton Park | 0.928 |
| Northfields | South Ealing | 0.928 |
| Kentish Town | Tufnell Park | 0.928 |
| Northwood Hills | Pinner | 0.928 |
| Kilburn Park | Queen's Park | 0.928 |
| Barking | East Ham | 0.935 |
| Boston Manor | Northfields | 0.935 |
| Camden Town | Chalk Farm | 0.935 |

**Table 15 (continued)**

| | | |
|---|---|---|
| Stockwell | Clapham North | 0.935 |
| Archway | Tufnell Park | 0.935 |
| Northwood | Northwood Hills | 0.935 |
| Kensal Green | Queen's Park | 0.935 |
| Barking | Upney | 0.942 |
| Finsbury Park | Manor House | 0.942 |
| Boston Manor | Osterley | 0.942 |
| Belsize Park | Chalk Farm | 0.942 |
| Clapham Common | Clapham North | 0.942 |
| Archway | Highgate | 0.942 |
| Moor Park | Northwood | 0.942 |
| Kensal Green | Willesden Junction | 0.942 |
| Becontree | Upney | 0.949 |
| Fulham Broadway | West Brompton | 0.949 |
| Hounslow East | Osterley | 0.949 |
| Manor House | Turnpike Lane | 0.949 |
| Clapham Common | Clapham South | 0.949 |
| Belsize Park | Hampstead | 0.949 |
| East Finchley | Highgate | 0.949 |
| Hanger Lane | North Acton | 0.949 |
| Harlesden | Willesden Junction | 0.949 |
| Becontree | Dagenham Heathway | 0.956 |
| Fulham Broadway | Parsons Green | 0.956 |
| Hounslow Central | Hounslow East | 0.956 |
| Eastcote | Rayners Lane | 0.956 |
| Turnpike Lane | Wood Green | 0.956 |
| Balham | Clapham South | 0.956 |

**Table 15 (continued)**

| | | |
|---|---|---|
| East Finchley | Finchley Central | 0.956 |
| Golders Green | Hampstead | 0.956 |
| Hanger Lane | Perivale | 0.956 |
| Harlesden | Stonebridge Park | 0.956 |
| Dagenham East | Dagenham Heathway | 0.963 |
| Parsons Green | Putney Bridge | 0.963 |
| Hounslow Central | Hounslow West | 0.963 |
| Eastcote | Ruislip Manor | 0.963 |
| Bounds Green | Wood Green | 0.963 |
| Brent Cross | Golders Green | 0.963 |
| Balham | Tooting Bec | 0.963 |
| Greenford | Perivale | 0.963 |
| Stonebridge Park | Wembley Central | 0.963 |
| Dagenham East | Elm Park | 0.970 |
| East Putney | Putney Bridge | 0.970 |
| Finsbury Park | Seven Sisters | 0.970 |
| Arnos Grove | Bounds Green | 0.970 |
| Hatton Cross | Hounslow West | 0.970 |
| Ruislip | Ruislip Manor | 0.970 |
| Brent Cross | Hendon Central | 0.970 |
| Tooting Bec | Tooting Broadway | 0.970 |
| Chorleywood | Rickmansworth | 0.970 |
| Wembley Park | Kingsbury | 0.970 |
| Buckhurst Hill | Loughton | 0.970 |
| Greenford | Northolt | 0.970 |
| North Wembley | Wembley Central | 0.970 |
| Elm Park | Hornchurch | 0.978 |

**Table 15 (continued)**

| | | |
|---|---|---|
| East Putney | Southfields | 0.978 |
| Seven Sisters | Tottenham Hale | 0.978 |
| Hatton Cross | Heathrow Terminal 4 | 0.978 |
| Ickenham | Ruislip | 0.978 |
| Arnos Grove | Southgate | 0.978 |
| Colindale | Hendon Central | 0.978 |
| Colliers Wood | Tooting Broadway | 0.978 |
| West Finchley | Woodside Park | 0.978 |
| Chalfont & Latimer | Chorleywood | 0.978 |
| Kingsbury | Queensbury | 0.978 |
| Debden | Loughton | 0.978 |
| Northolt | South Ruislip | 0.978 |
| North Wembley | South Kenton | 0.978 |
| Gunnersbury | Kew Gardens | 0.985 |
| Hornchurch | Upminster Bridge | 0.985 |
| Southfields | Wimbledon Park | 0.985 |
| Blackhorse Road | Tottenham Hale | 0.985 |
| Hillingdon | Ickenham | 0.985 |
| Oakwood | Southgate | 0.985 |
| Burnt Oak | Colindale | 0.985 |
| Colliers Wood | South Wimbledon | 0.985 |
| Totteridge & Whetstone | Woodside Park | 0.985 |
| Canons Park | Queensbury | 0.985 |
| Ruislip Gardens | South Ruislip | 0.985 |
| Debden | Theydon Bois | 0.985 |
| Kenton | South Kenton | 0.985 |
| Earl's Court | Kensington (Olympia) | 0.993 |

