Reducing the Risk of Failure in Interdependent National Infrastructure Network Systems

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Abstract

Infrastructure network systems support society and the economy by facilitating the distribution of essential services across broad spatial extents, at a range of scales. The complex and interdependent nature of these systems provides the conditions for which localised failures can dramatically cascade, resulting in disruptions that are widespread and very often unforeseen. This systemic vulnerability has been highlighted multiple times over the previous decades in infrastructures systems from around the world. In the future, the hazards to which infrastructure systems are exposed are set to grow with increasing extreme event risks caused by climate change. The aim of this thesis is to develop methodology and analysis for understanding and reducing the risk of failure of national interdependent infrastructure network systems.

This study introduces multi-scale, system-of-systems based methodology and applied analysis that provides important new insights into interdependent infrastructure network risk and adaptation. Adopting a complex network based approach; real-world asset data is integrated from the energy, transport, water, waste and digital communications sectors to represent the physical interconnectivity that exists within and between interdependent infrastructure systems. Given the often limited scope of real-world datasets, an algorithm is presented that is used to synthesise missing network data, providing continuous network representations that preserve the most salient spatial and topological properties of real multi-level infrastructure systems.

Using the resultant network representations, the criticality of individual assets is calculated by summing the direct and indirect customer disruptions that can occur in the event of failure. This is achieved by disrupting sets of functional service flow pathways that transcend sectorial and operational boundaries, providing long-range connectivity between service originating source nodes and customer allocated sink nodes. Kernel density estimation is used to integrate discrete asset criticality values into a continuous surface from which statistically significant infrastructure geographical criticality hotspots are identified. Finally, a business case is presented for investment in infrastructure adaptation, where adaptation costs are compared to the reduction in expected damages that arise from interdependency related failures over an assets lifetime.

By representing physical and geographic interdependence at a range of scales, this analysis provides new evidence to inform the targeting of investments to reduce risks and enhance system resilience. It is concluded that the research presented within this thesis provides new theoretical insights and practical techniques for a range of academic, industrial and governmental infrastructure stakeholders, from the UK and beyond.

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List of Abbreviations

CNI	Critical National Infrastructure
UK	United Kingdom
IPCC	Intergovernmental Panel on Climate Change
EA	Environment Agency
NaFRA	National Flood Risk Assessment
ENA	Energy Networks Association
NG	National Grid
DNO	Distribution Network Operator

1. Introduction

1.1 Background and Rationale

Infrastructure network systems support society by facilitating the distribution of services across broad spatial extents, at a range of scales. Such services include; electricity, gas, water, transportation, communications and waste. The term ‘Critical National Infrastructures’ (CNIs) recognises infrastructures are “vital for the continued delivery and integrity of the essential services, ...the loss or compromise of which would lead to severe economic or social consequences or to loss of life” (Cabinet Office, 2010).

Many modern CNIs have evolved into large spatially distributed systems having multiple interdependencies (Rinaldi et al., 2001; Rinaldi, 2004). The complex interactions established through interdependencies can facilitate the propagation of failure from one subsystem to another (Little, 2002; Buldyrev et al., 2010). A number of events from around the world have highlighted the potential for failure propagation with CNIs, resulting in unforeseen, widespread disruptions: In 1998, the failure of 4 incoming electricity network feeders resulted in a large-scale blackout in Auckland, New Zealand disrupting multiple essential services for 35 days (Davis, 1999). In 2003, failures within the high voltage electricity networks in North East America resulted in a blackout affecting 50 million people (United States - Canada power system outage task force, 2004). The 2011 Queensland floods resulted in extensive damage to public infrastructures; impacting significantly larger numbers of the population than were inundated by floodwaters – subsequent estimates of state-wide damages range between $5 and $6 billion (Queensland Government, 2011).

A number of climate related extremes have also highlighted the systemic vulnerability of infrastructure in the United Kingdom (UK): During the 2007 summer floods the Mythe water treatment works led to the loss of water supplies to 350,000 people for up to 17 days and almost resulted in the failure of Walham electricity substation (potentially disrupting 500,000 customers) (Pitt, 2008). In 2009, flooding in Cumbria led to bridge failures, resulting in disruptions not only to local transportation but also to water, electricity and telecoms utilities that were co-located (Miller et al., 2013). During the winter storms of 2013/2014 the failure of three electricity sub-stations at Gatwick airport, contributing towards the disruption of 13,000 airline customers (McMillan, 2014). The Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2014) suggest that, in the future, climate change is likely to negatively impact infrastructure networks and critical services due to increases in extreme weather. In the UK, the proportion of infrastructure exposed to flooding is projected to increase in all sectors by 2050 (CCC, 2014).

Given these historic events and the threats posed by a changing climate, characterisation of the current and future risks of failure of the UKs CNI to climate hazards become a national priority (CST, 2009; POST, 2010; Cabinet Office, 2010; Cabinet Office, 2011; DEFRA, 2011). This has resulted in coordinated governmental efforts to understand the severity of risks and target adaptation interventions, (Environment Agency, 2009; DEFRA, 2012; DEFRA, 2013). As a direct result of the 2007 summer flooding, the Environmental Agency (EA) released the National Flood Risk Assessment (NaFRA) that quantified the number of CNI assets that existed within different flood likelihood zones (Environment Agency, 2009). Using information on assets located in flood zones, the Energy Networks Association (ENA) released ETR 138: Resilience to

Flooding of Grid and Primary Substations – flood adaptation guidance document (ENA, 2009). Though these studies are useful, they may be considered limited for the following reasons:

- All infrastructure assets are considered to be equally critical for the operation of the system being considered.
- No spatial network effects are considered.
- Infrastructure interdependency is not considered.
- No customer disruption estimates are considered.
- No economic disruption estimates are considered.

Addressing these limitations is inherently difficult due to the complex nature of modern infrastructure provisions (Kröger, 2008). For example, historically, policy and decision making for individual infrastructure sectors has been made in isolation with little regard for other interconnected infrastructures (Tran et al., 2014). This segregation not only exists between sectors but also within *sub-systems* of an individual sector, which, in many cases have different owners and operators. Take for example, electricity provision in England and Wales: A single company, the National Grid (NG), operates the transmission network. Six different Distribution Network Operators (DNOs) operate the distribution networks. A variety of different companies own and operate electricity generation assets that are embedded at various voltage levels in the transmission and distribution networks. Electricity assets are dependent on the function of a variety of other infrastructures; water for cooling purposes, digital communications for control, transportation networks for the workforce etc. Assets from other sectors are dependent on electricity; electrified rail, electricity for pumping water, electricity for data centres etc. In order to develop an understanding of the role of electricity provision in the UK for applied network failure, risk analysis and adaptation planning, we are therefore required to understand how these, and other, individual sub-systems interact when operated as a whole – as a *System-of-Systems* (Eusgeld et al., 2011). Such an approach requires the assimilation of information and data that is not only maintained by different companies but is typically sparsely available due to its sensitive nature (Kröger, 2008; Ouyang, 2014).

1.2 Aims and Objectives

Given the importance of CNIs to society and the economy, the overall aim of this thesis is to *develop methodology and analysis for understanding and reducing the risk of failure of national interdependent infrastructure network systems*. The methods and accompanying demonstrations use real, national-scale data for the UK; from the energy, water, transportation, waste and digital communications sectors. Real, national-scale data has been chosen to provide useful insights for a range of academic, industrial and governmental infrastructure stakeholders, both within and outside of the UK. Contributing towards the overall aim, the thesis is structured around four research challenges and related sub-objectives:

- **Research challenge 1:** *How can national infrastructure network models be built using only limited amounts of data?*
- **Sub-objectives established for research challenge 1:**

- To formalise the multi-level structure of infrastructure network systems.
- To characterise the most salient spatial and topological properties of real-world infrastructure network systems.
- To apply network theory and develop general algorithms for replicating the topology of UK infrastructure networks.
- To build representative multi-level infrastructure models for the UK using real-world data sets and a synthesis algorithm to provide continuous representations at the national scale.

- **Research Challenge 2:** *How can the potential disruptions arising from failures within interdependent national infrastructures be estimated?*
- **Sub-objectives established for research challenge 2:**
    - To provide a system-of-systems formalisation for multi-scale critical national infrastructure systems.
    - To represent physical dependencies within and between infrastructure systems.
    - To develop methods to estimate failure propagation and customer disruptions within the system-of-systems.
    - To demonstrate the disruption analysis with multiple infrastructures at the national scale.

- **Research Challenge 3:** *How can assets and geographic areas that should be targeted for investment for risk reduction and resilience planning be identified?*
- **Sub-objectives established for research challenge 3:**
  - To develop a universal criticality metric that allows individual infrastructure network assets within the system-of-systems to be directly compared to one another in the same framework.
  - To provide methodology for exploring the consequences of physical and geographic interdependent infrastructure.
  - To provide methodology for identifying geographic concentrations of infrastructure criticality.
  - To use the developed methodology to identify assets and locations within the UK that can be targeted for investments for reducing risks and enhancing resilience.

- **Research Challenge 4:** *How can the benefits of adaptation of critical infrastructures for the purpose of reducing hydrometeorological hazard risks be evaluated?*
- **Sub-objectives established for research challenge 4:**
  - To develop risk-based methods for calculating the expected annual damages of interdependent critical infrastructure assets due to failure through exposure to hydrometeorological hazards.
  - To integrate expected annual damages and adaptation costs into a coherent cost-benefit framework for the purpose of adaptation investment appraisal and prioritisation.

- To demonstrate the methodology at the national scale for critical infrastructures in the UK.
- To evaluate the progress made so far, in terms of losses averted, due to investment in adaptation of critical infrastructures in the UK.

1.3 Related Publications

The following first author journal papers form the main substantive content of the DPhil Thesis. The papers are themselves integrated into the thesis through their inclusion as Chapters 3-6. Paper contribution statements, signed by all co-authors, are located in Appendix A. A description of each paper, including its status in terms of publication, is given below:

I. Thacker, S., Hall, J. W., Pant, R. 2015. Synthesis of multi-level infrastructure network systems. *ASCE Journal of Infrastructure Systems*. In review.

II. Thacker, S., Pant, R., Hall, J. W. 2015. System-of-systems formulation and disruption analysis for multi-scale critical national infrastructures. *Reliability Engineering and System Safety*. In review.

III. Thacker, S., Barr, S., Pant, R., Hall, J. W., Alderson, D. 2015. Geographic hotspots of critical national infrastructure. *Risk Analysis*. In review.

IV. Thacker, S., Kelly, S., Pant, R., Hall, J. W. 2015. Evaluating the benefits of adaptation of critical infrastructures to hydrometeorological risks. *Risk Analysis*. In review.

1.4 Outline of the Thesis

The thesis is divided into 7 chapters. Following the introduction, Chapter 2 provides a literature review that underpins the theoretical and methodological development of the thesis. This includes an introduction to risk and vulnerability analysis, a characterisation of interdependent infrastructures, an overview of approaches for modelling interdependent infrastructure systems and an in-depth review of network-based modelling approaches.

Chapter 3 responds to Research Challenge 1 by presenting methodology and analysis for producing continuous representations of real-world multi-level infrastructure network systems. The chapter is presented through the related publication [I]: *A methodology for the synthesis of multi-level infrastructure network systems.*

Chapter 4 responds to Research Challenge 2 by providing methodology and analysis to perform a system-of-systems formulation and disruption analyses for critical national infrastructure systems that are operational across multiple-scales. The chapter is presented through the related publication [II]: *System-of-systems formulation and disruption analysis for multi-scale critical national infrastructures.*

Chapter 5 responds to Research Challenge 3 by detailing methodology and analysis to characterise the criticality of individual infrastructure assets and to identify geographic 'hotspot' concentrations of criticality. The chapter is presented through the related publication [III]: *Geographic hotspots of critical national infrastructure.*

Chapter 6 responds to Research Challenge 4 by providing methodology and analysis to determine the benefits of adapting interdependent infrastructures against hydrometeorological hazards. The chapter is presented through the related publication [IV]: *Evaluating the benefits of adaptation of critical infrastructures to hydrometeorological risks.*

Chapter 7 presents the conclusions of the thesis. Firstly by providing a summary of the thesis; secondly by explicitly highlighting the main research and applied contributions, then finally by outlining potential future work in this area.

Supporting materials are presented in Appendix B. This includes Table B.0.1: an overview of the datasets utilised and produced during the thesis (including a mapping to the papers in which the datasets are described in additional detail); Table B.0.2: an overview of the software tools utilised and developed during the thesis.

2. Modelling Interdependent Critical Infrastructures

2.1 Interdependent Infrastructure System Classification

The UK government Cabinet Office (2010) defines the national infrastructure as "those facilities, systems, sites and networks necessary for the functioning of the country and the delivery of essential services upon which daily life in the UK depends". The UK national infrastructure is categorised into nine sectors: energy, food, water, transportation, communication, emergency services, healthcare, financial services and government. Due to the lack of availability of data, the focus of this thesis relates to infrastructures from the energy, water, transportation and communication sectors only. Decomposed further, electricity, gas, drinking water, wastewater, solid waste, rail transportation, road transportation, sea transportation, air transportation and digital communications. Broadly these infrastructures are considered 'technical infrastructures' consisting of physical and non-physical assets that can be defined by certain attributes: they are often capital intensive, long-lived and large-scale (Bollinger et al., 2013). Though non-physical assets (such as human control) are often required for the operation of CNIs, the lack of available data (due to security concerns) makes them beyond the scope of this thesis.

Motivated by economies of scale and unequal distributions of national resources and economic activity, modern CNIs have evolved into large spatially distributed systems with complex interconnectivity and multiple interdependencies. The term interdependency is used to characterise a bidirectional relationship established between two CNIs whereas the term dependency is used to characterise a unidirectional relationship (Rinaldi, 2001).

In order to ‘unpick’ this complexity, formal methods of classification of interconnectivity and interdependency have been developed. A number of different definitions for interdependency have been proposed in the literature, including from Rinaldi (2001); Zimmerman (2001); Dudenhoeffer (2006); Lee et al. (2007) and Zhang and Peeta (2011). In a comparative review of these proposed definitions by Ouyang (2014), it was concluded that Rinaldi’s definition provided the most effective means to sort a number of hypothetical real-world interdependency scenarios developed by the author. Though merits exist for each different set of definitions, we utilise Rinaldi’s characterization to provide examples of infrastructure interdependencies (Rinaldi, 2001): (i) *Physical*; where the state of an asset is dependent on the material output of another asset. (ii) *Cyber*; where the state of an asset depends on information transmitted through information infrastructure. (iii) *Geographic*; occurs when multiple assets are in close geographical proximity (iv) *Logical* dependency occurs when there exists a dependency between two assets that cannot be characterized by physical, cyber or geographic dependency. Methods and applied analyses developed within this thesis examine physical and geographical dependency only.

2.2 Modelling to Inform Risk-Based Decision Making

Infrastructure systems can fail for a number of reasons, amongst others, this could be due to aging, human error, exposure to natural hazards or deliberate attacks. When they do fail, the consequences can be widespread and unforeseen, impacting not only technical infrastructure systems, but also social systems and economic systems. System-of-Systems models (theoretical, mathematical and computational) help us understand the interactions of these individual systems in the event of a failure and can provide evidence to inform decision-making (Eusgeld et al., 2011).

Risk based decision-making, such as required to inform the targeting of investments to reduce CNI failure risks and enhance system resilience, uses evidence of risks to inform choices that affect the future (Hall and Borgomeo, 2013). Risk, in the broadest sense, can be defined as a function of the probability of an unwanted event and the severity of the consequences of the event (Kaplan and Garrick, 1981). Thus to characterise the risk of extreme climate events impacting CNIs methodology is required that recognizes the interrelationship between hazards, infrastructure exposure and vulnerability, and potential societal and economic impacts (Hall et al., 2003a,b).

Synergistically, risks can also be expressed as a function of the threats, the vulnerability and the consequences (Peerenboom and Fisher, 2007). Haimes (2006) defines vulnerability as “the manifestation of the inherent states of the system (e.g. physical, technical, organisational, cultural) that can be exploited to adversely affect (cause harm or damage to) that system”. Therefore the assessment of vulnerability is considered a more direct assessment of the CNI when compared to a traditional risk assessment, which adopts a more hazard centric approach.

In recent years, resilience has developed as an overarching concept within the field, which can broadly be seen as the ability of infrastructure systems to resist (prevent and withstand) any possible hazards, absorb the initial damage and recover to normal operations (Ouyang and Dueñas-Osorio, 2012). Though multiple definitions of resilience exist, most centre on the ability of a system to withstand stress (i.e. a hazard impact) and recover in a timely fashion.

Despite their differences, risk, vulnerability and resiliency analysis have one thing in common: to better understand and to improve the performance of infrastructure systems with respect to failure. Therefore, each is able to offer a different but complementary perspective and provide important information to the system being studied. Within this thesis, risk perspectives derived from both traditional risk analysis and vulnerability assessment techniques are developed: Chapter 4 and 5 develop risk perspectives through understanding CNI vulnerability and, through inclusion of probabilistic information on climate hazards, Chapter 6 centres on a traditional risk-based approach. Specific perspectives from resilience are less developed within the thesis due to the lack of availability of temporal data for UK infrastructure systems, more specifically on systems recovery data.

2.3 An Overview of Modelling Approaches

Given the inherent complexities of CNIs it is understood that no single model can answer all the questions for even one infrastructure (Brown et al., 2004). Murray et al. (2008) and Eusgeld et al. (2009) share this sentiment, suggesting that no universal model is achievable. Indeed, a growing body of literature over the last two decades highlights the variety of perspectives and approaches that can be adopted for analysing interdependent infrastructure systems. A number of review papers have been developed during this time to summarise developments and to present the state-of-the-art modelling and simulation techniques classified in a range of taxonomies (e.g. Pederson et al. 2006; Eusgeld et al. 2008; Xiao et al. 2008; Ouyang, 2014).

Such classifications include empirical based techniques that use historic examples of failure to identify systems risks and vulnerabilities (e.g. McDaniels et al. 2007; Chou and Tseng, 2010). Despite being able to accurately reproduce historic events, this approach is ultimately limited by its reliance on historic data and therefore may not be able to provide good predictions for new events that have not previously been observed or recorded.

A second class of models, that simulates the behaviour of infrastructure systems from the bottom up, is agent-based models (ABMs). The key assumption in ABMs is that complex 'emergent' behaviour can arise through the interactions of autonomous agents encoded with simple behaviours (Kaegi et al. 2009). One limitation of this approach is that the simple behaviour that is prescribed to agents is difficult to define and validate, therefore making these models highly sensitive to model design choices. A second limitation, highlighted by Ouyang (2014), is that, due to high computational and data costs, applications of ABMs to model CNIs are typically limited to one set of interdependencies and applications at local scales.

Systems dynamics models characterise CNIs from the top down, representing the system as a series of stocks and flows between objects that form a set of interacting feedbacks (Forrester, 1961). The level of abstraction of these models, make them incapable of resolving component-level dynamics and risks.

Input-output based models, such as described by Leontief (1986), are static linear models of purchases and sales in an economy that are related via technological relationships of production. These relationships allow interdependencies to be characterised between infrastructure sectors, but do not allows interdependencies to be characterised at the scale of individual components. Computable general equilibrium (CGE) models, such as proposed by Rose (2004), can be seen as extensions to input-output techniques through the incorporation of non-linear feedbacks. The extension in capability does also come at the cost of requiring difficult-to-find data on production and utility functions. Like input-output techniques, CGEs are also not applicable at the component scale.

Physics-based (flow) models can be applied for a variety of different infrastructure types. For example, using the AC power flow equations for electricity or the gas flow equations for gas. The high computational costs and large data requirements needed to parameterise models, make this class of model difficult to apply beyond very localised scales. This therefore limits the scope of potential studies and restricts insights that can be gained at the systems level.

In a comprehensive review of the literature by Ouyang (2014), an evaluation of different approaches (including a number of the above) is offered using the following criteria: quality of input data, accessibility of input data, types of interdependencies, computational complexity and maturity. It is shown that relative merits exist with all approaches and that ultimately the choice of approach will depend not only on the suggested criteria but, as with many instances of mathematical modelling, on the specific questions being addressed in the study.

Within this thesis the major theoretical and methodological developments centre on network-based methods. These methods provide an intuitive, spatially accurate, representation of the physical structure of the CNI or combination of CNIs under investigation. This has the following advantages:

- Risk-based investments for protection/reinforcement are typically targeted at individual assets – detailed (asset-level) models provide the ability to explore heterogeneous behaviours at this scale.
- The ability to represent physical infrastructure interdependencies at the scale of individual infrastructure assets.
- The ability to represent geographic interdependencies explicitly through spatial embedding of individual CNI assets.
- The ability to accurately map infrastructure provision to socio-demographic data.
- The ability to provide detailed (GIS based) spatial intersections of infrastructure assets and probabilistic hazard data.
- The ability to model asset interactions from different sectors at large (national scales) – capturing important systems-level behaviours.
- The ability to build models that are computationally tractable and have achievable data requirements at the national-scale.

Following a short introduction to graph theory and network science, the following subsection of this thesis provides and in-depth review of the current state-of-the-art literature of network-based methods for infrastructure risk analysis - providing an underpinning for developments within this thesis.

2.4 Network Based Methods

Graph theory is a branch of discrete mathematics that studies graphs consisting of nodes and their pairwise connections: edges (Bondy and Murty, 2008). Often credited as the first formal work within this discipline was the formal proof of the Seven Bridges of Königsberg problem by Leonhard Euler in 1736 (Barabási, 2003). The original problem posed was to find a route through the city of Königsberg that would involve crossing each of the seven bridges within the city exactly once. Within his proof, Euler's breakthrough came with the representation of the city as a graph, where the land was grouped together to form nodes and the bridges represented edges. Using this formalisation he was able to rigorously prove that no solution to this problem exists.

Following the inception of graph theory by Euler, a number of developments have resulted in the emergence of the field of network science. Using graph theory and other applied theories and methods, network science studies complex networks that are present in the real-world, such as, social networks, biological networks, power grids etc. A number of introductory texts have been produced to provide an introduction to the field, these include, (Strogatz, 2001; Lewis, 2011; Newman, 2010). Foundational study in network science, such as provided in these introductory texts, introduces a variety of terms and metrics that are commonly used to describe the topological structure of networks. Given the prevalence of this material in popular literature and in modern educational programmes, descriptions of the basic conceptual underpinnings of network science are omitted from this thesis.

In addition to exploring network representations of real-world systems, a number of generative network models have been developed to explore the underlying structure and behaviour of complex networks. Examples include the random graph (Erdös and Rényi, 1959), the scale free graph (Watts and Strogatz, 1998), and the small world graph (Albert and Barabaśi, 1999). These models produce networks with characteristic statistical properties and network metrics that describe their structure, including their degree distribution and clustering coefficient. Models that are able to reproduce these characteristic properties are particularly important given that a network's topological structure is highly correlated to network function (Newman, 2003). There are many applications for such models and their resulting networks are frequently used in complex network studies. For example, one question important to many practical network applications is "how will the network be effected with the removal of a given node?" To address this, Albert et al. (2000) investigated the error and attack tolerances of a variety of abstract and real networks. Through the removal of nodes they found that scale-free networks are particularly tolerant to random failures, however this comes at the cost of being vulnerable to targeted attacks.

In addition to topological characterisations, many real world network systems can be characterised by their spatial arrangement. One important consequence of the spatial embedding of networks is that there is a cost associated with the length of edges, which in turn influences the topological structure of the network (Barthelemy, 2011). Spatial variants of the range of generative network methods exist, such as those proposed by Aldous and Shun (2010) and Ferretti and Cortelezzi (2011). Within these models, distance is used to constrain network growth in space during a preferential attachment process. These models can be used to produce networks that preserved characteristics including degree distribution, but are not flexible enough to accommodate any empirical information on known system properties.

Though networks exist in isolation, they also exist and can be characterised as larger structures, of multiple networks coupled together. One realisation of this is the 'network-of-networks' as given by D'Agostino and Scala

(2014). In addition to networks-of-networks, multiple terms exist for coupled-network classifications, including amongst others: multilayer networks and multiplex networks etc. Within this thesis we adopt the term multilayer networks as used in a comprehensive review paper on the topic by Kivelä et al. (2014). The definition and classification of specific layers within the networks can be used to effectively define systems boundaries and provide a useful formalisation for these systems.

One area of network science that has grown significantly over the last two decades has been the study of the structure and function of CNIs. Rather intuitively, nodes and edges are used to represent the structure and interconnections of real infrastructure systems.

A variety of complex network based modelling and simulation tools have been developed to study failure propagation within physically interdependent CNIs. This includes network topology-based methods, such as Bashan et al. (2013) and Shekhtman et al. (2014) that explore network vulnerability and robustness through the removal of individual components. Despite the advancements that these studies provide, care should be taken when applying practical insights to real CNIs such as the power grid (Hines et al., 2010; La Rocca et al., 2015). Detailed physics-based models, such as the AC electricity power flow equations, can capture many details of CNIs and CNI failures; however, the data and computational costs of such analyses are prohibitive to large-scale studies (Brummitt et al., 2013). Functional network models such as proposed by Johansson and Hassel (2010); Poljansek et al. (2010); Zio and Sansavini (2011); Hernandez-Fajardo and Dueñas-Osorio (2013) and Thacker et al. (2014) quantify failure and disruption propagation using functional connectivity and network-path based techniques that replicate the most salient behaviour of CNIs without excessive data and computational costs.

In a recent review of modelling and simulation approaches for interdependent infrastructure systems undertaken by Ouyang (2014), it was recognised that applied studies are limited to two or only a small number of CNIs, therefore potentially underestimating the consequences of failure. In order to compare the disruptive impacts of different assets from multiple interdependent CNI sectors, an informative, universal metric for physically interdependent CNIs is required. Casalicchio and Galli (2008) identify that in order to support decision-making for protection and resilience planning, "core metrics" such as those that act at the asset level are required. To this end, Zimmerman and Restrepo (2006) developed a ratio of the temporal disruptions to the supporting and dependent infrastructure, however, despite its universal quality, this metric does not incorporate the magnitude of user disruptions that result from failure events. Johansson and Hassel (2010) and Thacker et al. (2014) provide a universal metric of infrastructure service losses (user disconnections) applied to individual sectors, however this does not, at the asset level, explicitly incorporate the impacts of indirect disruptions that manifest through nth-order interdependency effects.

Another form of interdependence, less studied in the literature, is that of geographic interdependence. This form of interdependence is particularly important in the context of so-called common-cause failure mechanisms (Rinaldi et al., 2001). These include: weather related hazard events such as ice storms (Chang et al., 2007), flooding (Pitt, 2009), heat waves (McColl et al., 2012) or hurricanes (Loggins and Wallace, 2015); geo-hazards such as earthquakes (Dueñas-Osorio et al., 2007), volcanic activity (Wilkinson et al., 2012) and subsidence (Pritchard et al., 2013); co-location related infrastructure asset failures (BBC, 2011) and targeted attacks (Chernick, 2005; Prager et al., 2011).

Through the removal of infrastructures co-located within previously determined square grid cells, Johansson and Hassel (2010) explicitly address the issue of geographic interdependence by identifying critical geographic locations. This work performs an application of the 'cell-space' method that was demonstrated for a university campus (Patterson and Apostolakis, 2007) and a road network (Jenelius and Mattsson, 2008). Two major limitations of this technique are identified in Wilson (2012): (i) that all infrastructure locations are considered to be evenly spread across a cell, resulting in a loss of spatial information; (ii) Due to the distribution of point assets in space, the choice of grid cell shapes and locations can have a large impact of outcomes, this is otherwise know as the Modifiable Areal Unit Problem (Openshaw, 1994).

Though a number of studies within this field have focussed on systems risk and vulnerability, relatively few have offered contributions to risk reduction. One set of risks faced by infrastructure systems are those imposed by climate-related hazards. In recognition of this, a selection of recent studies has highlighted the large impacts that climate change is likely to have on infrastructure systems (e.g., Kirshen et al. 2008; Hunt and Watkiss 2011; McColl et al. 2012; van Vliet et al. 2012). Despite the contributions made by these studies, the current body of adaptation research does not adequately account for the interconnections within and between different infrastructures (Bollinger et al., 2013). In a review of the literature on adaptations of infrastructures to climate change, Chappin and van der Lei (2014) identify that interdependencies are primarily presented in qualitative, descriptive terms and that explicit interconnections are not dealt with. The failure to incorporate infrastructure interdependencies may result in the full impacts of cascading failures not being accounted for (DEFRA, 2013).

Despite numerous advances that have been made in this field over the previous two decades, a number of challenges remain for the application of network-based methods to real-world CNIs (Ouyang, 2014). These include:

- Limited number of applied studies.
- Poor availability of CNI systems data, for example, geospatial network data, interdependency relationships.
- Limited number of techniques available for reproducing network data (processing partial data), cleaning datasets that are half complete etc.
- Limited applicability of topological based network models to accurately describe system behaviour.
- High data and computational costs associated with flow based network models that replicate detailed system behaviour.
- Limited number of 'universal' metrics, capable of characterising and comparing the criticality of assets across multiple infrastructure sectors.
- Limited number of CNI types considered in a single study (typically only 2).
- Limited scale of applications (often local scale distribution networks etc.).
- Adaptation studies lack explicit representations of connectivity and interdependence.
- Limited evidence to support the business case for investment in critical infrastructure adaptation.
- Limited development of methods and models with practitioners.

- Lack of integrated tools to support decision making across different CNI types.

The theoretical and methodological developments outlined herein address these needs explicitly, offering new approaches to study the risk and vulnerability of real-world interdependent CNIs at the national scale. The incorporation of real-world, high-resolution, national-scale datasets support this effort and provide decision makers from industry and government with demonstrable tools to promote collaboration and knowledge transfer.

3. A Methodology for the Synthesis of Multi-level Infrastructure Network Systems

Abstract:

In the face of incomplete infrastructure network data we present methodology for the synthesis of multi-level infrastructure networks for use in applied network failure and risk analysis. The proposed algorithm is capable of producing networks that preserve a number of important spatial and topological properties of real-world networks including the multi-level structure of sub-systems, the geographic distribution of network nodes, the node degree distribution and the networks spatial connectivity. The algorithm can assimilate incomplete asset information that may be available. Validation of the algorithm is provided using a regional-scale electricity network. The practicality of the algorithm is demonstrated through the synthesis of the integrated electricity network in England and Wales; bridging the transmission, sub-transmission and distribution scales, consisting of more than 160,000 nodes.

3.1 Introduction

Infrastructure network systems play a critical role in modern societies by facilitating the distribution of resources and services across spatial extents at a range of scales. In recent years, tools and methods from the study of complex networks have revealed significant insights into the characteristics and the behaviour of these networked systems (Hernandez-Fajardo and Duenas-Osorio, 2013; Johansson and Hassel, 2010; Thacker et al. 2014). In such studies, network nodes and edges are intuitively used to represent the composition and connectivity of infrastructure systems. However, many potential applied studies are hindered by the lack of available data of both the spatial and topological components of the network. Reasons for the lack of available data include: (i) asset management systems have not collected all of the salient data; (ii) the multiple ownership of infrastructure systems; (iii) security concerns resulting from the release of systems data; and (iv) concerns over the release of potentially sensitive customer information.

Where data are available, they are very often incomplete. Although each case varies, typical deficiencies include incomplete spatial coverage or incomplete topological information. This can be problematic when constructing 'system-wide' models of infrastructures that typical operate over larger spatial extents and consist of interacting sub-systems that function at different scales. In most situations, the lack of data prohibits analysis or at least curtails it. Where these data are not available one solution is to produce a realistic synthetic representation of the network system. Whilst synthetic networks will be different to reality on the ground, if the salient properties of the network can be preserved, we argue that they provide a worthwhile basis for infrastructure network analysis that would otherwise be impossible.

A number of models exist for the synthesis of networks; these include the random graph (Erdös and Rényi, 1959), scale free graph (Watts and Strogatz, 1998), small world graph (Albert and Barabaśi, 1999). These models produce networks with characteristic statistical properties and network metrics that describe their structure. Understanding that the networks topological structure is highly correlated to network function (Newman, 2003) it is important that any synthetic representation preserves a number of these topological and spatially important characteristics. Multiple metrics exist and have been used to describe real-world network properties (Newman, 2010; Barthelemy, 2011). Of particular interest to the infrastructure community is the risk of network failure; one such property used to characterize failure is degree distribution (Albert et al. 2000). Newman, (2003) proposes a model that produces graphs that maintain specific degree distribution, however the model does not maintain any of the important spatial properties of 'real-world' networks. Spatial variants of the range of generative methods exist (Ferretti and Cortelezzi, 2011; Aldous and Shun, 2010), typically using distance as a means by which to constrain network growth in space during a preferential attachment process. Such methods produce networks that preserved characteristics including degree distribution, but that are not flexible enough to accommodate any empirical information on known system components.

Infrastructure network systems can be intuitively represented as multi-level networks (Kivelä et al. 2014; D'Agostino and Scala, 2014). Such a representation can be useful, not only in mapping the multiple owners or operators of a particular system, but to characterize sub-systems that form a part of the whole infrastructure that have distinct characteristics. Take for example electricity transmission networks (typically the focus of applied and abstract studies), which are generally considered to have a mesh structure whilst distribution networks are considered to be radial (Buchholz and Styczynski, 2014). Developing a multi-level representation allows these distinct network structures to be represented and hence synthesized to produce one continuous representation – bridging multiple operation scales whilst preserving the heterogeneous spatial and topological characteristics of the individual networks. Assembling data to build a continuous representation is a considerable challenge due in large part to the lack of techniques available to formalize such models. A further complication exists in managing data that are very often incomplete and are stored and maintained in various formats.

This study develops a novel approach for the synthesis of multi-level infrastructure network systems. The proposed algorithm encodes a number of important spatial and topological properties of real-world networks, including: (i) the multi-level structure of network sub-systems using known systems characteristics; (ii) The distribution of network nodes in space using known demographic data; (iii) the assignment of degree to each node based on sampling the known degree distribution for assets of differing type; and (iv) the assignment of edges to nodes to match the pre-defined degree by sampling known nearest-neighbour rank distributions. The modular nature of the algorithm allows for differing levels of known systems data to be incorporated into the synthetic network. This can be used to derive parts of, or complete networks that best represent actual networked systems. A further application for the algorithm includes the derivation of families of 'realistic networks' that can easily be characterized using data from real infrastructure systems.

There are a number of unique contributions made in this research. Firstly, by offering a formal description of multi-level infrastructure networks. Secondly, in characterizing their most important spatial-topological properties. Thirdly in encoding those properties in an algorithm, capable of synthesizing realistic representations of multi-level electricity networks. Fourthly, in providing a demonstration of the algorithm to produce an integrated national scale electricity generation, transmission, sub-transmission and distribution network consisting of over 160,000 nodes.

Following the introduction, Section 3.2 of the paper develops a mathematical formalization of multi-level infrastructure networks. Section 3.3 characterizes the most salient spatial and topological properties of multi-level infrastructure network systems. Section 3.4 introduces the synthesis algorithm and provides details for its implementation. Section 3.5 outlines a validation of the algorithm for a regional-scale electricity network and a demonstration for the integrated electricity network in England and Wales. Section 3.6 discusses the results, providing conclusions and insights gained from the study.

3.2 Multi-Level Infrastructure Network Formalisation

Within this section we develop a mathematical formalization for multi-level infrastructure networks. This formalization introduces the formal notation that is later used to characterize these systems and for developing the synthesis algorithm. It also acts as an exemplar as to the complete set of data and attribution that is required to build any system-wide infrastructure representation.

Through the paper we use electricity power systems as an example of multi-level infrastructure networks. Despite the singular use of electricity networks in the paper, the methods presented herein are transferable to a range of infrastructure networks that can be characterized as taking a multi-level form.

We consider the infrastructure *system S* as a set of interconnected assets whose collective function is to facilitate the production and transfer of a resource or service to customers, such as electricity infrastructures. Many infrastructure systems are comprised of multiple interacting sub-systems, where an individual *sub-system S_k* is defined as fulfilling a specific function within the system and can be characterized as having unique attributes. Within electricity networks, sub-systems are typically classified as the transmission, sub-transmission and distribution network infrastructure. In England and Wales the classification is based on the sub-systems attributed operational voltage, typically 400kV, 275kV, 132kV, 33kV and 11kV. We consider the system S to be comprised of z individual sub-systems which we denote as $S = \{S_1, \dots, S_z\}$. Infrastructure systems that contain multiple sub-systems are classified as *multi-level*, with individual sub-systems forming levels in the multi-level structure.

We represent infrastructure systems as networks consisting of nodes and edges: Nodes are used to represent assets of the infrastructure that produce, consume and transform the resource being distributed. Respectively these are known as source nodes, sink nodes and intermediate nodes. Within electricity networks, respective examples include power plants, load points and sub-stations. Edges are used to represent physical connections between nodes and can be seen as conduits of flow. Within electricity networks, edges are used to represent overhead and underground cables.

The nodes that are associated with a particular sub-system are sampled from the exhaustive set of all nodes $N = \{n_1, \dots, n_Y\}$ in the system. The node set N_k of the sub-system S_k is defined as the subset of the Cartesian product set of N and S_k, as given in Eq. (3.1).

$$N_k \subseteq N \times S_k = \{(n_1, S_k), \dots, (n_Y, S_k)\} \tag{3.1}$$

We can identify nodes that have an attribute plurality and are hence present in two or more sub-systems. Electricity substations perform this functional in electricity networks; stepping down or stepping up the voltage between sub-system levels. This is described in Eq. (3.2), where node n_i is assigned the set $\tilde{S}$ of all sub-systems where it is present.

$$n_i \equiv \left(n_i, \tilde{S}\right) \tag{3.2}$$

The connectivity of the nodes within and across different sub-systems is defined in terms of the edge set E, which we denote as

$$E = \left\{e_{i\alpha,j\beta} = \left((n_i, S_\alpha), \left(n_j, S_\beta\right)\right), \forall i, j, \alpha, \beta\right\} \tag{3.3}$$

From the above set definition we identify two distinct edge types:

Intra-sectorial edges E_k which are given as $E_k = \left\{e_{ik,jk} = \left((n_i, S_k), \left(n_j, S_k\right)\right); \forall i, j, k, i \neq j\right\}$, where it is assumed that within the sub-systems nodes do not have self-edges incident on themselves. In electricity infrastructures, these edges are overhead lines or underground cables.

Bridging edges B which are given as $B = \left\{e_{i\alpha,i\beta} = \left((n_i, S_\alpha), \left(n_i, S_\beta\right)\right); \forall i, \alpha, \beta, \alpha \neq \beta\right\}$, establishing the connectivity of nodes between sub-system levels. In electricity infrastructure systems, these edges are the bridge between the two halves of a transformer.

Infrastructure systems are common entities in our landscape with nodes and edges within S having a specific location given in Cartesian coordinates, derived by the location function $l(S)$:

$$l(S): S \to \mathbb{R}^2 \tag{3.4}$$

Figure 3.1 provides a simplified network example to demonstrate the multi-level infrastructure network formalization.

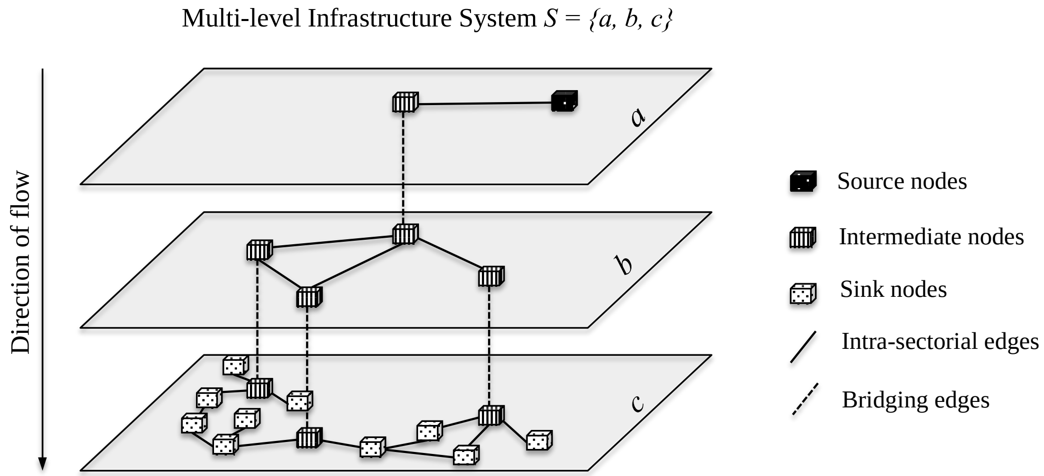

Figure 3.1: Representation of the multi-level infrastructure system *S* decomposed into the sub-systems: *a*, *b* and *c* representing individual levels. Flows of resources and services are facilitated from source to sink nodes within sub-systems by intra-sectorial edges and between levels (sub-systems) by bridging edges.

3.3 Spatial Topological Infrastructure Network Characterisation

Representations of real infrastructure systems such as those described in Section 3.2 of this paper provide a means to understand the behaviour of infrastructure systems for a range of applied analyses. Our aim is to provide methodology in the form an algorithm that is capable of producing 'realistic' synthetic representations of the network system being investigated. Within this section we describe the essential set of spatial and topological characteristics that the synthetic representation of the real infrastructure should preserve. In encoding these properties in the synthetic network, we argue that the synthetic networks produced by the algorithm will provide a worthwhile basis for infrastructure network analysis that would otherwise be impossible.

We identify four minimum requirements for synthetic networks: (i) To preserve the number of node assets distributed within each level of the multi-level structure; (ii) To preserve the spatial distribution of these nodes; (iii) To preserve global network connectivity for different levels; and (iv) To preserve the local spatial connectivity between node assets for different levels.

In the following sub-sections we present a justification for these requirements through a characterization of the spatial and topological properties of real infrastructure network systems. The conceptual development is once again complimented with real data from electricity network systems - providing a link between the mathematical formalization and the real systems under investigation.

3.3.1 Multi-level assignment of nodes

Our first requirement is to ensure that the correct number of nodes $|N_k|$ is assigned to each level of the multi-level structure. This characteristic follows our understanding that in the upper levels of the system (that are responsible for the bulk transmission of the service or resource) there are relatively fewer nodes with high capacities compared to assets in lower levels that are greater in number but have lower capacities. This is demonstrated with data (ENA, 2009) that we have for the number of nodes (substations) for given levels of the integrated electricity network system in England and Wales, presented in Table 3.1.

Table 3.1: Provides details for substation (node) assets in England and Wales: The table highlights the typical operational voltage levels, approximate number and typical number of customers supplied for substations of four types; grid, bulk, primary and distribution that correspond to four levels in the integrated electricity network system.

Substation (node) type	**Typical voltage transformation levels**	**Approximate number**	**Typical number of customers supplied**
Grid (Transmission)	400kV to 132kV	377	200,000/500,000
Bulk (Sub-transmission)	132kV to 33kV	1,000	50,000/125,000
Primary (Sub-transmission)	33kV to 11kV	4,800	5,000/30,000
Distribution	11kV to 415V	160,000	1/500

As recognized earlier in this paper, substation assets function to step up or down the voltage between separate network levels. These assets therefore have a plurality and we formally recognize their existence in two or more levels of the system, connected by a bridging edge. Considered locally, a sink node on the upper side of the transformer is therefore regarded as a source node on the lower side of the transformer. It is this node property that allows us to build a continuous representation that bridges operational scales.

3.3.2 Spatial distribution of nodes

Not only is it important to preserve the number of nodes, it is also important to preserve their spatial distribution. We characterize the spatial distribution of node assets in England and Wales as follows:

Consider $Q \subset \mathbb{R}^2$ the set of all two-dimensional coordinates of locations within the boundaries of a spatial extent such as the countries of England and Wales. Q can be partitioned into n smaller regions (regional boundaries: Local Authority District regions (LAD) etc.) $Q_i \subset \mathrm{Q} : i = 1, \dots, n$. Each boundary area can be associated with a population count, such as those derived during a national census. The set of Cartesian coordinates $P \subset \mathbb{R}^2$ are the locations of residences of all the national populace. We use the notation $|P|$ to represent the national populace count, which is the total number of people in the residences within the coordinates of P. The intersection of P and each sub-region Q_i is equal to the set of people living in one region, so the population count $|P_i|$ in Q_i is:

$$|P_i| = |P \cap Q_i| : \ i = 1, \dots, n \tag{3.5}$$

The number of nodes from the network system S that are located within the regional area Q_i is calculated as

$$\tilde{n}_i = |l(N) \cap Q_i| \tag{3.6}$$

Where $l(N)$ denotes the locations of all nodes in the set N. Figure 3.2 plots the number of electricity assets (substations and pole mounted transformers) intersecting LAD regional population boundaries for England and Wales. The plot highlights that there is a strong correlation ($R^2 = 0.78444$) between the population of the region and the number of nodes that reside in that area.