**Table 15 (continued)**

| | | |
|---|---|---|
| Kew Gardens | Richmond | 0.993 |
| Upminster | Upminster Bridge | 0.993 |
| Wimbledon | Wimbledon Park | 0.993 |
| Brixton | Stockwell | 0.993 |
| Blackhorse Road | Walthamstow Central | 0.993 |
| Cockfosters | Oakwood | 0.993 |
| Hillingdon | Uxbridge | 0.993 |
| Burnt Oak | Edgware | 0.993 |
| Morden | South Wimbledon | 0.993 |
| High Barnet | Totteridge & Whetstone | 0.993 |
| Croxley | Watford | 0.993 |
| Canons Park | Stanmore | 0.993 |
| Epping | Theydon Bois | 0.993 |
| Ruislip Gardens | West Ruislip | 0.993 |
| Harrow & Wealdstone | Kenton | 0.993 |

**Table 16. Fraction Coefficient (functional vulnerability) of edges between station *s* and station *t*- AM Peak.**

Edges with fc > 0 are only listed below.

| **Station s** | **Station t** | **Fracture Coefficient, *fc*** |
|---|---|---|
| Clapham North | Stockwell | 0.059 |
| Bow Road | Mile End | 0.059 |
| Leyton | Stratford | 0.056 |
| Clapham Common | Clapham North | 0.056 |
| Bow Road | Bromley-by-Bow | 0.054 |

**Table 16 (continued)**

| | | |
|---|---|---|
| Bromley-by-Bow | West Ham | 0.052 |
| Clapham Common | Clapham South | 0.049 |
| Plaistow | West Ham | 0.048 |
| Leyton | Leytonstone | 0.048 |
| Plaistow | Upton Park | 0.044 |
| Fulham Broadway | West Brompton | 0.042 |
| Balham | Clapham South | 0.042 |
| Finsbury Park | Seven Sisters | 0.039 |
| Camden Town | Kentish Town | 0.037 |
| East Ham | Upton Park | 0.037 |
| Finsbury Park | Manor House | 0.035 |
| Fulham Broadway | Parsons Green | 0.035 |
| Kentish Town | Tufnell Park | 0.034 |
| Camden Town | Chalk Farm | 0.034 |
| Paddington | Warwick Avenue | 0.032 |
| Balham | Tooting Bec | 0.031 |
| Archway | Tufnell Park | 0.031 |
| Belsize Park | Chalk Farm | 0.030 |
| Manor House | Turnpike Lane | 0.029 |
| Parsons Green | Putney Bridge | 0.029 |
| Barking | East Ham | 0.028 |
| Maida Vale | Warwick Avenue | 0.028 |
| Acton Town | South Ealing | 0.027 |
| Belsize Park | Hampstead | 0.026 |
| Kilburn Park | Maida Vale | 0.025 |
| Tooting Bec | Tooting Broadway | 0.025 |
| Archway | Highgate | 0.025 |