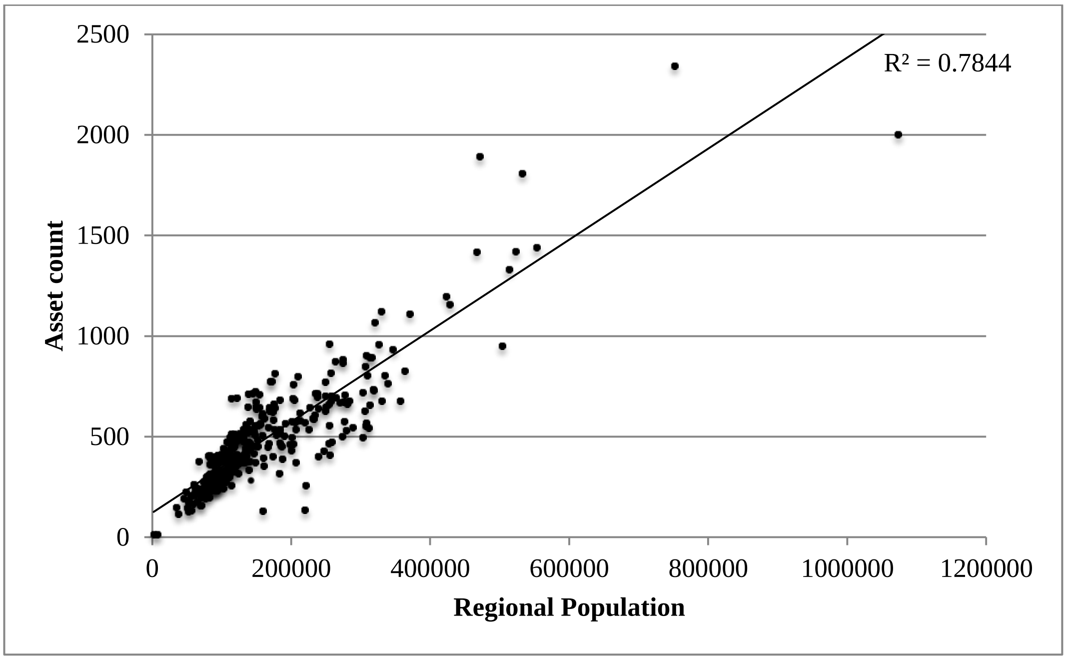

Figure 3.2: Represents the number of electricity node assets (substations and pole mounted transformers) intersecting Local Authority District regional population boundaries in England and Wales.

3.3.3 Global network connectivity

Our next characteristic is the preservation of global network connectivity for different sub-system levels. Connectivity is established through edges, but can be viewed as a node characteristic: Where the degree k of a node is the number of connections that the node has to other nodes. The degree distribution $P(k)$ of a network is defined to be the fraction of nodes in the network with degree k. Therefore in a network with c number of nodes, and c_k of them have degree k, we have $P(k) = c_k/c$.

We recognize that different sub-system levels can have different network topologies (Buchholz and Styczynski, 2014). A further disaggregation can be made for the degree distribution for either source and sink nodes in any separate level S_k. Figure 3.3 (a) shows the degree distribution for England and Wale's electricity transmission network disaggregated for both source and sink nodes. The plot shows that there are more sink nodes in each level than source nodes, reflecting the increase in the number of nodes at lower levels of the multi-level structure and difference in their respective probability distributions.

3.3.4 Local network connectivity

We also recognize the importance of local spatial connectivity between node assets for different sub-system levels. We propose the metric of neighbour rank connectivity as a measure of this, derived as follows:

For any node i we can compute the distance to all other network nodes and place them in the ordered set

$$\begin{gathered} D_E(i) = \{d_E(i,1), d_E(i,2), \dots, d_E(i,t)\}: \\ d_E(i,j) < d_E(i,k)\ \forall\, j < k\ \in \{1,2,\dots,t\}\backslash\{i\} \end{gathered} \tag{3.7}$$

Where $d_E(i,j)$ is the Euclidian distance between node i and it j^{th} closest neighbor. If the node pair (i,j) corresponding to the distance $d_E(i,j)$ are actually connected then this connectivity is represented as an edge e_{ij}. For each node in the network we can construct the edge set in terms of the ordered set of nearest neighbour distances which results in the rank nearest neighbour edge set

$$C(i) = \{1_j e_{ij}\}: 1_j = \begin{cases} 1 : \exists j \\ 0 : \nexists j \end{cases} \quad (3.8)$$

By constructing the above set $C(i)$ for all nodes in the network we have an understanding of the nearest neighbour connectivity in the network. Derived from this, the neighbour-rank distribution $P(c)$ of a network is defined to be the fraction of edges in the network with neighbour-rank c. Therefore in a network with x number of edges, and x_c of them have neighbour-rank c, we have $P(c) = x_c/x$.

Figure 3.3 (b) presents the neighbour-rank distribution for England and Wales's electricity transmission network. The graph highlights that although most assets intuitively connect to their nearest neighbours in space, some connect to assets that are further away – providing some level of long-range connectivity in the network.

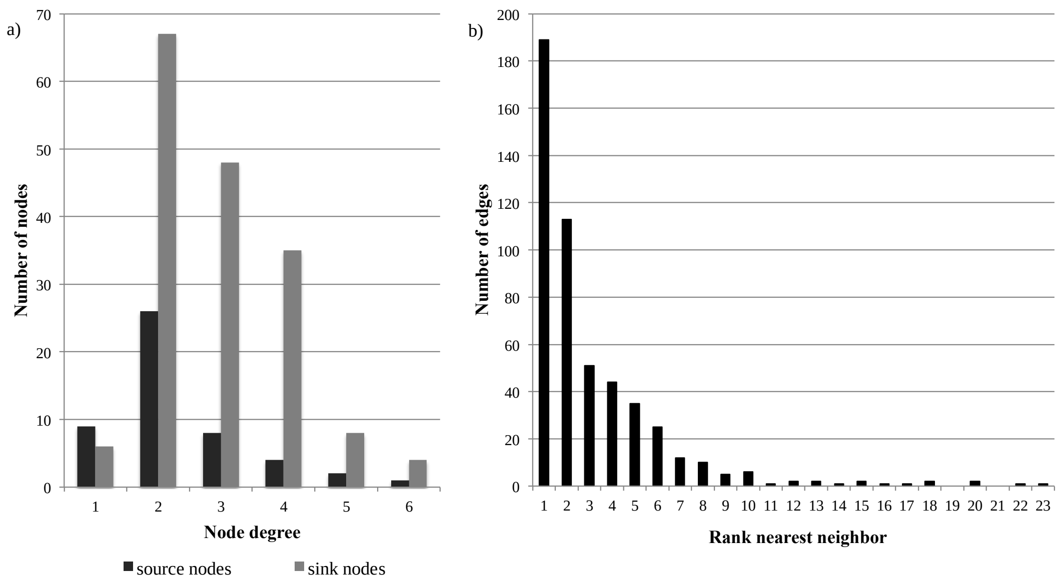

Figure 3.3: highlights global connectivity measures for England and Wales's electricity transmission networks: (a) shows the network degree distribution with the degree of sink and source nodes being presented separately (b) shows the neighbour-rank distribution of edges within the network.

3.4 Synthesis Algorithm

We propose an algorithm that can be used to produce synthetic representations of multi-level infrastructure network systems. The algorithm iterates through successively levels of the multi-level structure. When missing spatial or topological information is identified, sub-routines are implemented to produce synthetic representations of the missing elements that maintain the minimal spatial and topological requirements established in Section 3.3 This results in a final network representation that forms a continuous representation over the specified spatial extent, at a range of declared operational scales. The main steps in the algorithm are outlined below, with Part 1, 2.2, and 2.4 highlighted due to their role in explicitly incorporating the required synthetic characteristics identifies in Section 3.3 of this chapter:

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1. **Given: Collect all available node $\boldsymbol{N}$ and edge $\boldsymbol{E}$ data and assign to sub-systems depending on their attribution to give $\boldsymbol{S} = \{\boldsymbol{S_1}, \dots, \boldsymbol{S_z}\}$**
2. For the subsystem S_k in the system:

   2.1. Does node set N_k exist?

   2.1.1. Yes: Go to step 2.3

   2.1.2. No: Go to step 2.2

   2.2. Create missing nodes and distribute in space:

   2.2.1. For each regional area Q_i:

   2.2.1.1. Calculate population p_i of that area

   2.2.1.2. Calculate the number of nodes of correct type required in that area $\tilde{n}_{S,i}$

2.2.1.3. Assign $\tilde{n}_{S,i}$ nodes to locations in Q^i

2.2.2. Go to step 2.3

2.3. Does edge set E exist?

2.3.1. Yes: Go to step 2.5

2.3.2. No: Go to step 2.4

2.4. Assign edges to node:

2.4.1. For all nodes with missing edges:

2.4.1.1. Assign degree to node of specific type by sampling known degree distribution $P(k)$

2.4.2. Assign edges to nodes by sampling rank-neighbour distribution $P(c)$ to match expected degree distribution:

2.4.3. Go to step 2.5

2.5. Sub-system S_k representation complete: If S_k = S_z Go to step 3, else return to step 2 to evaluate S_{k+1}

3. End – System S network representation complete

Implementation of the algorithm is heavily dependent on the raw data that may be available. In most cases it will be beneficial to include as much data from the actual system as possible, therefore only synthesizing parts of the system that have data missing from them. By reducing the constraint of real data, other generic distributions of node locations and connectivity can be used to build abstract representations that can be considered as alternative configurations.

Figure 3.4 provides an example of how the synthesis algorithm would be implemented to produce a sub-system c for the infrastructure network system $S = \{a, b, c\}$ introduced earlier in the paper. Having collected all know data and assigned them to levels in the multi-level system, we start our iteration through the system at sub-system *a* and find that all data is complete, the next sub-system is *b*, this is also complete, the next sub-system is *c*, this is incomplete and therefore the focus of the synthesis algorithm implementation – the process of iteration is represented in part (a) of the figure. Part (b) of the figure highlights the data that is available for that level. We next identify that nodes are missing from level c and we proceed to distribute nodes as given in part 2.2 of the algorithm, shown in part (c) of the figure. The next stage of the algorithm ascertains that no edges are present. A degree is therefore assigned to each node based on sampling known degree distributions for nodes that belong to level c. Finally, edges are assigned in an iterative process to meet the expected degree distribution; this is shown in part (d) and (e) of the figure and completes part 2.4 of the algorithm. The algorithm terminates as all nodes and edges are present for the infrastructure network system s, as shown in part (f) of the figure and given as step 5 of the algorithm.

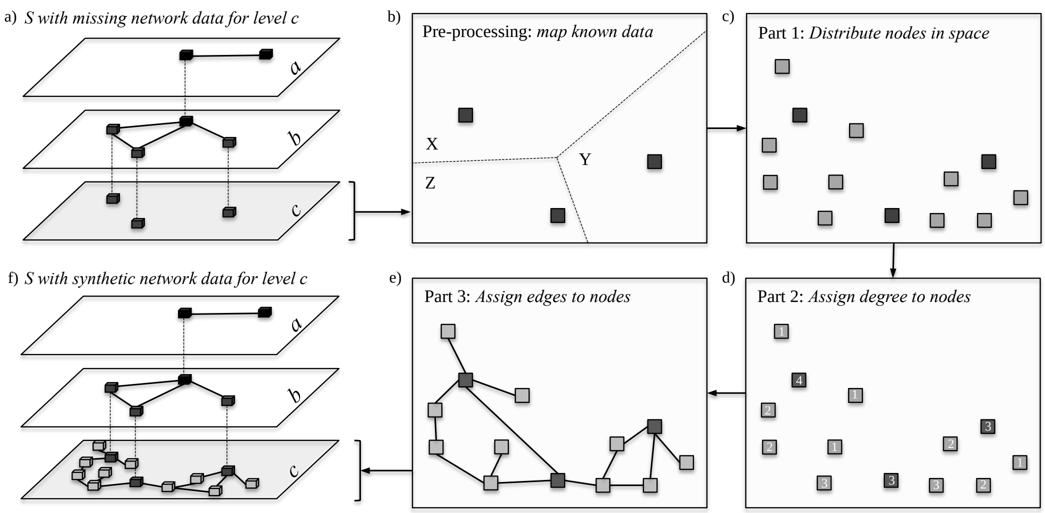


Figure 3.4: (a) Provides a representation of infrastructure system *S* with network information missing for level c. (b) Shows the pre-processing stage where known information on the position of nodes and regional population data is mapped. (c) Highlights Part 2.2 of the algorithm, where the missing distribution network nodes are distributed in space. (d) Shows 2.4.1.1 of the algorithm, where degree is assigned to each node. Finally 2.4.3 of the algorithm is highlighted in (e) where edges are added to match pre-defined degree values. (f) Provides a complete representation of *S* with real and synthetic data integrated.

3.5 Algorithm Validation and Demonstration for England and Wales

We present two practical applications of the algorithm: (i) *Validation of the algorithm using a regional electricity network* – The validation highlights the ability of the algorithm to produce synthetic network representations that preserve the most salient properties of the desired network. The validation is performed on a regional scale electricity network; and (ii) *Building an integrated electricity network for England and Wales*– provides a demonstration of the algorithm by outlining the methods and data used to build a continuous representation of the integrated electricity network for England and Wales; bridging the transmission, sub-transmission and distribution scales.

3.5.1 Validation of the algorithm using a regional electricity network

We provide a validation of the multi-level network synthesis algorithm based on its ability to reproduce the encoded characteristics set out in section 3.3. This is performed using a regional electricity network from the North West of England. The network operates at the 132kV; distributing electricity between local sources (275kV/132kV substations) and local sinks (132kV/33kV substations). The network contains 82 nodes that are located in different land-use types, from the urban city of Manchester to the rural Cumbrian hills. Figure 3.5 (a) gives a fully topographic GIS representation of the network and (b) provides a spatial network representation, showing edge geometries as straight lines between nodes.

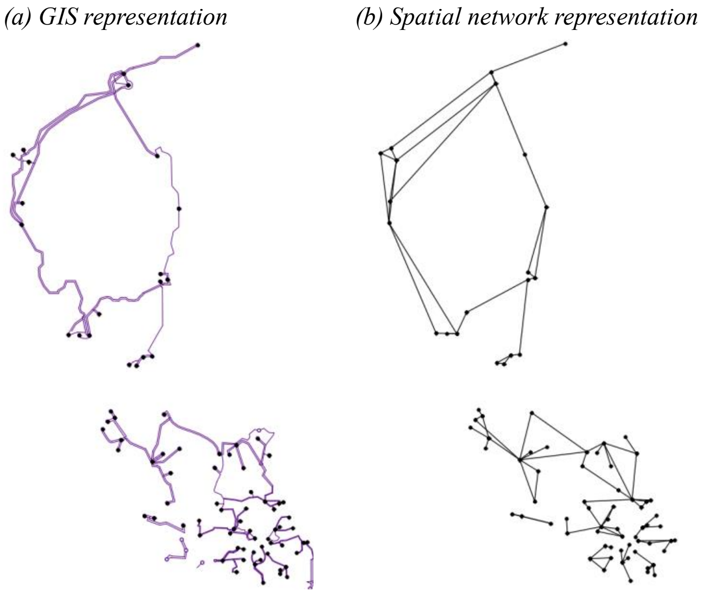


Figure 3.5: Displays the regional electricity network used for the validation of the network synthesis algorithm: (a) The GIS representation highlights the actual spatial locations of nodes and edge in the network (b) The spatial network representation shows the network with straight line edge geometries

Constraining the algorithm with differing levels of the actual systems data tests the sensitivity of each stage of the algorithm. Stages of the algorithm correspond to the characteristics outlined in Section 3.3:

- *Stage 1: Multi-level structure – outlined in Section 3.3.1* – requires the algorithm to preserve the number of node assets distributed within each level of the system
- *Stage 2: Node location – outlined in Section 3.3.2* – requires the algorithm to preserve the spatial distribution of these nodes
- *Stage 3: Node degree – outlined in Section 3.3.3* – requires the algorithm to preserve global network connectivity for different levels
- *Stage 4: Edge connectivity – outlined in Section 3.3.4* – requires the algorithm to preserve the local spatial connectivity between node assets for different levels

Table 3.2 provides an overview of the testing framework; highlighting the data constraints that result in four different realizations of the network. The table shows that the real network contains all the data and therefore is completely constrained. Types A, B and C all preserve the first constraint ‘multi-level structure’– this is because in each representation we are only producing a single synthetic level of the system: 132kV level and hence do not need to implement for multiple levels in the system. Types A, B and C differ however based on the constraints 2-4, providing a means to test the sensitivity of the algorithm to the amount of real data that may be available. In order to test the algorithms ability to reproduce the encoded characteristics, we have produced synthetic representations of the network that are constrained with differing levels of available data. A number of randomly selected samples are presented below in Figure 3.6 for visual inspection.

Table 3.2: Testing constraints for the network synthesis algorithm. 1 indicates where actual system data is used and 0 represents where the network synthesis algorithm generated data has been used

Network	**Constraint 1: Multi-level structure**	**Constraint 2: Node Location**	**Constraint 3: Node Degree**	**Constraint 4: Edges**
Real Network	1	1	1	1
Synthetic Type A	1	1	1	0
Synthetic Type B	1	1	0	0
Synthetic Type C	1	0	0	0

Networks follow a good visual adherence to the actual network, however, as expected this coherence lessens where networks are created with synthetic instead of real data. This is particularly apparent in synthetic Type C networks that do not preserve the peripheral structure of the northern part of the network (Cumbria region), which has evolved due to geographic constraints.

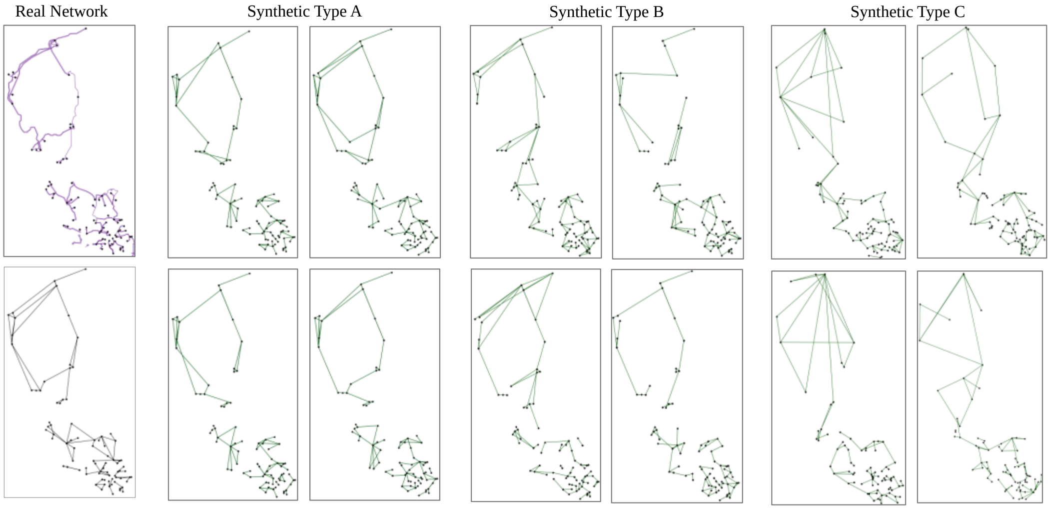


Figure 3.6: Synthetic networks generated under varying constraints to produce multiple variants of the network, characterized as Type A, Type B and Type C

3.5.2 Building England and Wale's integrated electricity network

We provide a demonstration of the algorithm to produce a representation of England and Wale's integrated electricity network. Table 3.1 provides an overview of the data used in the representation. Whilst data are available for the location of power generators (DECC, 2012) and the transmission grid (National Grid, 2012), no data are available for either the sub-transmission and distribution networks. Due to the multi-level nature of system we are required to produce synthetic networks for each voltage level sequentially. This starts with the transmission 132kV level where transmission level sinks and medium level power generators are used as local source nodes. The algorithm outlined in this paper was then implemented to complete the 132kV level before then producing synthetic representations of the 33kV and finally the 11kV levels. In running the algorithm we preserve constraints 1, 2 and 3: where constraint 1 is maintained using national data on the composition of network-layers as described in Table 3.1; constraint 2 is maintained by sampling from known substation locations (locations are known, but no voltage attribution is given) from OS MasterMap topography layer node data (Ordnance Survey, 2015); constraint 3 comes directly from the electricity network data for the North West of the country, as presented in the validation. A representation of the synthetic integrated network alongside the numbers of nodes within each level is given below in Figure 3.7.

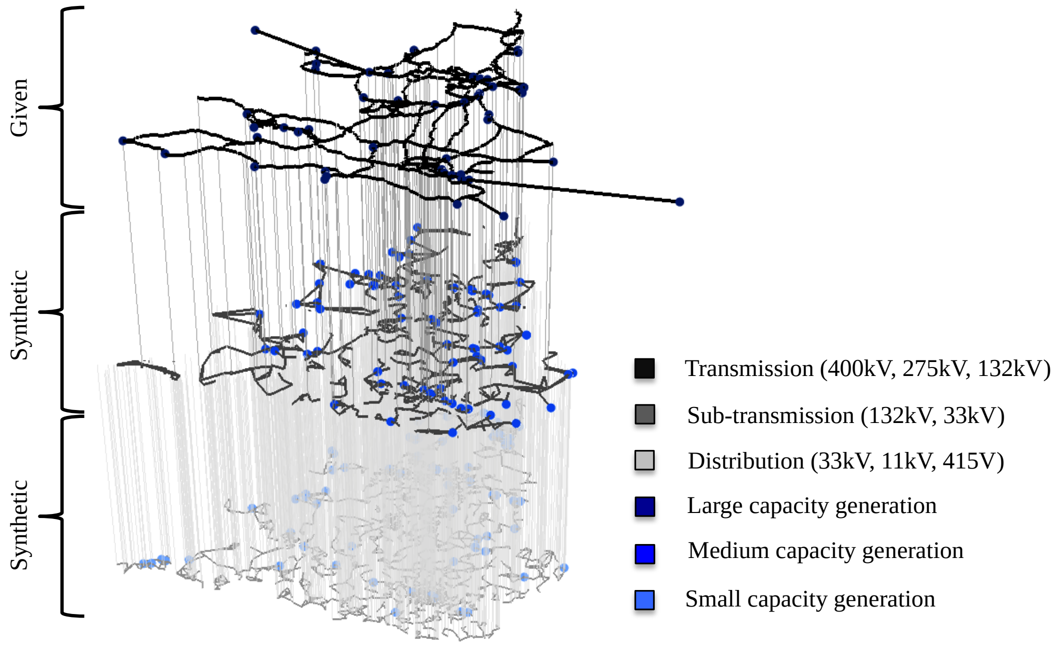


Figure 3.7: Representation of the electricity network in England and Wales: Showing the given 'real' transmission network and synthetic sub-transmission and distribution networks.

In England and Wales, National Grid operates the transmission system, whilst six different distribution network operators operate the sub-transmission and distribution networks. The synthetic representation of England and Wale's integrated electricity network provides a continuous network that bridges these operation scales – providing, for the first time, a network model that integrates the different distribution networks with a representation of transmission and power generation. Such a ‘system-level’ representation provides a means to explore failure propagation within and between levels of the system and even between infrastructure sectors that are dependent on electricity at a certain voltage for their operation, such as water pumps, railway stations and gas compressors. Doing so builds towards a ‘system-of-systems’ based understanding of the national infrastructure, providing key insights into potential failure and disruptions, highlighting areas of criticality for risk and adaptation planning.

3.6 Discussion and Conclusions

Within this study we have presented an algorithm for the synthesis of multi-level infrastructure networks for use in applied network failure and risk analysis. The proposed algorithm is capable of producing networks that preserve a number of important spatial and topological properties of real-world networks including multi-level structure of sub-systems, the geographic distribution of network nodes, the node degree distribution and the networks spatial connectivity. Due to its modular structure, the algorithm is highly flexible and can accommodate different levels of data availability.

The algorithm has been validated using a regional electricity network. The validation highlights the ability of the algorithm to generate synthetic networks that maintain the properties with which they have been encoded. It also highlights the ability to produce synthetic networks that are close approximations to real networks. A demonstration is offered for England and Wale’s integrated electricity network consisting of over 160,000 nodes. The demonstration highlights the potential of the algorithm to synthesize a multi-level infrastructure network that spans broad spatial extents at a range of operation scales. This unique representation provides a platform for understanding risks and failures of this systems that have, until now, been impossible.

Although a demonstration is offered for an electricity network, the methodology has the potential to be applied for a range of infrastructure network systems that take a networked' and multi-level form. For example, fluid network systems such gas or water infrastructures that typically have a high capacity transmission systems and local, low capacity, distribution systems. The applicability of the algorithm beyond electricity networks would be an intuitive next-step for this research.

The synthetic nature of the networks produced by the algorithm mean that the networks generated may be different to the reality on the ground. The algorithm is however capable of maintaining the most salient network properties, providing a worthwhile basis for infrastructure network analysis at an appropriate scale and level of interpretation.

Methodology from the study of complex networks has been used in a number of applied studies of infrastructure network systems – providing important insights into network failure and risk analysis. Many studies are however impossible due to the lack of availability of spatial and topological network data. This paper provides the means to address these concerns, providing methods to produce realistic synthetic network representations, enabling a multitude of studies in applied network analysis.

4. System-of-Systems Formulation and Disruption Analysis for Multi-Scale Critical National Infrastructures

Abstract:

The complex and interdependent nature of modern critical national infrastructures provides the conditions for which localized failures can propagate within and between network systems, resulting in disruptions that are widespread and often unforeseen. Within this study we characterize critical national infrastructures as a system-of-systems and develop methodology to perform a multi-scale disruption analysis. To achieve this we map functional pathways between network source and sink assets across a range of operational scales. Customer demands are attributed to these pathways and are used to build a weighted network. The resultant functional path set and weighted network are used to perform a disruption analysis that encodes information on the long-range functionality within and between infrastructures, providing insights into failure propagation and the functional dependencies that exist between assets from multiple sectors. We supplement the methodological development with a detailed national scale demonstration for England and Wales using a unique representation of the integrated electricity network and the domestic flight network. The results highlight the potentially large disruptions that can result from the failure of individual electricity assets from a range of different sub-systems.

4.1 Introduction

Infrastructure network systems support society by facilitating the distribution of services across broad spatial extents, at a range of scales. The term

‘Critical National Infrastructures’ (CNIs) recognizes infrastructures are “vital for the continued delivery and integrity of the essential services, ...the loss or compromise of which would lead to severe economic or social consequences or to loss of life” (Cabinet Office, 2010).

Many modern CNIs have evolved into large interdependent systems with complex interconnectivity (Rinaldi et al. 2001). Such interconnectivity can facilitate the propagation of failure from one subsystem to another (Little, 2012; Buldyrev et al. 2010). A number of events from around the world have highlighted the potential for failure propagation with CNIs, resulting in unforeseen, widespread disruptions: The failure of a 110kV electricity cable resulted in a large-scale blackout in Auckland, New Zealand in 1998, disrupting multiple essential services for 35 days (Davis, 1999). In 2003, a combination of failures within the high voltage electricity networks in North East America resulted in a blackout affecting 50 million people (United States – Canada power system outage task force, 2004). The United Kingdom (UK) has also experienced a number of such events, including: In 2011, power failure at a major exchange in Birmingham resulted in the loss of broadband connection for hundreds of thousands of customers across the UK (BBC, 2011). During the 2013-2014 winter floods, failure within the low voltage electricity distribution system at Gatwick airport contributed towards the disruption of 13,000 airline customers (McMillan, 2013).

The consequences of such events has triggered interest in the analysis and protection of interdependent CNIs from governmental institutions around the world, including amongst others, in the USA, Canada, Australia the Netherlands, Germany and the UK (Ouyang, 2014). In order to support decision making for reducing risks and enhancing resilience, it is recognized that CNIs should be evaluated as system-of-systems; and therefore incorporate the effects of interdependencies (Kröger, 2008; Eusgeld et al. 2011). One practical difficulty in adopting this approach is that historically, policy and decision making for individual infrastructure sectors has been made in isolation with little regard for other interconnected infrastructures (Tran et al. 2014). This segregation not only exists between sectors but also within sub-systems of an individual sector, which, in many cases have different owners and operators. Given this complex arrangement, a major challenge exists in integrating real-world data to model and simulate the behaviour of interdependent CNIs.

In recent years the study of complex networks has provided insights into the behaviour of infrastructure systems (Strogatz, 2001; Lewis, 2006, Lewis, 2011). In such studies, nodes and edges are used intuitively to represent the structure and interconnections of real infrastructure systems. Within this field, the study of infrastructure interdependencies (Rinaldi et al. 2001; Rinaldi, 2004) has provided a means to explore the behaviour of one or more systems connected together. A number of mathematical and simulation models and approaches have been developed to explore the negative consequences associated with failure events. These include: abstract topological based approaches where interdependent network robustness is explored, such as (Bashan et al. 2013; Gao et al. 2011; Shekhtman et al. 2014). Though many useful insights are gained from such studies, care should be taken when applying insights from performance measures for infrastructure systems, such as electricity power grids (LaRocca et al. 2015). Physics based models such as those that use the AC power flow equations are considered to provide a good representation of reality of real-world infrastructure systems, at the expense of computational complexity and large data requirements to drive the analysis (Ouyang, 2014). A series of models of intermediate complexity, such as the uniform network flow model proposed by Lee et al. (2007), and functional network models (e.g. Hernandez-Fajardo and Duenas-Osorio, 2013; Johansson and Hassel, 2010; Poljansek et al. 2010) provide a useful means to explore interdependent related infrastructure failures of real systems.

Within this study, we adopt an intermediate complexity approach to explore the behaviour of CNIs. In doing so, our aim is to provide new insights into disruption and applied network failure analysis. Drawing on recent developments from the study of multilevel networks (Kivelä et al. 2014), we provide new methods to build and analyse multi-scale infrastructures; from customers, to assets, to network sub-systems, to systems and finally to a system-of-systems. This complete representation allows us to explore the potential for failure propagation through the presence of functional dependencies established through demand-driven network service pathways, both within and between infrastructures at a range of operation scales. Customer demands are attributed to pathways and are used to build a weighted network that highlights the potentially disruptive consequences of infrastructure asset failures.

We supplement the methodological development with a detailed national scale demonstration for England and Wales using a unique representation of the integrated electricity network consisting of the transmission, sub-transmission and distribution networks in addition to the domestic flight network. In developing this analysis provides a powerful tool to explore the relationships and responsibilities established between multiple organizations and decision makers who are charged with the safe, reliable and efficient management of CNIs.

Following the introduction, Section 4.2 provides a system-of-systems infrastructure characterization. Section 4.3 outlines methodology to perform a disruption analysis for critical national infrastructures. In Section 4.4 we provide a demonstration of the methodology for England and Wales. Finally, Section 4.5 offers discussion and conclusions from the study.

4.2 System-of-System Infrastructure Characterisation

Figure 4.1 provides an overview of our system-of-systems CNI representation. We herein provide a generalized description of components within the figure that share similarities, building up from the local scale, describing the multiple interconnections that span and bridge different operational scales, leading towards a *multi-scale* structure.

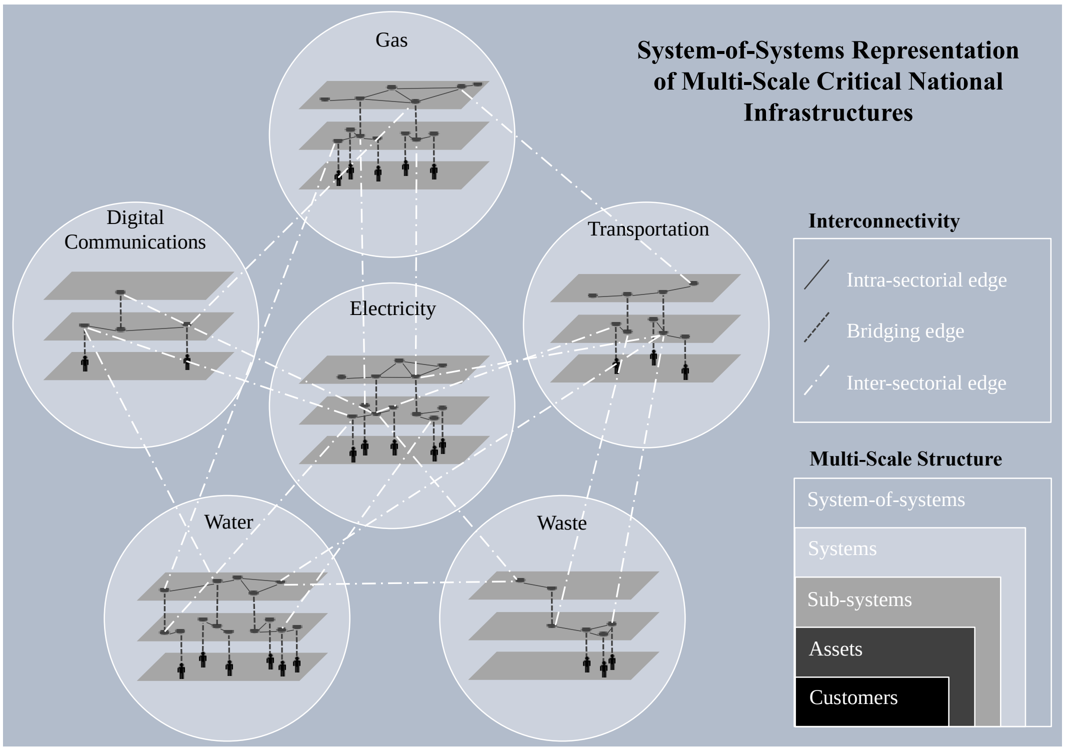


Figure 4.1: System-of-systems representation of six CNIs: electricity; gas; transportation; water; waste; and digital communications. The multi-scale structure is highlighted, building from customers to assets, to network sub-systems, to systems and finally to a system-of-systems. Three different edge types: intra-sectorial, bridging and inter-sectorial provide the connectivity that bridges multiple operational scales.

From the demand side the lowest level of representation is that of *Customers*. Customers are used to represent consumers who place demand on one or more infrastructure services; they can be defined as individual members of the population, households, business or industrial installations at a local scale.

From the supply side (the infrastructure side), assets are the lowest level of representation in the system-of-systems. *Assets* are defined as distinct physical components of the infrastructure that perform a specific function and that are critical for its operation. Examples include electricity sub-stations, railway stations, or airports. It is possible to consider assets at more disaggregate scale, for example, individual electricity transformers and bus-bars; individual railway platforms or individual airport terminals, it is understood that the data and computational requirements to perform a national scale analysis at this level of representation may be prohibitive. Ultimately, the level of aggregation will vary between studies, depending on these factors and the studies' aim.

The collective arrangement of interconnected assets produces a *network* through which we aim to understand complex interactions within and beyond our system-of-systems. The networks consist of nodes and their pair-wise connections that define the edges, which together produce the network topology. The demand for services (goods and resources) created by customers is aggregated at individual nodes, and the pathways of service distribution through the edges are determined by these demand aggregations.

We group assets into different categories based on common operational attributes, in electricity networks this is operating voltage, in water networks this is operating pressure and in road networks this is the road speed. The network comprising nodes and edges in the same infrastructure category is called a *sub-system,* defined as fulfilling a specific function. Examples of sub-systems include; production networks, which function to produce the good or service being delivered; transmission networks, that facilitate the bulk distribution of the good or services; and distribution networks that provide the interface between the infrastructure and the customers. The edges that connect pair-wise nodes within a sub-system are defined as *intra-sectorial edges*.

Viewed collectively, sub-systems form an infrastructure *system*, defined as a set of interconnected assets whose collective function is to facilitate the production and transfer of a service towards the customer. Such systems have evolved to take a *multi-level* form. Upper levels comprise of sub-systems that support production or the bulk transport of a service across large spatial extents, while low layers comprise of sub-systems that support localized distribution of a service and traverse progressively shorter distances, albeit in large numbers, until the service is delivered to the customer. Different sub-systems interact with each other through common nodes with which we can associate multiple operational characteristics. In our system we replicate these common nodes at each of their associated sub-system and introduce *bridging edges* to connect these nodes and hence the sub-systems across multiple operational scales. The bridging edges therefore allow a continuous system representation from production nodes to the customers through multiple levels of transmission and distribution infrastructure. Examples of bridging edges include; substation transformers that transform the voltage in the same substation, gas compressors that change the pressure in the same gas storage unit, and road junctions that change the speed between major and minor roads. We consider this multi-level structure to form a *functional hierarchy* where, at the lowest level, customers are located; these customers then have a dependence on successive levels in the hierarchy, until the top level is reached, the production level. Due to the complex distribution of society and space, the multi-level hierarchical structure of real-world infrastructure is not rigidly maintained; instead bridging edge connections can exist between non-consecutive and lateral layers.

Individual infrastructure systems do not function in isolation; instead they support society as a much larger *system-of-systems*, being held together by *inter-sectorial edges* that connect pair-wise nodes of two separate infrastructures. Such edges establish a relation between different infrastructures sectors that are commonly know as *interdependencies*. A number of different definitions for interdependency have been proposed in the literature, including from Rinaldi (2004); Lee et al. (2007); Zimmerman (2001); Dudenhoeffer (2006) and Zhang and Peeta (2011). In a comparative review of these proposed definitions by Ouyang (2014), it was concluded that Rinaldi's definition provided the most effective means to sort a number of hypothetical real-world interdependency scenarios developed by the author. Though merits exist for each different set of definitions, we utilise Rinaldi's characterization to provide examples of infrastructure interdependencies (Rinaldi, 2004): (i) *Physical*; where the state of an asset is dependent on the material output of another asset. (ii) *Cyber*; where the state of an asset depends on information transmitted through information infrastructure. (iii) *Geographic*; occurs when multiple assets are in close geographical proximity (iv) *Logical* dependency occurs when there exists a dependency between two assets that cannot be characterized by physical, cyber or geographic dependency.

In addition to having different physical attributes, individual sub-systems may also have different non-physical attributes, examples include: different owners, operators and regulators. Take for example, electricity provision in England and Wales: A single company, the National Grid, operates the transmission network. Six different distribution network operators (DNOs) operate the distribution networks. A variety of different companies own and operate electricity generation assets that are embedded at various voltage levels in the transmission and distribution networks. Electricity assets are dependent on the function of a variety of other infrastructures; water for cooling purposes, digital communications for control, transportation networks for the workforce etc. Assets from other sectors are dependent on electricity: electrified rail, electricity for pumping water, electricity for data centres etc.

Formulation of the complex interactions between CNIs therefore provides the opportunity to explore the relationships between the assets and networks of functionally dependent systems at a variety of scales. The focus of this paper is to develop this formulation, with a focus on failure propagation and disruption analysis. Organizations charged with the responsibility of managing and operating these systems could use such information to understand the potential for failure due to: (i) *up-scale failures*; through assets that they have a dependency on; and (ii) *down-scale failures*; through assets that have a dependency on them. This provides the basis for understanding the risks of infrastructure failure; helping to inform decision making for risk reduction, operational contingencies and adaptation planning.

4.3 Disruption Analysis for Critical National Infrastructures

Within this section we introduce the mathematical formulation leading to the methodology for a systems-of-systems disruption analysis of CNIs. This includes: (i) *System-of-systems network representation*: methods to map the spatial and topological characteristics of CNIs across a range of scales; (ii) *Functional understanding of infrastructure dependencies*: methods to understand functional dependencies that transcend the operational limits of most real infrastructure systems based on an understanding of network service pathways; and (iii) *Failure propagation and disruption calculation*: methods to estimate failure propagation; providing a means to perform the system-of-systems disruption calculation.

4.3.1 System-of-systems network representation

Following from the definitions introduced in Section 4.2, our system-of-system $\boldsymbol{S}$ is a set comprised of individual sub-systems S_k. This is represented in Eq. (4.1), where z sub-systems exist in the system-of-systems.

$$\boldsymbol{S} = \{S_1, \dots, S_z\} \tag{4.1}$$

While the characteristics of a single system (or infrastructure) are implicit in the definition of $\boldsymbol{S}$, if we want to explicitly represent such a system then we need to collect all sub-systems to form the set $\tilde{\boldsymbol{S}}_w \subseteq \boldsymbol{S}$ that belong to the required system. For example, $\tilde{\boldsymbol{S}}_E$ is used to represent the electricity power system and $\tilde{\boldsymbol{S}}_A$ to represent the airlines systems.

The nodes that are associated with a particular sub-system are a subset of the exhaustive set of all nodes $N = \{n_1, \dots, n_z\}$ in the system-of-systems. The node set N_k of the sub-system S_k is defined as the subset of the Cartesian product set of N and S_k, as given in Eq. (4.2).

$$N_k \subseteq N \times S_k = \{(n_r, S_k), \dots, (n_t, S_k)\} \tag{4.2}$$

We can identify nodes that have an asset attribute plurality and are hence present in two or more levels of the system. Such nodes include those that represent electricity substations, gas compressors and road junctions etc. This is described in Eq. (4.3), where node n_i is assigned the set $\overline{\boldsymbol{S}}$ of all sub-systems where it is present.

$$n_i \equiv (n_i, \overline{\boldsymbol{S}}) \tag{4.3}$$

The connectivity of the nodes within and across different sub-systems is defined in terms of the edge set E, which we denote as

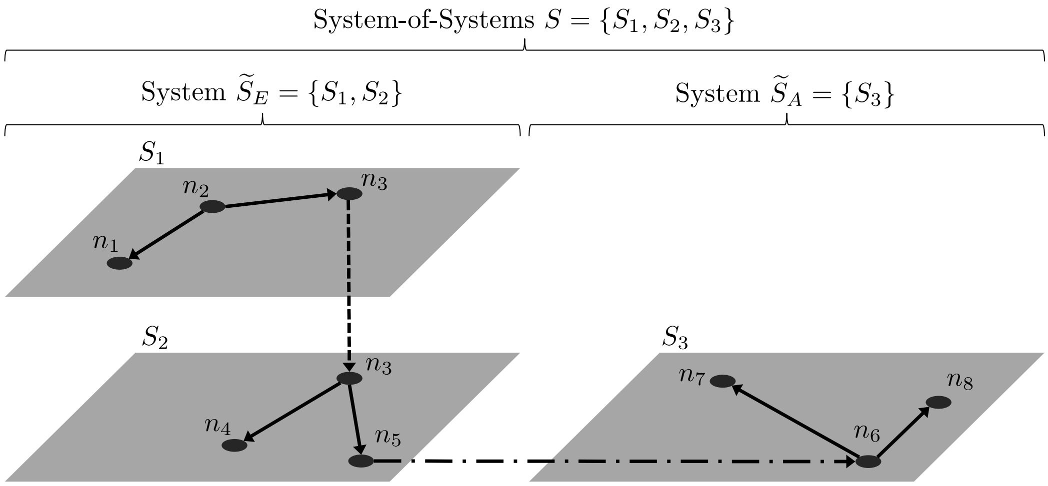
$$E = \left\{e_{i\alpha,j\beta} = \left((n_i, S_\alpha), (n_j, S_\beta)\right), \forall i, j, \alpha, \beta\right\} \tag{4.4}$$

Where α and β are two different infrastructure sub-systems. We note that all edges in our system-of-systems are directed edges, i.e., $e_{i\alpha,j\beta} \neq e_{j\beta,i\alpha}$, since there might be different types or quantities of service being distributed in separate directions.

From the above set definition we can identify the sets of edges defined in Section 4.2. The set of intra-sectorial edges is given as $E_k = \Big\{e_{ik,jk} =$

$\left((n_i, S_k), (n_j, S_k)\right); \forall i, j, k, i \neq j\Big\}$, where it is assumed that within the sub-systems nodes do not have self-edges incident on themselves. The graph (N_k, E_k) is a representation of the network that captures all internal operations in the sub-system S_k. The set of bridging edges is given as $B = \left\{e_{i\alpha,i\beta} = \left((n_i, S_\alpha), (n_i, S_\beta)\right); \forall i, \alpha, \beta, \alpha \neq \beta\right\}$, which establishes the connectivity of nodes across sub-systems within the same system. Finally the set of inter-sectorial edges is given as $I = \left\{e_{i\alpha,j\beta} = \left((n_i, S_\alpha), (n_j, S_\beta)\right); \forall i, j, \alpha, \beta, i \neq j, \alpha \neq \beta\right\}$, which establishes the dependencies across different systems, thereby producing the system-of-systems.

Figure 4.2 provides a simplified network example to demonstrate the system-of-systems formulation for an electricity system $\tilde{\boldsymbol{S}}_E$, consisting of two subsystems and an airport system $\tilde{\boldsymbol{S}}_A$, consisting of one subsystem.



Nodes		$N_1 = ((n_1, S_1), (n_2, S_1), (n_3, S_1))$ $N_2 = ((n_3, S_2), (n_4, S_2), (n_5, S_2))$ $N_3 = ((n_6, S_3), (n_7, S_3), (n_8, S_3))$
Intra-sectorial edges		$E_1 = (((n_2, S_1), (n_1, S_1)), ((n_2, S_1), (n_3, S1)))$ $E_2 = (((n_3, S_2), (n_4, S_2)), ((n_3, S_2), (n_5, S_2)))$ $E_3 = (((n_6, S_3), (n_7, S_3)), ((n_6, S_3), (n_8, S_3)))$
Bridging edges		$B = ((n_3, S_1), (n_3, S_2))$
Inter-sectorial edges		$I = ((n_5, S_2), (n_6, S_3))$

Figure 4.2: An example highlighting a system-of-systems S, comprising two systems: An electricity system which has two subsystems and an airlines systems that has one subsystem. Three different edge types are demonstrated in the figure: Intra-sectorial edge, bridging edge and inter-sectorial edge. Directed edges connect spatially embedded node assets.

The system-of-systems formulation developed here is similar to multi-layer networks formulation developed by Kivelä et al. (2014). Here we develop an applied formulation for infrastructure systems that allows the multi-scale structure to be explored for a varied of practical purposes.

4.3.2 Functional understanding of infrastructure dependencies

Infrastructure networks function to support the flow of services between a set of *source nodes* Θ (where the service originates) to the set of *sink nodes* Φ (where the service terminates). Examples of system sources would be electricity power generators, gas import terminals or railway stations. Continuing the example for the same sectors; examples of sink nodes could include electricity distribution sub-stations, end of line gas terminals and railway stations. In most cases, the source and sinks will be different nodes, in some cases however they may be the same node – examples include making a circular journey on a railway network or an electricity power station that consumes some proportion of the energy it produces for its operation.

We develop an understanding of the flow of services within and between networks using a mapping of the *functional paths* that connect different sources to sinks through intermediate nodes. Such a mapping facilitates an exploration into the distribution of services within and between networks that transcend typically localized operational boundaries. The mapping of multiple functional paths builds a weighted network, similar to that developed in (Newman, 2004). Developing this approach further, we assign weights to node and edge assets as aggregations of the attributes of the paths that utilize them.