**Table 16 (continued)**

| | | |
|---|---|---|
| Seven Sisters | Tottenham Hale | 0.024 |
| East Putney | Putney Bridge | 0.024 |
| Northfields | South Ealing | 0.024 |
| Kilburn Park | Queen's Park | 0.023 |
| Turnpike Lane | Wood Green | 0.023 |
| Golders Green | Hampstead | 0.022 |
| East Finchley | Highgate | 0.020 |
| Boston Manor | Northfields | 0.020 |
| Brixton | Stockwell | 0.020 |
| East Putney | Southfields | 0.019 |
| Boston Manor | Osterley | 0.019 |
| Kensal Green | Queen's Park | 0.019 |
| Barking | Upney | 0.018 |
| Blackhorse Road | Tottenham Hale | 0.017 |
| Hounslow East | Osterley | 0.017 |
| Brent Cross | Golders Green | 0.017 |
| Kensal Green | Willesden Junction | 0.017 |
| Becontree | Upney | 0.016 |
| Hanger Lane | North Acton | 0.016 |
| North Harrow | Pinner | 0.015 |
| Brent Cross | Hendon Central | 0.015 |
| Bounds Green | Wood Green | 0.015 |
| Colliers Wood | Tooting Broadway | 0.015 |
| East Finchley | Finchley Central | 0.015 |
| Hounslow Central | Hounslow East | 0.014 |
| Becontree | Dagenham Heathway | 0.014 |
| Eastcote | Rayners Lane | 0.013 |

**Table 16 (continued)**

| | | |
|---|---|---|
| Southfields | Wimbledon Park | 0.013 |
| Northwood Hills | Pinner | 0.013 |
| Hanger Lane | Perivale | 0.013 |
| Harlesden | Willesden Junction | 0.012 |
| Blackhorse Road | Walthamstow Central | 0.012 |
| Northwood | Northwood Hills | 0.011 |
| Wimbledon | Wimbledon Park | 0.011 |
| Gunnersbury | Kew Gardens | 0.011 |
| Eastcote | Ruislip Manor | 0.011 |
| Hounslow Central | Hounslow West | 0.011 |
| Greenford | Perivale | 0.011 |
| Harlesden | Stonebridge Park | 0.011 |
| Kingsbury | Wembley Park | 0.011 |
| Arnos Grove | Bounds Green | 0.010 |
| Dagenham East | Dagenham Heathway | 0.010 |
| Colindale | Hendon Central | 0.010 |
| Colliers Wood | South Wimbledon | 0.010 |
| Ruislip | Ruislip Manor | 0.009 |
| Moor Park | Northwood | 0.009 |
| Stonebridge Park | Wembley Central | 0.009 |
| Hatton Cross | Hounslow West | 0.009 |
| Kew Gardens | Richmond | 0.009 |
| Dagenham East | Elm Park | 0.008 |
| Buckhurst Hill | Loughton | 0.008 |
| Ickenham | Ruislip | 0.008 |
| Kingsbury | Queensbury | 0.008 |
| Greenford | Northolt | 0.008 |

**Table 16 (continued)**

| | | |
|---|---|---|
| Hillingdon | Ickenham | 0.007 |
| West Finchley | Woodside Park | 0.007 |
| Arnos Grove | Southgate | 0.007 |
| Hatton Cross | Heathrow Terminal 4 | 0.007 |
| Morden | South Wimbledon | 0.006 |
| North Wembley | Wembley Central | 0.006 |
| Burnt Oak | Colindale | 0.006 |
| Elm Park | Hornchurch | 0.006 |
| Hillingdon | Uxbridge | 0.006 |
| Debden | Loughton | 0.006 |
| North Wembley | South Kenton | 0.005 |
| Canons Park | Queensbury | 0.005 |
| Totteridge & Whetstone | Woodside Park | 0.005 |
| Kenton | South Kenton | 0.004 |
| Hornchurch | Upminster Bridge | 0.004 |
| Northolt | South Ruislip | 0.004 |
| Chorleywood | Rickmansworth | 0.004 |
| Debden | Theydon Bois | 0.003 |
| Burnt Oak | Edgware | 0.003 |
| Chalfont & Latimer | Chorleywood | 0.003 |
| Oakwood | Southgate | 0.003 |
| Harrow & Wealdstone | Kenton | 0.003 |
| Upminster | Upminster Bridge | 0.003 |
| Earl's Court | Kensington (Olympia) | 0.003 |
| Canons Park | Stanmore | 0.003 |
| Epping | Theydon Bois | 0.003 |
| High Barnet | Totteridge & Whetstone | 0.003 |

**Table 16 (continued)**

| | | |
|---|---|---|
| Ruislip Gardens | South Ruislip | 0.002 |
| Croxley | Watford | 0.002 |
| Ruislip Gardens | West Ruislip | 0.001 |
| Cockfosters | Oakwood | 0.001 |

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