This mapping starts with an understanding of the most simple structural network elements: given as two adjacent connected nodes (n_i, n_j) and their connecting edge $(e_{i\alpha,j\beta})$ that are connected into a directed 3-tuple, i.e., $p_{ij} = (n_i, e_{i\alpha,j\beta}, n_j)$, which is the smallest 'network unit' whose properties affect the flow of services. This understanding is similar to the bar-bell concept introduced by Lewis (2006). Each 3-tuple has a number of attributes. These relate to either its structural properties, i.e. geographic length, number of components etc. or service attributes related to the goods, resources or customers that they are distributing. In this study we are interested in the length l_{ij} and a general customer demand metric d_{ij} associated with each 3-tuple.

A path is a collection of all such directed 3-tuples that are connected, generating a sequence $\{p_{ij}, p_{jk}, \dots\}$ where the second subscript of an element is the same as the first subscript of the one that follows it. A path $P_r(n_o, n_l)$ between a source node $n_o \in \Theta$ and a sink node $n_l \in \Phi$ is represented in Eq. (4.5), which shows all nodes and edges traversed in the direction of service flows to meet customer demands.

$$P_r(n_o, n_l) = \{p_{oi}, p_{ij}, \dots, p_{km}, p_{ml}\} \tag{4.5}$$

For each path we can find the path-length ($\ell_r(n_o, n_l)$) which is sum of the lengths of all its 3-tuple, i.e. $\ell_r(n_o, n_l) = \sum_{\forall i,j \in P_r(n_o,n_l)} l_{ij}$. The customer demand distributed along the path ($d_r(n_o, n_l)$) is in general a complex combination of several operational properties and demand factors affecting the system. For example, the electricity customer demands distributed along a path depends upon the voltages of sub-stations, resistance of cables and the spatially heterogeneous customer demands throughout the system. The scope of this study is not to develop different models for assigning customers demands across paths, but rather to develop an understanding of network criticality and potential disruptions using customer demands that are assigned to functional paths using established methods. Hence at present we assume we can estimate the customer demands assigned to individual paths through the network.

There could be multiple paths between the same source-sink pair that are used to satisfy customer demands for the infrastructure service, producing a *source-sink functional path set* $\mathbf{P}(n_o, n_l) = \{P_1(n_o, n_l), \dots, P_c(n_o, n_l)\}$, and further a *system-of-systems functional path set* $\boldsymbol{\mathcal{P}} = \{P_r(n_o, n_l); \forall r, n_o \in \Theta, n_l \in \Phi\}$. Associated to this we can assemble the set of path-lengths $\mathcal{L}(n_o, n_l) =$

$\{\ell_1(n_o, n_l), \ldots, \ell_c(n_o, n_l)\}$ and path customer demand allocations $\mathfrak{C}(n_o, n_l) = \{d_1(n_o, n_l), \ldots, d_c(n_o, n_l)\}$.

Based on the types of edges, different types of path sets can be developed to further understand the flows of resources within sub-systems and across systems. The *intra-sectorial functional path set* within the sub-system S_k is described as $\boldsymbol{\mathcal{P}}_k = \{P_r(n_o, n_l) \text{ s.t.} P_r(n_o, n_l) \subseteq N_k \times E_k \times N_k; \forall r, n_o \in \Theta, n_l \in \Phi\}$. The *bridging functional path set* that denotes transfer services between sub-system levels is denoted as $\boldsymbol{\mathcal{B}} = \{P_r(n_o, n_l) \text{ s.t.} P_r(n_o, n_l) \cap N_\alpha \times B \times N_\beta \neq \emptyset; \forall r, n_o \in \Theta, n_l \in \Phi, N_\alpha, N_\beta \in N\}$. Similarly the *inter-sectorial functional path set* that denotes transfer services across systems is denoted as $\boldsymbol{\mathcal{I}} = \{P_r(n_o, n_l) \text{ s.t.} P_r(n_o, n_l) \cap N_\alpha \times I \times N_\beta \neq \emptyset; \forall r, n_o \in \Theta, n_l \in \Phi, N_\alpha, N_\beta \in N\}$. It is noted that $\boldsymbol{\mathcal{P}}_k \subseteq \boldsymbol{\mathcal{P}}$, $\boldsymbol{\mathcal{B}} \subseteq \boldsymbol{\mathcal{P}}$ and $\boldsymbol{\mathcal{I}} \subseteq \boldsymbol{\mathcal{P}}$. Given that multiple path types can exist within a system and system-of-systems, we implement an ordering of path types such that: $\boldsymbol{\mathcal{B}} = \{P_r(n_o, n_l) \subseteq N_k \times E_k \times N_k \cup N_\alpha \times B \times N_\beta\}$ and $\boldsymbol{\mathcal{I}} = \{P_r(n_o, n_l) \subseteq N_k \times E_k \times N_k \cup N_\alpha \times B \times N_\beta \cup N_\alpha \times I \times N_\beta\}$

There are several merits of constructing the above classifications of functional path sets in order to assess key system-of-system topological and operational characteristics. Some metrics of interest are:

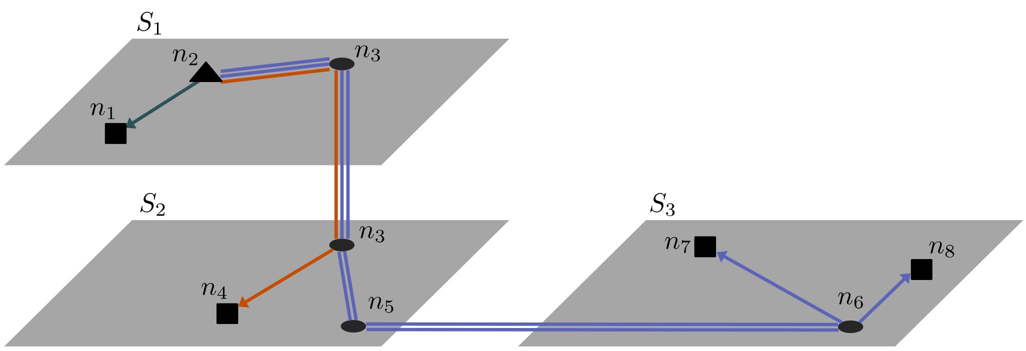
Shortest-path characteristics: The shortest-path between a source-sink pair ($\min \mathcal{L}(n_o, n_l)$) tells us about the path that is most likely to meet customer demands. We can estimate the closest source to a particular sink $\min_{\forall n_o \in \Theta}\{\mathcal{L}(n_o, n_l)\}$) or the closest sink to a source $\min_{\forall n_l \in \Phi}\{\mathcal{L}(n_o, n_l)\}$) to know the most preferable source-sink pairs to meet customer demands.

Customer demand weightings: Comparing the customer demand values between the different source-sink paths gives us an understanding of which paths are more utilised in comparison to others. We can analyse and visualize the system-of-systems as a weighted network, providing a means to explore functional network centrality. In particular the customer demand weight d_{ij} can be expressed in terms of summation of the individual path customer demand attributions using the following mapping

$$d_{ij} = \sum_{\forall n_o \in \Theta} \left(\sum_{\forall n_l \in \Phi} \left(\sum_{\forall P_r(n_o,n_l) \in \mathbf{P}(n_o,n_l)} 1_{p_{ij}} d_r(n_o, n_l) \right) \right) \tag{4.6}$$

where $1_{p_{ij}}$ is an indicator function whose value is 1 if $p_{ij} \in P_r(n_o, n_l)$ and 0 otherwise.

Figure 4.3 highlights the source, sink and intermediate nodes for the previously introduced system-of-systems example. The figure also provides examples of the three different functional path types.



Source nodes	▲	(n_2, S_1)
Sink nodes	■	$((n_1, S_1), (n_4, S_2), (n_7, S_3), (n_8, S_3))$
Intermediate Nodes	⬬	$((n_3, S_1), (n_3, S_2), (n_5, S_2), (n_6, S_3))$
Intra-sectorial functional paths		$P_r((n_2, S_1), (n_1, S_1)) = ((n_2, S_1), (n_1, S_1))$
Bridging functional paths		$P_r((n_2, S_1), (n_4, S_2)) = ((n_2, S_1), (n_3, S_1),$ $(n_3, S_2), (n_4, S_2))$
Inter-sectorial functional paths		$P_r((n_2, S_1), (n_7, S_3)) = ((n_2, S_1), (n_3, S_1),$ $(n_3, S_2), (n_5, S_2), (n_6, S_3), (n_7, S_3))$ $P_r((n_2, S_1), (n_8, S_3)) = ((n_2, S_1), (n_3, S_1),$ $(n_3, S_2), (n_5, S_2), (n_6, S_3), (n_8, S_3))$

Figure 4.3: Example system-of-systems network highlighting nodes characterized as; source, sink and intermediate. Three different path types are demonstrated: (i) Intra-sectorial functional paths (ii) Bridging functional paths (iii) Inter-sectorial functional paths

4.3.3 Failure propagation and disruption calculation

Infrastructure systems can fail for a number of reasons including aging, human error, exposure to natural hazards and deliberate attacks. Such *events* can trigger the failure of one or more assets. We define *failure* as a condition of the node or edge asset such that it is no longer able to perform its functional purpose. In our description of infrastructure provision this means that the service demand satisfied by the path is reduced. In the extreme case, this means that the pathway supplies no customers – these are called *complete failures*. A less extreme case allows only a fraction of the customers demands to be met, these are called *partial failures*.

Individual assets can be described as having *directly failed* when they are the first assets to fail in the event. *Indirectly failed* assets fail through the loss of a functional dependency - *functionally dependent assets* are those assets that exist in same functional paths as the directly failed asset. For any event (the failure of an individual asset), we can resolve all direct and indirect failures to give the total failed asset set for all systems. The remainder of this sub-section provides formalization for this process:

The set of all assets in the system-of-systems, which is a collection of nodes and edges, is given as $A = \{N, E\} = \{a_1, \ldots, a_w; w = |N| + |E|\}$. For any asset $a_s \in A$ we can construct the set $\boldsymbol{\mathcal{P}}(a_s)$ of all paths that contain this asset by sampling from the overall system-of-systems path set $\boldsymbol{\mathcal{P}}$. In doing so we are able to map the potential influence of asset a_s within the system-of-systems for the source-sink flow pathways established within $\boldsymbol{\mathcal{P}}$.

We assume that all directly failed assets are collected in the set $\tilde{A}_{\mathrm{di}}$, which also gives the set of assets not failed directly, represented as $\bar{A} = A \backslash \tilde{A}_{\mathrm{di}}$. We assemble the set of paths that contain all assets in the set $\tilde{A}_{\mathrm{di}}$, which is denoted as $\boldsymbol{\mathcal{P}}(\tilde{A}_{\mathrm{di}})$. The set of remaining paths in the system-of-systems can then be estimated as $\widetilde{\boldsymbol{\mathcal{P}}} = \boldsymbol{\mathcal{P}}(A) \backslash \boldsymbol{\mathcal{P}}(\tilde{A}_{\mathrm{di}})$. For any individual asset $\bar{a}_s \in \bar{A}$ we also assemble all paths that contain this asset into the set $\boldsymbol{\mathcal{P}}(\bar{a}_s)$. The asset $\bar{a}_s$ is said to be indirectly failed if none of its paths are contained in the set of remaining paths, i.e. if $\widetilde{\boldsymbol{\mathcal{P}}} \cap \boldsymbol{\mathcal{P}}(\bar{a}_s) = \emptyset$. By checking for every asset in the set $\bar{A}$ we can estimate the set of all indirectly failed assets $\tilde{A}_{\mathrm{in}}$ and also the set of total asset failures $\tilde{A} = \tilde{A}_{\mathrm{di}} \cup \tilde{A}_{\mathrm{in}}$.

We define *disruption* as the interruption to customer service demands caused by the initial failure. To calculate the total disruptions we need to sum up the disruptions relating to every functional path that is affected by the failure propagation. We first estimate the total customer demands, which is expressed in Eq. (4.7) as

$$\kappa(A) = \sum_{\forall P_r(n_o,n_l) \in \boldsymbol{\mathcal{P}}} d_r(n_o, n_l) \tag{4.7}$$

The customer demands associated with the assets in the failure set $\tilde{A}$ is similarly estimated from Eq. (4.8) as

$$\kappa(\tilde{A}) = \sum_{\forall P_r(n_o,n_l) \in \boldsymbol{\mathcal{P}}(\tilde{A})} d_r(n_o, n_l) \tag{4.8}$$

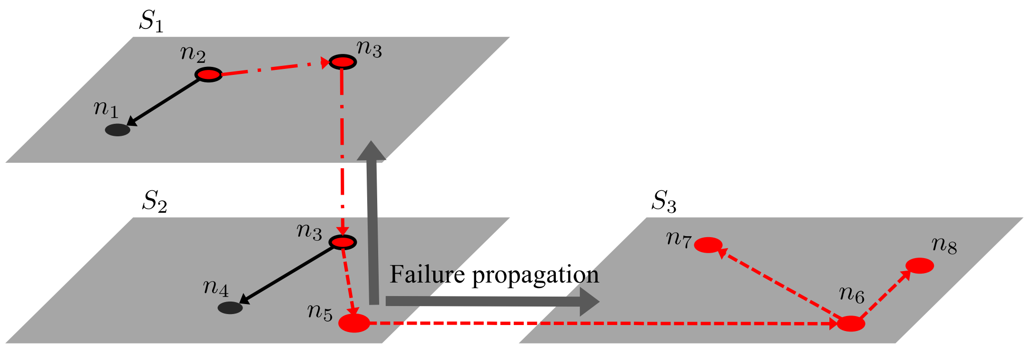
The loss of customer demand is the difference between these two demand estimates and is expressed as $\Delta\kappa = \kappa(A) - \kappa(\tilde{A})$.

The effect of disruption on the performance of the individual 3-tuple network unit can also be estimated in terms of the residual demand ($\tilde{d}_{ij}$) met by it following the failures. This is estimated in a similar manner to the Eq. (4.6) calculations, and is expressed in Eq. (4.9).

$$\tilde{d}_{ij} = \sum_{\forall n_o \in \Theta} \left(\sum_{\forall n_l \in \Phi} \left(\sum_{\forall P_r(n_o,n_l) \in \tilde{\boldsymbol{\mathcal{P}}}} 1_{p_{ij}} d_r(n_o, n_l) \right) \right) \tag{4.9}$$

where $1_{p_{ij}}$ is again an indicator function whose value is 1 if $p_{ij} \in P_r(n_o, n_l)$ and 0 otherwise. While for a directly or indirectly failed asset $\tilde{d}_{ij} = 0$, for all other assets we expect $0 \le \tilde{d}_{ij} \le d_{ij}$.

Figure 4.4 shows the process of failure propagation for the example system-of-systems, following a failure of (n_5, S_2).



Operational nodes		$((n_1, S_1), (n_4, S_2))$
Failed nodes (complete)		$((n_5, S_2), (n_6, S_3), (n_7, S_3), (n_8, S_3))$
Failed nodes (incomplete)		$((n_3, S_2), (n_3, S_1), (n_2, S_1))$
Operational edges		$(((n_2, S_1), (n_1, S_1)), ((n_3, S_2), (n_4, S_2)))$
Failed edges (complete)		$(((n_3, S_2), (n_5, S_2)), ((n_5, S_2), (n_6, S_3)), ((n_6, S_3), (n_7, S_3)),$ $((n_6, S_3), (n_8, S_3)))$
Failed edges (incomplete)		$(((N_3, S_1), (n_3, S_2)), ((n_2, S_1), (n_3, S_1)))$

Figure 4.4: System-of-systems representation highlighting failure propagation. Complete failure of node (n_5, S_2) initializes failure propagation in the system-of-systems. This propagation leads to nodes and edges failing completely (when they can no longer satisfy customer service demand) or incompletely (when they are able to satisfy a fraction of the originally allocated customer service demand).

4.4 Demonstration for England and Wales

We provide a demonstration for England and Wales that incorporates the integrated electricity network and the domestic flight network. Our aim is to map the functional dependencies that exist within and between the electricity supply, transmission, sub-transmission and distribution network and the domestic flight network. This mapping provides a means to explore asset influences across networks and to estimate potential customer disruptions in the event of a failure. The following sections provide a detailed account of the analysis.

4.4.1 Building a system-of-systems network representation

Central to the operation of England and Wales's infrastructure is the integrated electricity network. This multi-level network system distributes electricity to a range of customers. In order to model this system, we make use of the unique dataset consisting of more than 160,000 nodes. The dataset integrates network information from the transmission system that is owned and operated by the National Grid and from six Distribution Network Operators (DNOs) who manage the sub-transmission and distribution networks. A number of generators are embedded at different levels of the integrated electricity network, with large-capacity generators typically connected to the transmission systems and smaller generators embedded at lower levels. A representation of this network is given below in Figure 4.5. In accordance with the notation introduced earlier in the paper, the integrated electricity system $\tilde{\boldsymbol{S}}_E = \{S_1, S_{2,} S_3\}$ where S_1represents the transmission system, S_2 represents the sub-transmission system operating and S_3 represents the distribution system.

We extend our demonstration to include the domestic flight network for England and Wales. Figure 4.5 provides a representation of this system, given as $\tilde{\boldsymbol{S}}_A = \{S_4\}$. In the representation nodes in the network are used to represent airports and edges to represent airline routes between different airports. Airports are dependent on electricity for their operation. Connections between electricity network assets and airports are established through the addition of an edge that connects the airport to its nearest sub-station (132kV/33kV) (UK Power Network Service, 2004). The collective function of both systems forms the system-of-systems $\boldsymbol{S} = \{S_1, S_{2,} S_3, S_4\}$. Table 4.1 provides details of the data sources and methods used to build the representations within $\boldsymbol{S}$.

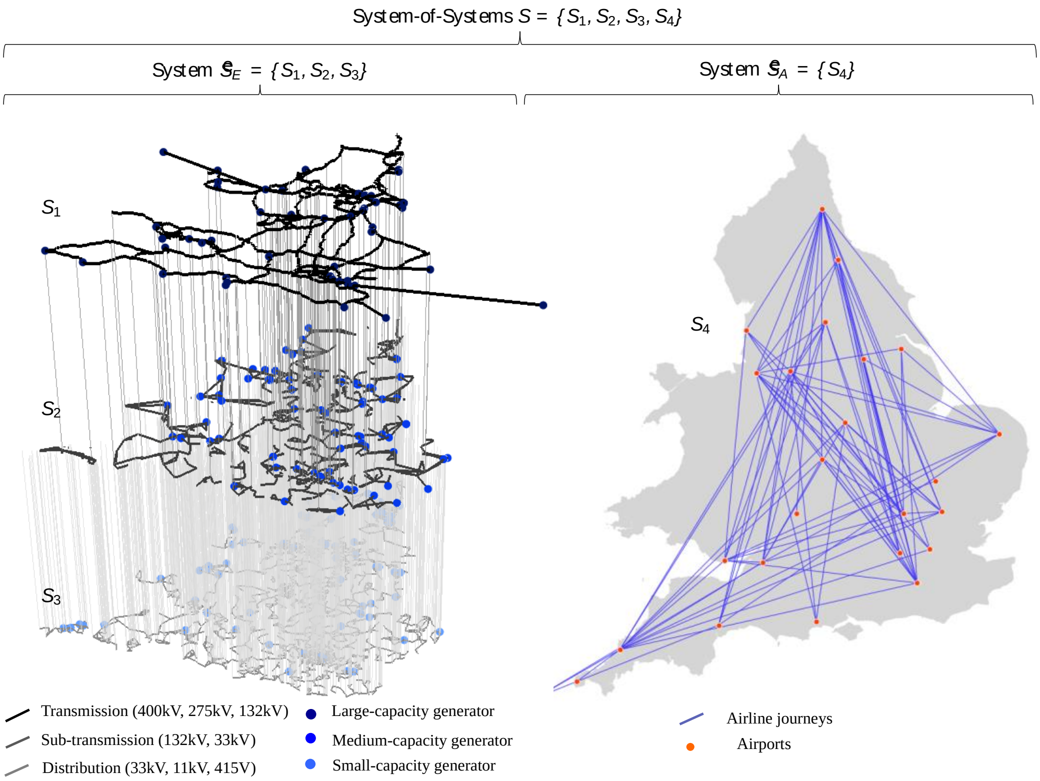


Figure 4.5: Representation of the infrastructure system-of-systems S under analysis within England and Wales. The integrated electricity network consisting of generators of three capacity classifications embedded in the transmission, sub-transmission and distribution levels of the multi-level network. The domestic flight network: showing nodes as airports and edges used to represent flight paths.

Table 4.1: Description of data used in the demonstration for England and Wales's integrated electricity network and the domestic flight network. Including: Network details, spatial, topological, demand and capacity attributes

Sub-system	Network	Spatial and Topological Attributes	Capacity and Demand Attributes
S_1, S_2, S_3	Electricity generation • Owners: Multiple • Nodes: 207	Generator point asset locations derived using DECC 2012 DUKES data (DECC, 2012)	Individual generator capacity values derived using DECC 2012 DUKES data (DECC, 2012)
S_1	Electricity transmission • Owners: National Grid • Voltage: 400kV, 275kV, 132kV • Nodes: 437	Transmission network nodes and edges recreated using National Grid maps (National Grid, 2012), using spatial network recreation (Barr et al.	Demand estimated using capacity constrained location-allocation path model – see Algorithm 4.1: Steps 1-7 for details

		2013)	
S_2	Electricity sub-transmission • Owners: Multiple DNOs • Voltage: 132kV, 33kV • Nodes: 4798	Network derived using OS MasterMap topography layer node and edge data (Ordnance Survey, 2015), using spatial network recreation (Barr et al. 2013)	Demand estimated using capacity constrained location-allocation path model – see Algorithm 4.1: Steps 1-7 for details
S_3	Electricity Distribution • Owners: Multiple DNOs • Voltage: 33kV, 11kV, 415V • Nodes: 164,069	Network derived using OS MasterMap topography layer node and edge data (Ordnance Survey, 2015), using spatial network recreation (Barr et al. 2013)	Customer demands estimated using a Voronoi based assignment technique – see Algorithm 4.1: Step 4 for details
S_4	Airports • Owners: Multiple • Nodes: 32	Network derived using airport locations from OS MasterMap topography layer node data (Ordnance Survey, 2015). Edges derived from CAA 2010 flight statistics (CAA, 2010)	Demands derived directly from CAA 2010 flight statistics by summing total passenger flows in and out of airports (CAA, 2010)
$S_3 - S_4$	Electricity – Airport inter-sectorial edges • Owners: multiple DNOs and airports • Voltage: 33kV • Edges: 32	Inferred from spatial and engineering information: edge created between airport and nearest substation operating at 132kV/33kV (UK Power Network Service, 2004).	Demand estimated using capacity constrained location-allocation path model – see Algorithm 4.1: Steps 1-7 for details

4.4.2 Mapping functional dependencies

We map functional dependencies based on an understanding of the system-of-systems functional pathways set $\boldsymbol{\mathcal{P}}$. For the domestic flight network, these pathways are defined by the passenger movements between airports, derived from datasets outlined in Table 4.1. Total passenger demand service flows on nodes and edges are calculated by summing the passenger demands in and out of individual airports along flight routes.

Airports require electricity for their operation. Without electricity we assume the airport and all flights that pass through it to be disrupted. The disruptions at Gatwick airport during 2013 (McMillan, 2014) demonstrate that such circumstances do arise in reality. In addition to supporting airports (and indirectly airline customers), electricity networks support the transmission and distribution of electricity from generators to electricity customers. Service flows on the electricity network are therefore seen to be the flow of electricity from generation nodes to both distribution sub-station nodes (operating at 11kV/415V - where electricity domestic demand is aggregated) and at 132kV/33kV where airport demand is connected.

Flows on this network are highly dynamic, varying with time as a function of the complex arrangement of output generation, network properties and the spatial arrangement of demand. Resolving these flows is not only computationally very expensive but also requires dynamic representation of control of this network system (i.e. manual or automatic switch control) that is not currently available for the whole network. We provide an approximation of these flows using an understanding that electricity propagates through a circuit on a path of least resistance within capacity constraints. In doing so, we have formalized a capacity constrained location-allocation optimization algorithm to estimate the functional pathway set $\boldsymbol{\mathcal{P}}$ that we attribute with customer demand values.

Algorithm 4.1 below highlights this process as a series of steps: (1) Assembling topological connectivity data for the system-of-systems, in this case, the integrated electricity and national flight network for England and Wales. (2) From the data, identify nodes that are sources and sinks in the representation: electricity generators and distribution substations respectively. (3) Using data described in Table 4.1 to assign electricity generator capacity values to source nodes. (4) Assigning demands to electricity distribution substation sink nodes. (5) Calculate the shortest path between every source and every sink in the system-of-systems. (6) Execute the location allocation algorithm to select the functional path set (the set of shortest paths) that satisfies demand at sink nodes whilst operating within generator capacity constraints. The exact number of paths selected is dependent on capacity constraints, but is at a minimum one for every sink. (7) Assign customer demands across assets in accordance with EQ.4.6.

In the absence of real demand data, we assign estimated demand values to sink nodes using the Voronoi decomposition asset footprint technique (Poljansek et al. 2010; Thacker et al. 2014). Figure 4.6 represents the steps that are required to perform this task: Part A: the derivation of distribution level asset footprints using a Voronoi decomposition, this assumes that each asset provides an equally weighted service and that assets influence only the closest space around them. Part B: the collection of low-level population density data, which is obtained from national demographic statistics database (Office for National Statistics, 2011). Part C: a spatial union between the low-level population data and the infrastructure asset footprints. Part D: assignment of population (demand) to asset footprints by summing the product of the population density by the intersecting area of each footprint. Part E highlights a demonstrative output for this process. Formal details of Algorithm 4.1 are provided below:

Algorithm 4.1:

1. Build system-of-system $\boldsymbol{S}$ network representation
2. Assemble the sets of source and sinks nodes: Θ and Φ
3. Assign maximum generation capacity to source nodes $\mathcal{C} = \{c(n_o), \forall\, n_o \in \Theta\}$ using capacity data outlined in Table 4.1
4. Assign estimated demands to sink nodes $\mathcal{D} = \{d(n_l), \forall\, n_l \in \Phi\}$. Detailed below in steps (a-d). This corresponds to Figure 4.6 (a-d) with (e) providing a map view of assignments for England and Wales
   a. Estimate the area of influence of each sink node by performing a Voronoi decomposition of the space in which it is located
   b. Prepare census level population polygons
   c. Intersect the Voronoi polygons with the population polygons
   d. Assign demands to sink level assets by summing the product of the intersecting areas and the associated population densities
5. Calculate the shortest path between every source and every sink in the system-of-systems
6. Estimate the functional path set $\boldsymbol{\mathcal{P}}$ and their customer demands $\mathfrak{C}$ using a capacity constrained location allocation algorithm:

$$\min \sum_{\forall n_{o \in \Theta}} \left(\sum_{\forall n_l \in \Phi} \mathcal{L}(n_o, n_s) \right)$$

s.t.

$$\sum_{\forall n_l \in \Phi} d(n_l) \leq c(n_o)\ \forall\, n_o \in \Theta$$

- 7. Assign cumulative customer demands to network assets using EQ. (4.6)

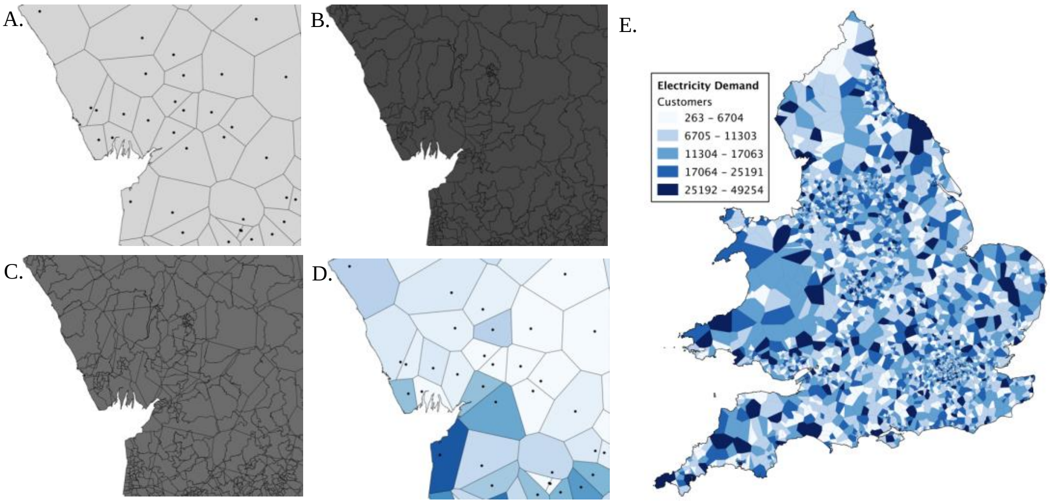


Figure 4.6: Stages in the assignment of demand to electricity sink nodes (a) asset areas of influence, derived through a Voronoi decomposition (b) census level population polygons (c) intersection of Voronoi polygons and population polygons (d) assignment of demand to Voronoi polygons and assets – colouring used to show the magnitude of demand (e) Voronoi decomposition and demand assignments for 33kV substations in England and Wales.

To compute the shortest paths we make use of the *all_shortest_paths* function from the Python library NetworkX (Hagberg et al. 2008). The function employs Dijkstra's algorithm with a worst-case performance $O(|E| + |V| \log|V|)$, where $|V|$ is the number of vertices (nodes) and $|E|$ is the number of edges in the network (Fredman and Tarian, 1987). Despite this being the fastest know shortest path algorithm, like many other network algorithms, it suffers from scaling issues. A large portion of the computational time depends on the network structure, in the case of electricity, we benefit from the highly radial nature of the sub-transmission and distribution networks, as reflected in our model and widely known (Sallam and Malik, 2011; Buchholz and Styczynski, 2014). Within such and arrangement, many sinks are connected to directly (or via a limited number of intermediates) to their nearest sources and hence the potential combination of source-sink paths is dramatically reduced. We exploit this structural property of the network, mapping all shortest paths for a combination of 207 source nodes and 4798 sink nodes (at 33kV level) then separately mapping 33kV-11kV connections. Using a 2.4GHz quad-core Intel-Core i7 processor with 8.00GB RAM, this ‘one-time’ mapping in the analysis (distributed across 8 cores) was approximately 7 hours.

Following the derivation of paths and assignment of customer service demands, we are able to explore the distribution of these demands within the system-of-systems. Figure 4.7 Part A. presents the estimated demands (in terms of electricity customers) aggregated at electricity network node assets from the 33kV, 132kV and 275kV-400kV sub-systems. Demands accumulate at assets located in the top levels of the integrated electricity network hierarchy (where most of the generation, source nodes are located). As one would expect, demand aggregations predominantly align spatially with population density, as highlighted in Figure 4.7 Part C. There are however a number cases where large demand aggregations occur outside of populated areas. These assets can be seen to convey electricity between load centres and large generators, which are typically not located close to concentrations of population.

Figure 4.7 Part B. highlights airport customer demands aggregated onto electricity network assets from the 33kV, 132kV and sub-systems that are used to support them. We see that fewer assets are required to support their operation due to the reduced number and demand of sink nodes. These assets are typically located close to the airports, but also include assets that are at a further distance due to the transmission of electricity from generators (located in central Wales) to the sink nodes that demand the electricity; this is shown in Figure 4.7 Part D.

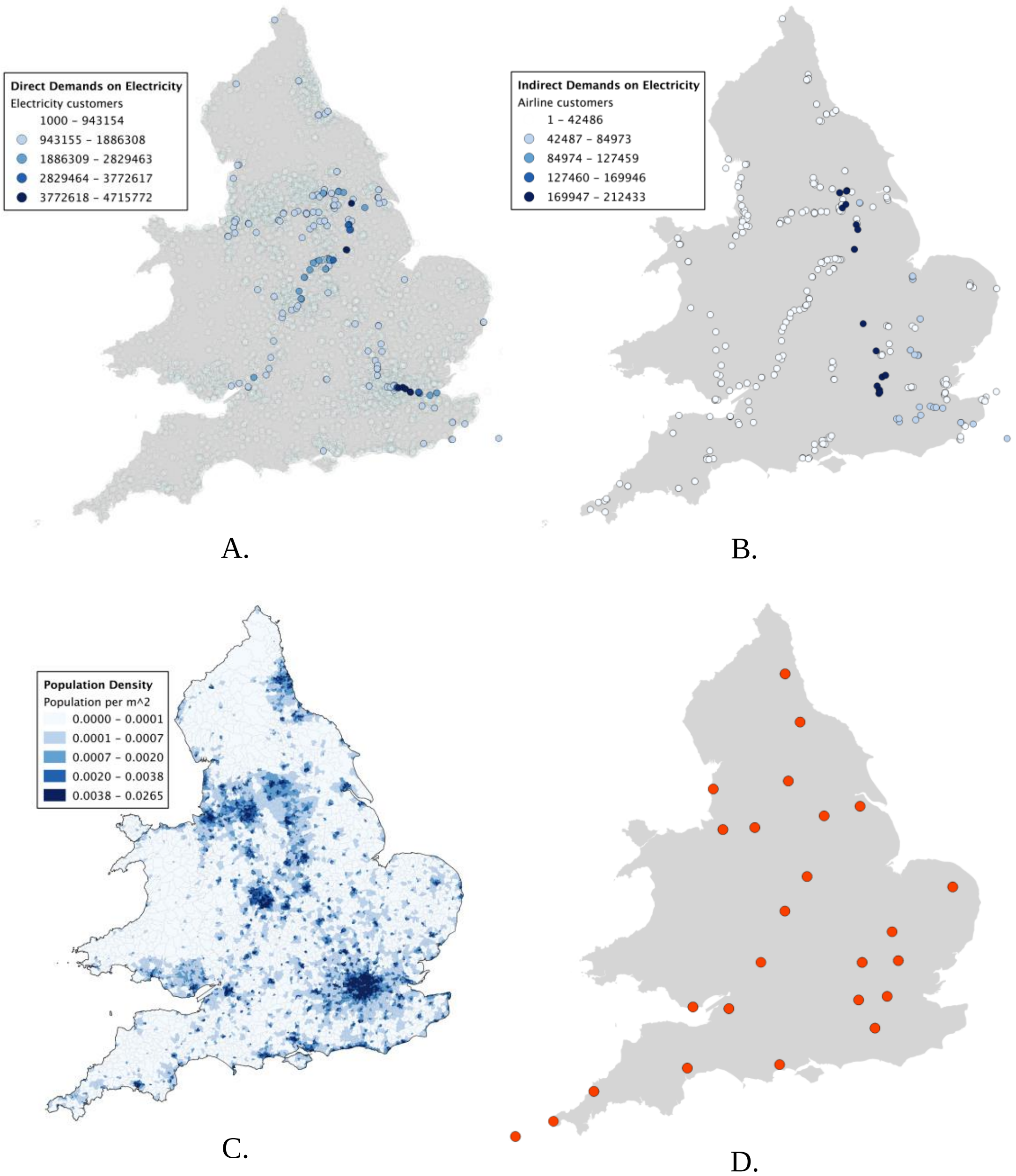


Figure 4.7: Part A: Electricity nodes from the 33kV, 132kV and 275kV-400kV networks, with coloring based on direct electricity customer demand assignments. Part B: Electricity nodes from the 33kV, 132kV and 275kV-400kV networks, with coloring based on indirect airline passenger demand assignments. Part C: Population density map for England and Wales. Part D: Airport location map for England and Wales

4.4.3 Disruption analysis

We adopt the metric of potential customers without supply as a measure of disruption following a failure and subsequent propagation. This potential disruption assumes that the steady state assignment of demands estimated in the previous section are not re-routed when disrupted, either manually or automatically. Such rerouting could have the potential to reduce disruptions through demand reallocation or may cause overloading leading to cascading failures, resulting in further failures and increased levels of disruption. Traditionally, network design has been developed, at least in the transmission system, to allow for re-routing following single line failures. Despite this redundancy, given that multiple single lines can pass through a single substation, security requirements do not provide for the complete loss of a grid substation, in such circumstance, customers may suffer a loss of supply (Energy Networks Association, 2011). Given these considerations, the 'potential disruptions' presented within the chapter are considered as a 'worst case' scenario and provide an upper bound for disruption estimates.

Figure 4.8 highlights the potential disruptions that can arise from the failure of assets within the integrated electricity network. The disruptions associated with the failure of all 437 transmission level assets and the top 500 highest-ranking impact 132kV and 33kV substations are presented. We omit the failure of 11kV substations from the figure due to their relatively small customer impact (max. 10,000 customers). Predictably, nodes in the upper levels of the integrated electricity network (closer to service distributing source nodes) have the potential to cause large disruptions, whereas assets located close to the bottom of the network hierarchy have relatively smaller potential impacts.

The plot highlights the potential for a small number of assets to have large disruptive consequences. As well as high voltage assets, these also include a small number of 33kV substations, which forms as a result of non-consecutive connections that are established in the electricity hierarchy, for example, 33kV/275kV connections, established at a grid supply point transformer. Such assets are co-owned: the transmission side (275kV) by National Grid and the sub-transmission side (33kV) by the DNO. In our analysis, we consider the asset scale to be that of 'substations', as such, the failure of the 33kV side of the transformer also implies the failure of the whole substation, which, being part of the transmission system is also responsible for delivering electricity to large numbers of customers.

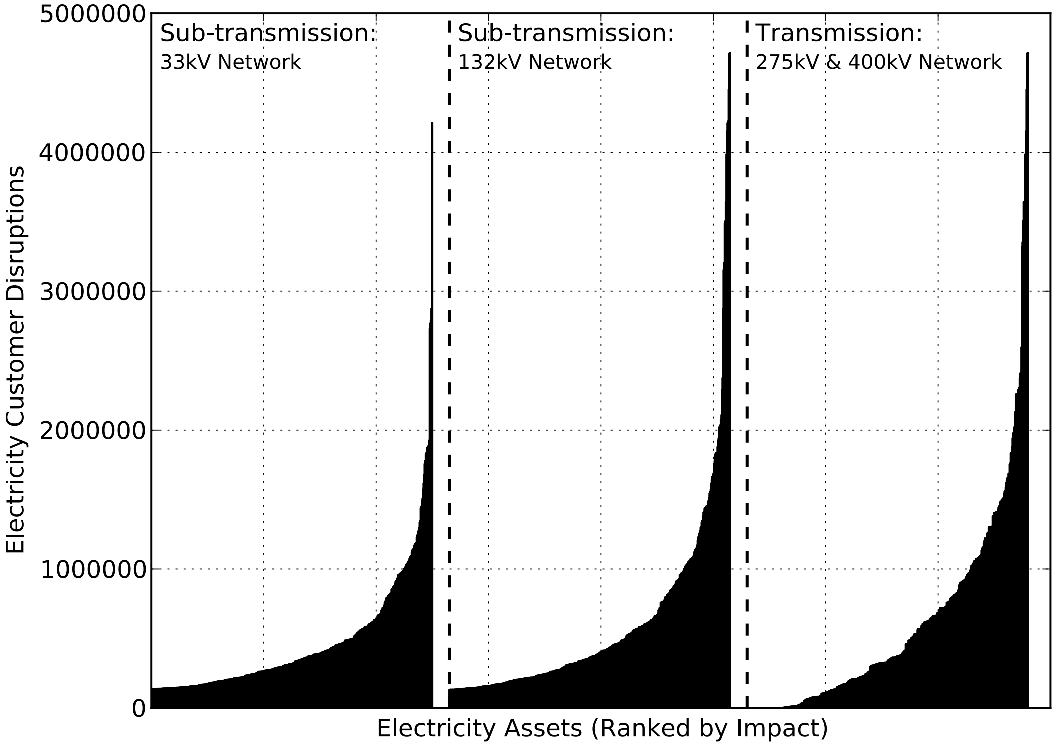


Figure 4.8: Representation of the potential disruptions to electricity customers from the failure of the top 500 impact ranked electricity assets, where electricity assets belong to three levels of the integrated electricity network: 33kV sub-transmission, 132kV sub-transmission and 275kV and 400kV transmission. The impacts of the failure of 11kV substations are excluded from this plot due to their relatively small magnitude (max 10,000 customers).

Figure 4.9 highlights the potential disruptions to airport customers through the failure of assets within the integrated electricity network. Results are presented for the 33kV, 132kV and 275kV-400kV levels. Airports connect to the network at the 33kV level and derive power from assets above them in the network hierarchy. As such, no airports utilize 11kV assets.

Following a similar trend to the directly connected electricity customers, indirectly connected airline customer's demands aggregate progressively at higher voltage levels in the integrated electricity network. Small numbers of potentially highly disruptive assets can also be found. As with the electricity network, non-consecutive hierarchical layering in the electricity network results in large 33kV rated disruptions.

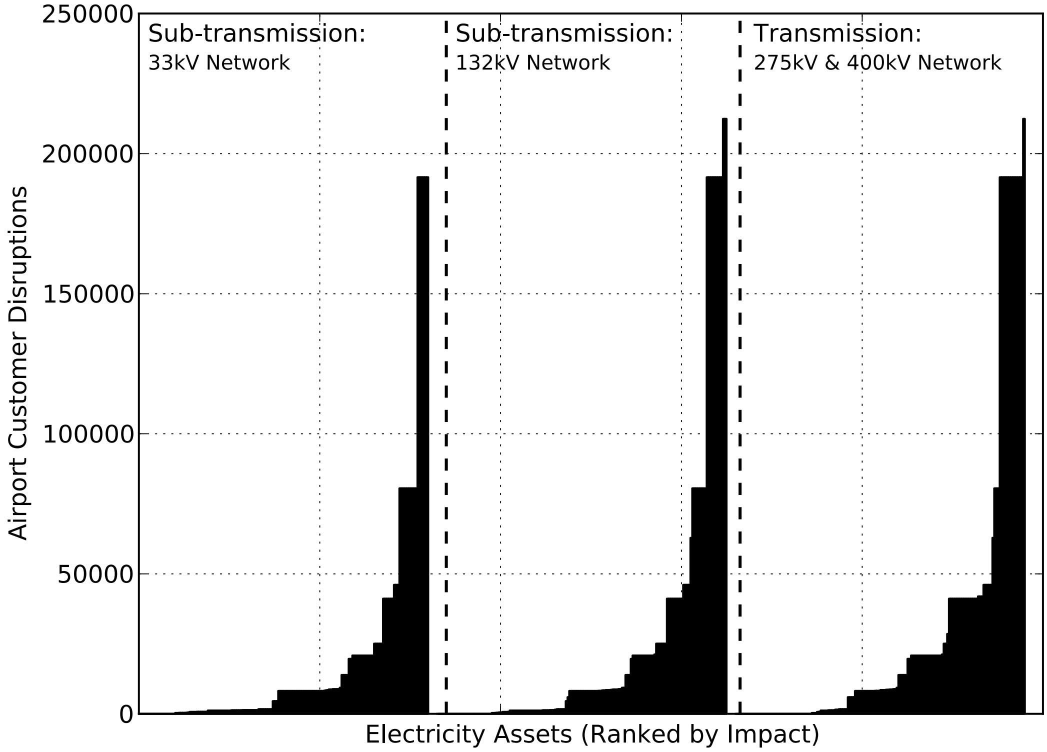


Figure 4.9: Representation of the potential disruptions to airport customers from the failure of impact ranked electricity assets, where electricity assets belong to three levels of the integrated electricity network: 33kV sub-transmission, 132kV sub-transmission and 275kV and 400kV transmission. The impacts of the failure of 11kV substations are excluded from this plot due because airports connect to the integrated electricity network at the 33kV level and derive flow from generators located above them in the network hierarchy.

The analysis reflects the power flows of today that typically flow downwards through the integrated electricity network hierarchy. In the future, larger numbers of small-scale distributed generators are likely to be installed at lower voltage levels, 33kV, 11kV etc. (Buchholz and Styczynski, 2014; Burt et al. 2008). This will result in changes to the arrangement of power flows and as a consequence, the customer dependencies of different assets (electricity and airports) at that scale.

4.5 Discussion and Conclusions

Within this study we have provided a formal system-of-systems characterization for critical national infrastructures and have outlined methodology to perform a multi-scale disruption analysis. A practical demonstration of the methodology is presented for England and Wales's integrated electricity network and the domestic flight network.

We find that a small number of electricity assets, if they were to fail, have the potential to cause large-scale customer disruptions. These assets are not only located in the transmission system, but also at the sub-transmission level. This information provides the multiple owners, operators and decision makers of these systems the opportunity to understand the potential for disruption of their assets due to the failure of others and also conversely, the potential disruptions resulting from the failure of their own assets. It is expected that such an understanding leads to more informed decision-making on disruption risk reduction and adaptation planning.

The general methodology presented within this paper has applicability for a wide range of other infrastructure sectors, providing the opportunity to explore the relationship of multiple infrastructure types. There are many natural extensions to this modelling approach, including (i) developing a spatial understanding of failure propagation and disruption analysis, leading to a new understanding of infrastructure criticality and meta-level functional centrality (ii) risk and reliability analysis for multi-scale CNIs (iii) adaptation planning using multi-sectorial disruption analysis (iv) understanding the risks of transformative change to distributed technologies (for example the increased use of distributed generation or deployment of electric vehicles within the integrated electricity network).

Assembling the geospatial network, functional path and demand data for such studies represents a significant challenge. Due to the complexities inherent in the physical operation and management of such systems we have adopted an instantaneous approach that seeks to estimate customer attributions along paths. The inclusion of dynamics in the modelling approach would be a valuable extension of this work, though the computational tractability and data requirements of such methods, particularly in large-scale studies may prove prohibitive.

The methods presented herein provide both researchers and the managers and operators of these systems the opportunity to explore failure disruptions within these highly important network systems. At a time when individual infrastructure operators are concerned with risks and opportunities associated with infrastructure dependencies, such mappings provide useful insights into the spatial and multi-scale spread of influence of their assets and customers.

5. Geographic Hotspots of Critical National Infrastructure

Abstract:

Failure of critical national infrastructures can result in major disruptions to society and the economy. Understanding the criticality of individual assets and the geographic areas in which they are located is essential for targeting investments to reduce risks and enhance system resilience. Within this study we provide new insights into the criticality of real-life critical infrastructure networks by integrating high-resolution data on infrastructure location, connectivity, interdependence and usage. We propose a metric of infrastructure criticality in terms of the number of users who may be directly or indirectly disrupted by the failure of physically interdependent infrastructures. Kernel Density Estimation is used to integrate spatially discrete criticality values associated with individual infrastructure assets, producing a continuous surface from which statistically significant infrastructure criticality hotspots are identified. We develop a comprehensive and unique national scale demonstration for England and Wales that utilises previously unavailable data from the energy, transport, water, waste and digital communications sectors. The testing of 200,000 failure scenarios identifies that hotspots are typically located around the periphery of urban areas where there are large facilities upon which many users depend or where several critical infrastructures are concentrated in one location.

5.1 Introduction

Critical National Infrastructures (CNIs) support society and the economy by providing essential services to households and industries. Examples of CNIs include electricity, water, transportation, gas, digital communications and waste networks. Motivated by economies of scale and unequal distributions of national resources and economic activity, modern CNIs have evolved into large spatially distributed systems with multiple interdependencies.

Such complexity provides the conditions for failure at a particular location to have disproportionate consequences. In the United Kingdom (UK), a number of recent events have highlighted this systemic vulnerability: In 2009, flooding in Cumbria (Miller et al. 2013) resulted in a bridge failure that not only caused disruptions to local transportation systems, but also to water, electricity and telecoms utilities that were co-located on the bridge. In 2011, power failure at a major exchange in Birmingham resulted in the loss of broadband connection for hundreds of thousands of users across the UK (BBC, 2011). On Christmas Eve 2013, the flooding and subsequent failure of three electricity sub-stations at Gatwick airport contributed towards the disruption of 13,000 airline passengers (McMillan, 2014). Motivated by historic failure events and the threats posed to the CNI from a changing climate and human threats, understanding this vulnerability for the purpose of targeting investments to reduce risks and enhance resilience, has become a national priority (CST, 2009; POST, 2010; DEFRA 2011; Cabinet Office, 2011; ASC, 2014).

In order to effectively target investments we are required to identify 'critical' infrastructure assets "the loss or compromise of which would leave to severe economic or social consequences or to loss of life" (Cabinet Office, 2010). Given the 'interconnectedness' of modern infrastructure systems, we are required to think beyond traditional sectorial silos and consider infrastructure as a system-of-systems (Kröger, 2008; Eusgeld et al. 2011; Tran et al. 2014). One major source of interconnection is established through the physical flow of resources between infrastructures, classified as physical interdependencies (Rinaldi et al. 2001).

A second form of interdependency proposed by Rinaldi et al. (2001) is geographic, where the spatial proximity between assets results in their exposure to similar local environmental conditions. Co-location can occur because of physical necessity (i.e. the assets physically depend upon one-another) or because sites are geographically attractive e.g. on the periphery of urban areas where land is cheaper and may be designated for industrial purposes. In the context of failures, co-location can result in correlated events, which are considered common-cause failure mechanisms (Rinaldi et al. 2001). These include: weather related hazard events such as ice storms (Chang et al. 2007), flooding (Pitt, 2009), heat waves (McColl et al. 2012) or hurricanes (Loggins and Wallace, 2015); geo-hazards such as earthquakes (Dueñas-Osorio et al. 2007), volcanic activity (Wilkinson et al. 2012) and subsidence (Pritchard et al. 2013); co-location related infrastructure asset failures (BBC, 2011) and targeted attacks (Chernick, 2005; Prager et al. 2011). Considering this form of interdependence, we extend our understanding of criticality beyond the scale of an individual asset to identify geographic areas that are in themselves critical.

Methods and tools from the study of complex networks provide an intuitive means to explore the behaviour of CNIs (Strogatz, 2001; Newman, 2010; Lewis, 2011). Using this approach, the spatial organisation and topological connectivity of CNI assets are explicitly represented by nodes and edges (Barthelémy, 2011). A variety of complex network based modelling and simulation tools have been developed to study failure propagation within physically interdependent CNIs. This includes topology-based methods, such as from Bashan et al. (2013) and Shekhtman et al. (2014) that explore network vulnerability and robustness through the removal of individual components. Despite the advancements that these studies provide, care should be taken when applying practical insights to real CNIs such as the power grid (Hines et al. 2010; La Rocca et al. 2015). Detailed physics based models can capture many details of CNIs and CNI failures; however, the data and computational costs of such analyses are prohibitive to large-scale studies (Brummitt et al. 2013; Ouyang, 2014). Functional network models such as proposed by Johansson & Hassel (2010), Poljansek et al. (2010), Zio and Sansavini (2011) and Hernandez-Fajardo and Dueñas-Osorio (2013) quantify failure and disruption propagation using functional connectivity and network-path based techniques that replicate the most salient behaviour of CNIs without excessive data and computational costs.

In a recent review of modelling and simulation approaches for interdependent infrastructure systems undertaken by Ouyang (2014), it was recognised that applied studies are limited to two or only a small number of CNIs - therefore potentially underestimating the consequences of failure. In order to compare the disruptive impacts of different assets from multiple interdependent CNI sectors, an informative, universal metric for physically interdependent CNIs is required. Casalicchio and Galli (2008) identify that in order to support decision-making for protection and resilience planning, "core metrics" such as those that act at the asset level are required. To this end, Zimmerman and Restrepo (2006) developed a ratio of the temporal disruptions to the supporting and dependent infrastructure, however, despite its universal quality, this metric does not incorporate the magnitude of user disruptions that result from failure events.

Johansson and Hassel (2010) and Thacker et al. (2014) provide a universal metric of infrastructure service losses (user disconnections) applied to individual sectors, however this does not, at the asset level, explicitly incorporate the impacts of indirect disruptions that manifest through nth-order interdependency effects.

Through the removal of infrastructures co-located within previously determined square grid cells, Johansson and Hassel (2010) identify critical geographic locations. This work performs an application of the 'cell-space' method that was demonstrated for a university campus (Patterson and Apostolakis, 2007) and a road network (Jenelius and Mattsson, 2008). Two major limitations of this technique are identified in Wilson (2012): (i) that all infrastructure locations are considered to be evenly spread across a cell, resulting in a loss of spatial information; (ii) Due to the distribution of point assets in space, the choice of grid cell shapes and locations can have a large impact of outcomes, this is otherwise know as the Modifiable Areal Unit Problem (Openshaw, 1994). Kernel Density Estimation (KDE) is a technique that has been developed to produce a single density surface from spatially distributed observations (Silverman, 1986). The KDE creates a continuous surface, any point of which integrates a number of observations (infrastructure assets) within a certain distance that are weighted using a specified kernel function. This addresses the limitations of the cell-space method by explicitly incorporating the distances between infrastructure assets, preserving detailed spatial information and secondly, providing a continuous (overlapping) kernel function across the entire surface, reducing the impacts of cell boundary choice. Statistical methods such as those proposed by Ord and Getis (1995) provide a means by which to analyse this continuous surface, identifying 'hotspot' locations that are considered as statistically significant outliers.

We present novel methodology and applied analysis that incorporates physical and geographic interdependencies to identify '*infrastructure criticality hotspots'* for risk and adaptation planning. In doing so this study makes a number of unique contributions to the literature, these include: (i) Methodology to calculate infrastructure asset *user criticality* as a universal disruption metric, allowing assets from different sectors to be compared directly with one another. The metric incorporates the potential direct and indirect user disruptions that can result from the failure of the infrastructures through physical interdependencies; (ii) The use of Kernel Density Estimates (KDEs) and statistical testing to calculate geographic hotspots of infrastructure criticality. Hotspots identify concentrations of critical infrastructure that might not otherwise be identified as being critical; (iii) The presentation of a comprehensive and unique national-scale infrastructure criticality assessment for England and Wales that tests 200,000 failure scenarios by integrating data from the energy, transportation, water, waste and digital communications sectors.

The remainder of this paper is organised as follows: Section 5.2 outlines methodology to identify geographic hotspots of critical national infrastructure; Section 5.3 provides a detailed description of an application of the methodology for England and Wales; Section 5.4 highlights results and findings from the applied analysis. Finally, Section 5.5 offers conclusions from the study.

5.2 Definition of Critical Infrastructure Hotspots

5.2.1 Infrastructure asset criticality

Consider $Q \subset \mathbb{R}^2$ the set of all two-dimensional coordinates of geographical locations within the boundaries of a spatial extent such as a country. Users residing within Q rely upon a variety of essential services that are delivered by the collective function of physical infrastructure assets that make up the national infrastructure. Such assets include electricity power stations, gas compressor stations and water pumps. Though service delivery also relies on non-physical assets (such as human control), the focus of this study centres on physical infrastructures only.

We collect all assets, a, belonging to the national infrastructure to form the set $A = \{a_1, \ldots, a_n\}$. Assets belonging to a specific infrastructure type can be collected to form the set $A^k \subseteq A$. For example, A^e contains all the electricity assets, A^g contains all the gas assets and A^w is the set of all the water assets. The number of users P dependent on a single infrastructure system A^k is given as $P^k \subseteq P$.

Infrastructure assets perform different functions in order to satisfy the users dependent on them. To describe this functionality we characterise three different asset types: sources – where services are generated, intermediate – where services are transmitted to other assets, and sink - which distribute services directly to users. This arrangement forms a functional hierarchy where, at the lowest level, demands for services are placed on sink assets and at the highest level, services are generated at source assets. Intermediate assets support the distribution of services between sources and sinks and in doing so establish directionality of flows within the hierarchy.

We consider each sink asset to serve a unique (non-overlapping) geographic area. As such, the set A^k of assets classified as sinks divide the space Q into disjoint partitions. Assuming there are m sink assets in the set A^k which divide the space Q into disjoint partitions $\{Q_1, \dots, Q_m\}$, we can estimate the number of users within each partition, we define this as the assets *user footprint*. Denoting the number of users associated with the sink node of infrastructure A^k serving the space Q_l as P_l^k, we can construct the sets of all unique subsets of users $\{P_1^k, \dots, P_m^k\}$ on the infrastructure A^k. Beyond sink assets, the exact demand placed by the users on the intermediate and source assets depends upon a range of factors that include: which sinks they are connected to, as well as other capacity and functional constraints of the system.

For any give asset (source, intermediate or sink) $a_j \in A^k$ we can assemble the set S^k of all sink assets of the same infrastructure type that it is supplying to. The *direct demand* placed on a_j is denoted by $P_j^{dir} = f(\bigcup_{\forall a_l \in S^k} P_l^k)$, where the function f depends upon the capacity of the asset to serve the total demand $\bigcup_{\forall a_l \in S^k} P_l^k$ of all sinks in the set S^k. Since assets are also connected across infrastructures (through physical dependencies), there is an indirect demand places on each asset a_j that is supplying resources to another infrastructure type. So for example, gas users place an indirect demand on electricity assets due to the existence of a physical dependency between the gas system and the electricity system. We calculate the *indirect demand* P_j^{indir} in a similar way to estimating P_j^{dir}. $P_j^{indir} = g\left(\bigcup_{S^v \neq S^k} \bigcup_{\forall a_l \in S^v} P_l^v\right)$, where the function g depends upon the capacity of the asset to serve the total demand $\bigcup_{\forall a_l \in S^v} P_l^v$ of all sinks in the sets S^v belonging to other infrastructures.

For the purpose of targeting investments, we are interested in identifying critical assets, the failure of which can have disproportionate consequences. In developing this analysis we seek to compare the criticality of all assets within A irrespective of which individual infrastructure system they belong to. To do this, we propose the universal metric: *user criticality* c_j *that we define as the total number of users who are directly or indirectly dependent on infrastructure asset* a_j: $c_j = \left|P_j^{dir}\right| + \left|P_j^{indir}\right|$. In the context of infrastructure asset failure, this would be the number of users without service.

Figure 5.1 provides a simplified illustrative example to demonstrate infrastructure asset user criticality that can arise through direct and indirect user demands that manifest through physical infrastructure interdependencies. The national infrastructure system A (Part A of Figure 5.1) consists of assets from the electricity system $A^e = \{a_1, a_2, a_3, a_4, a_{5,}\}$ and the gas system $A^g = \{a_6, a_7, a_8\}$. The arrows highlight the direction of service flows through the hierarchy, from source to sink assets to meet user demands. As well as supporting electricity demands, electricity assets also indirectly enable gas users due to a physical dependency established between the infrastructures. In Part B of Figure 5.1 the user criticality calculation for a_3 is given as the total sum demand imposed due to service flows through the network in supporting the direct user footprint established at electricity sink nodes a_4 and a_5 and indirect user footprints established at gas nodes a_7 and a_8.

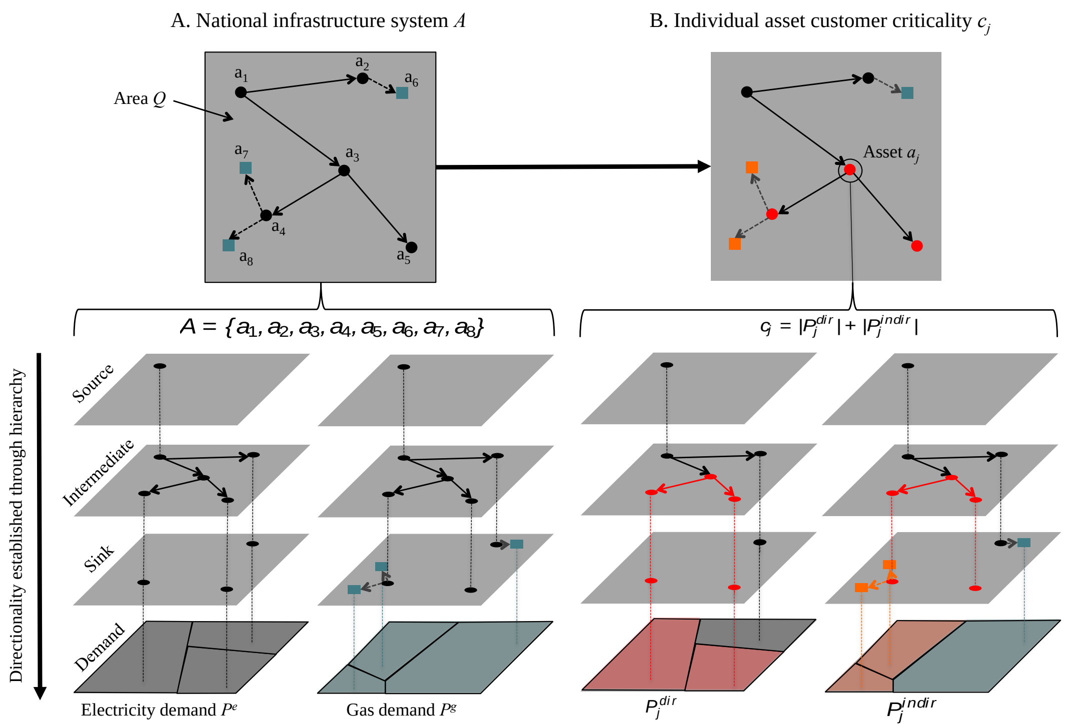


Figure 5.1: The calculation of individual infrastructure asset user criticality values from the mapping of infrastructure systems and their physical interdependencies and the summation of direct and indirect user demands

5.2.2 Geographical location of critical infrastructure hotspots

The disruptive consequences associated with infrastructure asset failures that are geographically interdependent provide motivation to look beyond the scale of individual assets and identify geographic areas that are in themselves characterised as critical. To address this we propose the concept of an *infrastructure criticality hotspot* - that we define as *a geographic location where there is a concentration of critical infrastructure, measured according to the number of users directly or indirectly dependent on the infrastructure in that location.*

The identification of statistically significant 'hotspot' areas requires us to calculate the infrastructure user criticality values at all locations within the geographic area being tested. To do this we use KDE, which incorporates discrete assets locations and criticalities to produce a continuous 'surface' for which a criticality density value is available at any location. Using a weighted KDE approach the density $g(x_i)$ at location x_i is given by

$$g(x_i) = \begin{cases} \sum_{j=1}^{n} \left\{ [w_j c_j] \frac{1}{\pi h^2} K\left(\frac{d_{ij}}{h}\right) \right\}, & if\ 0 < d_{ij} < h \\ 0, & otherwise \end{cases} \tag{5.1}$$

where w_j is the weight associated with infrastructure asset a_j, c_j is the *user criticality* associated with infrastructure asset a_j, h is the bandwidth of the density estimation (the search radius around the location) and $K\left(\frac{d_{ij}}{h}\right)$ is the kernel applied to point i. Multiple kernel functions can be selected based on a theoretical, empirical or other functional reason for its use (Wilson, 2012).

The resulting 'surface' can then be analysed to identify spatial concentrations of critical infrastructures that constitute statistically significant hotspots (high magnitude outliers) of infrastructure criticality. The Getis and Ord Gi* measure (Ord and Getis, 1995) provides a statistical *z*-score significance test that compares locally calculated values with global values, thus providing a significance test across the whole study area. The Gi^* value for the location i is given by

$$Gi^* = \frac{\sum_{j=1}^{n} w_{ij}\, g(x_j) - \bar{g} \sum_{j=1}^{n} w_{ij}}{\sigma \sqrt{\frac{n \sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)\left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \tag{5.2}$$

where w_{ij} is the spatial weight between feature i and asset a_j, $g(x_j)$ is the KDE value of the attribute of interest at location j, $\bar{g}$ is the global mean of attribute of interest and σ is the standard deviation of the attribute. *z*-score significance testing provides a means to identify both hot and cold spots for the analysis.

Figure 5.2 Part A. highlights the key elements of the KDE and how it is used to calculate a continuous criticality density surface. Part B. of the figure shows how statistical significance testing of the criticality surface can be used to identify geographic hotspot locations.

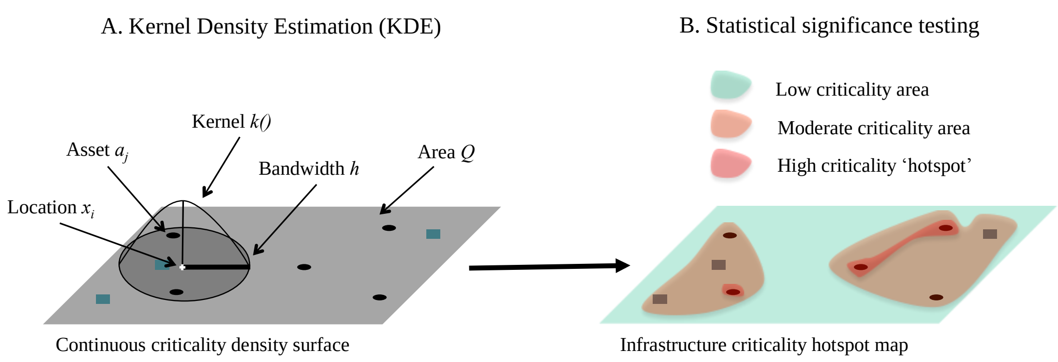


Figure 5.2: Part A. Shows the elements of the Kernel Density Estimation (KDE), which is used to create a continuous criticality surface. Part B. highlights how the statistical significance testing is used to derive infrastructure criticality hotspots from the criticality surface.

The infrastructure criticality hotspot methodology can be implemented in a number of ways to provide different insights into criticality. These are summarised below:

- *Single sector assets only:* Identifies hotspots using only the locations of assets from a single sector

- *Multiple sector assets only:* Identifies hotspots using the locations of assets from multiple sectors that are all mapped in the same space
- *Single sector with direct users:* Identifies hotspots using locations and direct user weightings for only a single sector
- *Multiple sector with direct users:* Identifies hotspots using locations and direct user weightings from multiple sectors that are all mapped in the same space
- *Single sector with direct and indirect users:* Identifies hotspots using locations and user criticality weightings (direct and indirect demand) for only a single sector
- *Multiple sector with direct and indirect users:* Identifies hotspots using locations and user criticality weightings (direct and indirect demand) from multiple sectors that are all mapped in the same space

The choice for implementation of the analysis will depend upon the questions that drive the analysis and practical constraints, such as lack of available data or computational constraints. The incorporation of increasing levels of data into the analysis (such as the analysis of multiple sectors and user criticality values) promotes the identification of geographic locations that might not otherwise have been identified.

In the following sections we provide a demonstration of this methodology for England and Wales using data from multiple sectors. We use direct and indirect demands to estimate asset user criticalities and produce hotspot maps for individual and multiple sectors to draw out important insights into national infrastructure criticality and vulnerability.

5.3 Application to Critical National Infrastructure in England and Wales

5.3.1 Overview of the analysis

We provide a comprehensive national scale demonstration of the methodology for England and Wales utilising unique data from the energy, transport, water, waste and digital communications sectors. For each sector, direct user estimates are used to derive asset user criticality values. The integrated electricity network is central to the national infrastructure provision, with all other sectors physically dependent on electricity for their operation. Given its importance, we characterise the user criticality of electricity assets based on direct and indirect users that are established due to this dependency. Geographic interdependency is characterised through the derivation of infrastructure criticality hotspots using KDEs.

The following sub-sections provide a detailed account of the methods and data used in the analysis, this includes: (5.3.2) *Infrastructure asset representation:* the integration of highly detailed data on infrastructure location, interconnectivity and interdependence to build a national infrastructure representation; (5.3.3) *Infrastructure criticality calculation:* applied methodology and data for calculating asset criticalities using user estimates derived from usage statistics, spatial density estimates and network-based path assignment techniques and (5.3.4) *Infrastructure criticality hotspot identification:* details for implementation of the KDE and statistical significance testing for the purpose of hotspot identification.

5.3.2 Infrastructure asset representation

In order to calculate asset criticality values we first map all infrastructure assets from the national infrastructure within the area of the study. Table 5.1 presents the real infrastructure asset data from multiple sectors that have been used in the analysis. This includes a representation of the integrated electricity network, where nodes are used to represent generation facilities and electricity substations and edges are used to represent overhead lines and underground cables. Figure 5.3 (a) provides a representation of this network, showing the different voltage levels at which connections to generators and other infrastructures are made. Other network infrastructures include the national road network, where nodes represent junctions and edges represent different road segments. Similarly, the national railway network in comprised of nodes that represent junctions and stations and edges represent track segments.

The location of airports, ports, water towers, wastewater treatment plants and telecommunication towers are represented as single point assets, identified by nodes. Each asset of these specific types is dependent on electricity for its operation. In many cases, the nature of the physical connection between the dependent asset and its supporting electricity asset is unknown. We build a dependency edge between the asset and its nearest (geographically closest) electricity asset of appropriate voltage. Figure 5.3 (b) provides an example of this, showing the physical connections that are established between gas take-off points and the 33kV electricity substation assets.

Table 5.1: List of assets included in the spatial criticality analysis. Detailing the data sources used to complete the spatial topological network representations and the capacity and demand data used to estimate the functional path set and assign user demands.

Sector	Spatial and Topological Attributes	Capacity and Demand Attributes
Electricity generation • Owners: Multiple • Nodes: 207	Generator node locations derived using DECC 2012 DUKES data (DECC, 2012)	Individual generator capacity values derived using DECC 2012 DUKES data (DECC, 2012)
Electricity transmission • Owners: National Grid • Nodes: 437	Transmission network derived from National Grid maps (National Grid, 2012), using spatial network recreation (Barr et al. 2013)	User demands derived using capacity constrained location allocation – detailed in paper, based on Thacker et al. (2014)
Electricity sub-transmission • Owners: Multiple DNOs • Nodes: 4798	Sub-transmission network derived from OS MasterMap topography layer node and edge data (Ordnance Survey, 2015), using spatial network recreation (Barr et al. 2013)	User demands derived using capacity constrained location allocation – detailed in paper, based on Thacker et al. (2014)
Electricity Distribution • Owners: Multiple DNOs • Nodes: 164,069	Distribution network derived using OS MasterMap topography layer node and edge data (Ordnance Survey, 2015), using spatial network recreation (Barr et al. 2013)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)
Gas transmission • Owners: National Grid • Nodes: 625	Gas network derived from National Grid maps (National Grid, 2012)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)
Airports • Owners: Multiple • Nodes: 32	Airport locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived from CAA 2010 flight statistics (CAA, 2010)
Ports • Owners: multiple • Nodes: 66	Port locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived from DfT 2012 maritime statistics (DfT, 2012a)
Water towers • Owners: multiple • Nodes: 2566	Water tower locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)
Waste-water treatment • Owners: multiple	Waste-water treatment locations derived from OS MasterMap topography layer	User demands derived using Voronoi decomposition – detailed in paper, based on

• Nodes: 1563	node data (Ordnance Survey, 2015)	Thacker et al. (2014)
Telecom masts • Owners: multiple • Nodes: 5226	Telecom mast locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)
Railways • Owners: multiple • Nodes: 3941	Railway locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	Passenger demands from a rail trip distribution model, documented in Pant et al. (2015)
Roads • Owners: multiple • Nodes: 24071	Road locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	Passenger demands from DfT AADF usage statistics (DfT, 2014) and DfT loading factors (DfT, 2012b)

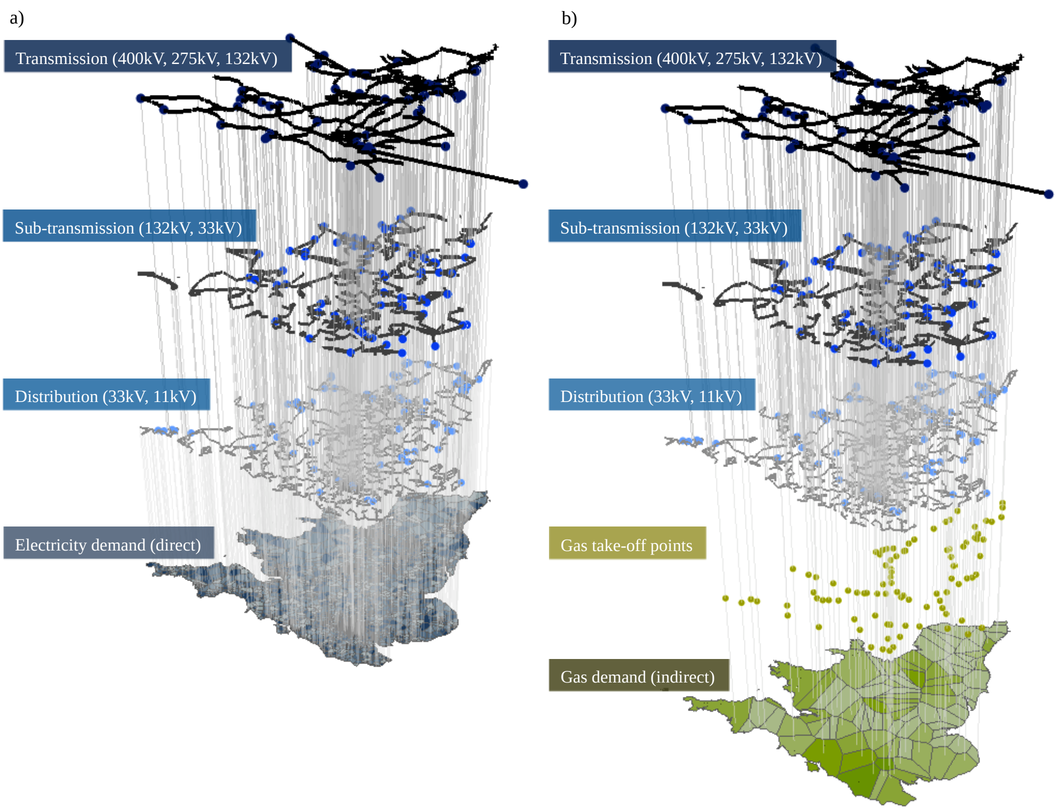


Figure 5.3: A representation of the integrated electricity network for England and wales; consisting of the electricity power generation, transmission, sub-transmission, distribution sub-systems. (a) Shows how domestic electricity users at distribution sub-stations place a direct demand. (b) Shows how gas users, connected through a dependency link between the gas and electricity infrastructure place an indirect demand on electricity assets.

5.3.3 Infrastructure criticality calculation

Having mapped the assets within England and Wales, we next calculate their criticality. The first step of this process is to calculate the numbers of users directly dependent on all assets. Table 5.1 provides details for how users are allocated to infrastructure assets from different sectors. In summary: Point assets representing airports are derived from annual flight statistics and are calculated as the total number of terminal passengers for an average day in 2009 (CAA, 2010). Similarly, average daily port users were derived using 2009 national port usage statistics (DfT, 2012a).

In the absence of data for the gas take-off points, electricity distribution substations, water towers, wastewater treatment plants and telecommunication towers assets, we estimate these using a Voronoi decomposition technique (Poljansek et al. 2010; Thacker et al. 2014) Assignment of users is a two part process comprising: (i) deriving infrastructure asset footprints to estimate spatial area of influence around each distribution level asset, and (ii) assigning user counts to each distribution level asset based on a spatial union of asset footprint with census derived population estimates (that we take as an estimate for domestic demand). This method assumes each asset provides an equally weighted service and assets influence only the closest space around them. Figure 5.4 (a)-(h) highlights the process of user assignments and provides results (with user counts highlighted on a colour scale) derived for wastewater treatment works, gas off-take points, telecommunication masts and water towers respectively.

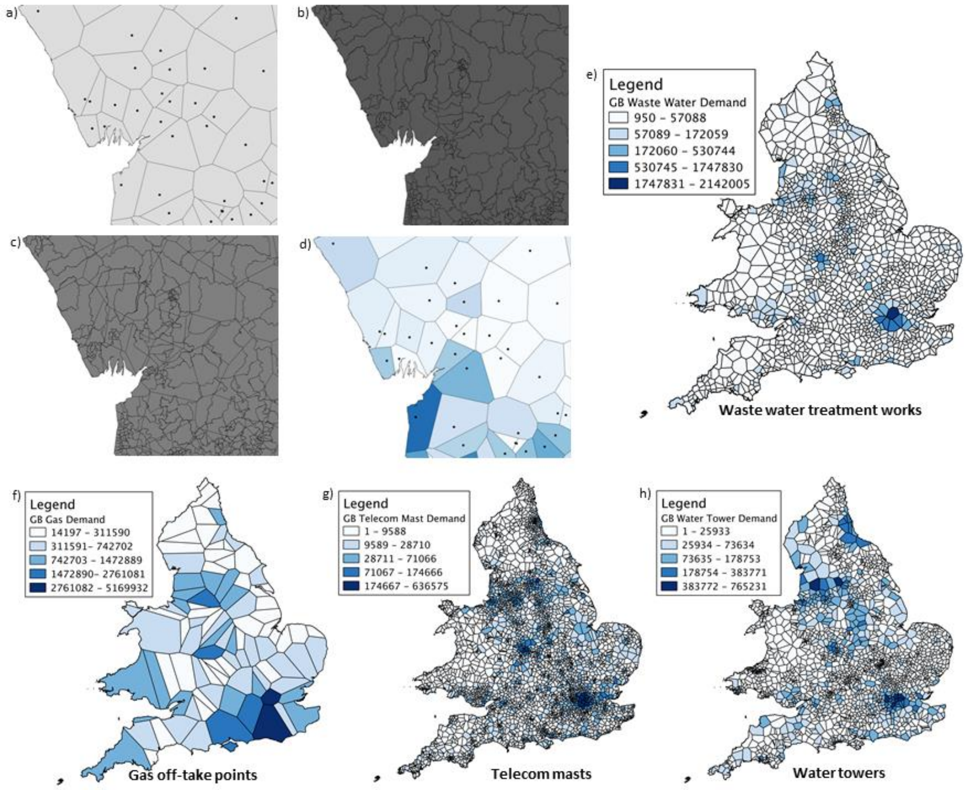
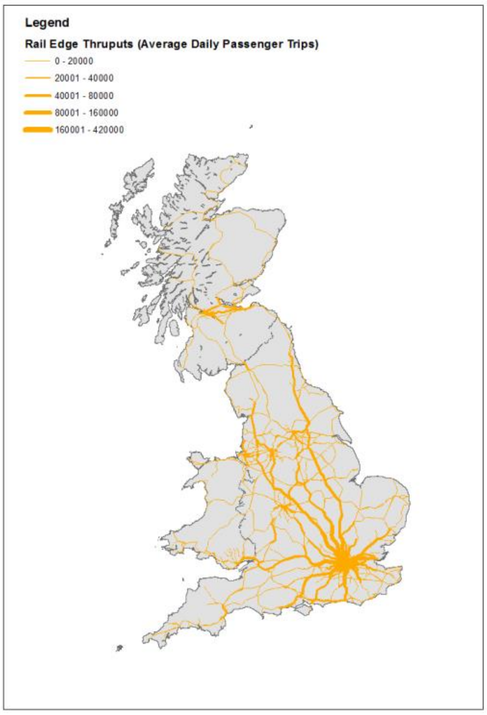


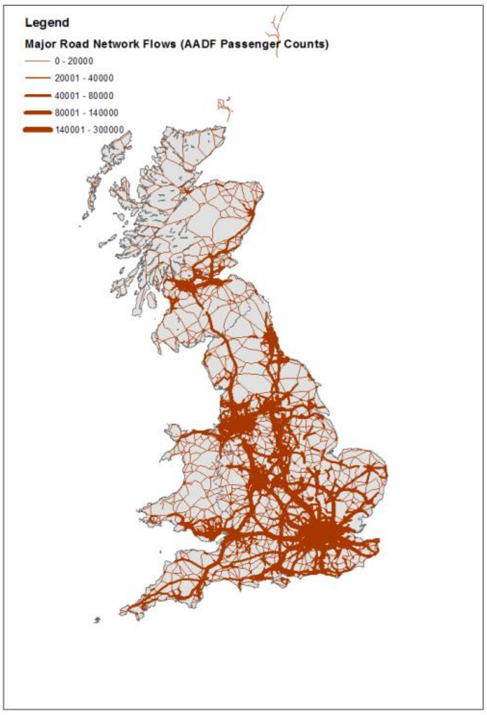
Figure 5.4: Stages in assigning users to assets; (a) introduces a set of asset footprints. (b) Provides a view onto ward level population data. (c) Represents the union of both the asset footprint and the bounded population data. (d) Gives user estimates transferred to asset footprints (e), (f), (g) and (h) provide user assignments, with user magnitude highlighted on a colour scale derived for waste water treatment works, gas off-take points, telecom masts and water towers respectively

Direct (electricity) and indirect (non-electricity) user demands that are concentrated at sink nodes are then allocated to intermediate and source nodes within the integrated electricity network. Due to the lack of availability of user demand data for these assets, allocations are made on the assumption that electricity flows are established along a path of the shortest electrical distance. To achieve this we perform an application of the capacity constrained location-allocation method as outlined in Thacker et al. (2014). In summary: The method calculates the set of shortest paths between source and sink nodes in the network that are required to satisfy user demand within generation availability constraints. Users are aggregated at assets within paths between sink and sources and these aggregations correspond to asset criticality values.

Usage of the railway network was derived from a rail trip distribution model developed in previous work by Pant et al. (2015). The model uses information from train timetables and station usage statistics to estimate trips being made between station pairs. The results are aggregated as origin-destination (O-D) daily trip assignments of passengers in the railway network. Figure 5.5 (a) represents the flows of all passengers through stations and along routes for the national railway network of Great Britain.

User demands for the major road network were derived from Department for Transport Average Annual Daily Flows (AADF) usage statistics (DfT, 2014) which give aggregated estimates of number of vehicles of different types (two-wheelers, cars, taxies, buses, coaches, light goods vehicles and heavy goods vehicles) along major roads in Great Britain. We have converted these to passenger counts by multiplying the vehicle numbers by passenger occupancy factors provided by transport analysis guidelines handbooks (DfT, 2012b). Figure 5.5 (b) shows the major road network with edges weighted based on traffic flows.





(a) (b)

Figure 5.5: (a) Edge Criticality: which represent the passenger throughputs at each railway network edge (track section). (b) Illustration of the average annual daily flows (passenger numbers) along links on the major road network from Great Britain.

5.3.4 Hotspot identification

A 1km sampled spatial lattice was constructed across all of England and Wales. The individual points in the lattice formed the sample locations at which KDE estimation was performed to obtain an estimate of the spatial density of infrastructure occurrence and related user density per infrastructure sector. The output units of the KDE analysis were density per-km^2

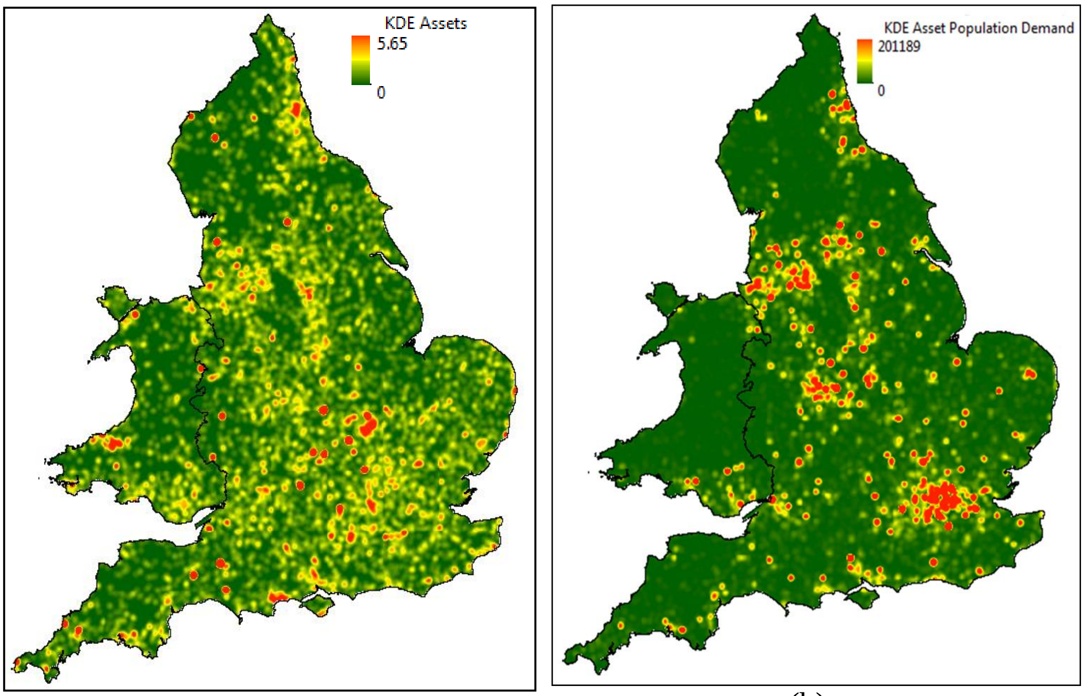
For each location in the lattice a spatial density estimate was derived using a weighted intensity KDE approach as presented in EQ. 5.1. A Gaussian kernel of the form $K\left(\frac{d_{ij}}{h}\right) = \left\{\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{d_{ij}^2}{2h^2}\right)\right\}$ was selected to incorporate the decay in spatial influence that is associated with a sampled location. For each infrastructure sector considered in Table 5.1 KDE surfaces were derived both in terms of the spatial frequency of infrastructure assets (i.e., without any measure of associated user criticality such that c_j was set to $1 \forall j \leq h$) and also in terms of user criticality, with c_j set to the user counts associated with a particular infrastructure asset j. A weighting of W_a = 1 was used for all infrastructure types, establishing no preference for a particular infrastructure systems type. All KDE surfaces were derived for a bandwidth (h) set to 5km by experimentation.

To recognize statistically significant spatial hotspots of infrastructure criticality the Getis and Ord Gi^* spatial hotspot statistical test was employed. Formally, the Getis and Ord Gi^* value for a location i is calculated using EQ.5.2. where in the case of this study, each 1km sampled lattice location in an infrastructure sector formed the locations i. To test for statistical significant hotspot locations, the Z-score of each location i was threshold at a 99% significance level ($Gi^* > 2.6$).

5.4 Results

5.4.1 Non-transport asset criticality

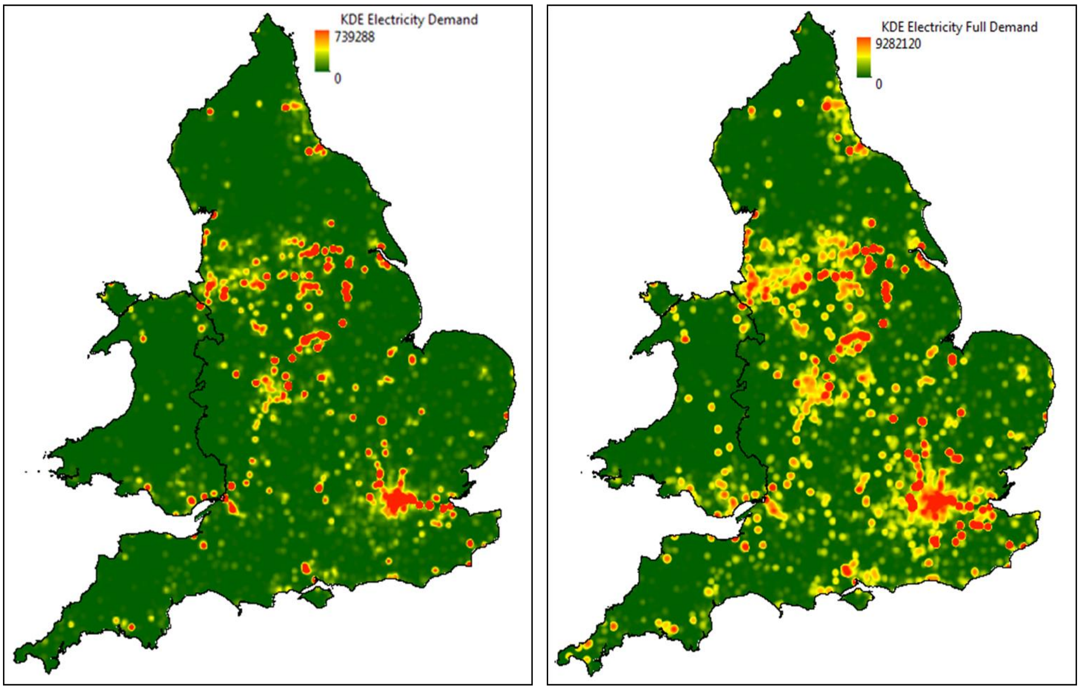
Figure 5.6 (a) shows the estimated spatial density of non-transport infrastructure assets for England and Wales (electricity transmission Grid Supply Points (GSP), gas transmission take-off points, water towers, waste water treatment works and telecom towers/masts). Large density values occur in south-west Wales, south-east Midlands and also in the west of England. However, in terms of criticality, the spatial density and subsequent hotspots are focused on the major urban conurbations of England and Wales Figure 5.6 (b); namely, London with a tapering to the surrounding south-east region, Liverpool and Greater Manchester, Birmingham and Leeds areas.



(a) (b)

Figure 5.6: (a) Kernel density estimated infrastructure asset spatial density (GSP, gas, telecoms, water and water treatment assets). (b) Kernel density estimated infrastructure asset user demand (GSP, gas, telecoms, water and water treatment assets).

The criticality metric based on direct users of electricity network assets is shown in Figure 5.7 (a). Not surprisingly the major urban conurbation of England and Wales form the major demand hubs for electricity infrastructure network assets. Indirect user dependence due to the dependence of of the GSP, gas, telecoms, water and water treatment assets on the electricity network is shown in Figure 5.7 (b). When physical interdependence is taken into account, the map of critical asset density is more spatially dispersed than when just considering the direct usage of electricity infrastructure. The overall electricity results suggest that a relatively small number of key geographical locations play a major role in satisfying electricity demand within England and Wales, particularly with respect to the dependence of other non-transport infrastructures on the electricity network. At critical sites, a small number of electricity assets are responsible for supporting a disproportionate number of indirect customer demands (relative to direct electricity demands). This occurs due to indirect demands from demand centres concentrating at certain assets on the electricity network.

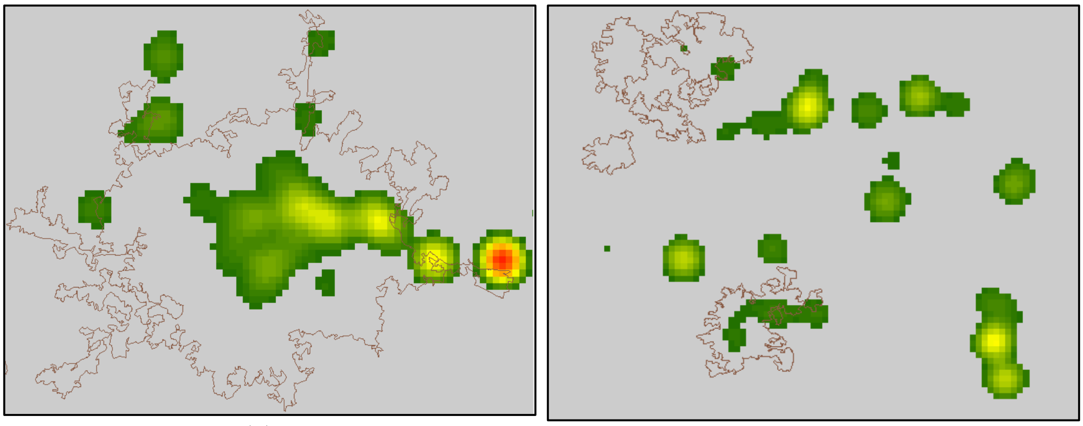


(a) (b)

Figure 5.7: (a) Kernel density estimated electricity user demand (no dependent demand). (b) Kernel density estimated full electricity user demand including GSP, gas, telecoms, water and water treatment assets dependency

The major spatial focus of this critical infrastructure lies to the east of London Figure 5.8 (a). It is worth noting that the actual largest magnitude hotspot of electricity demand in the south-east fall to the east of the Greater London Authority (GLA), showing the key role that large regional grid supply points play in satisfying the electricity demand of London and the south-east. This relationship of large non-urban regional electricity infrastructure assets satisfying urban users is more evident outside of London. For example, Figure 5.8 (b) shows the hotspots in South and West Yorkshire between Leeds and Sheffield. Similar non-urban demand hotspots are found running north to south through the east

Midlands and also to some extent in the Liverpool to Manchester corridor in the north-west.



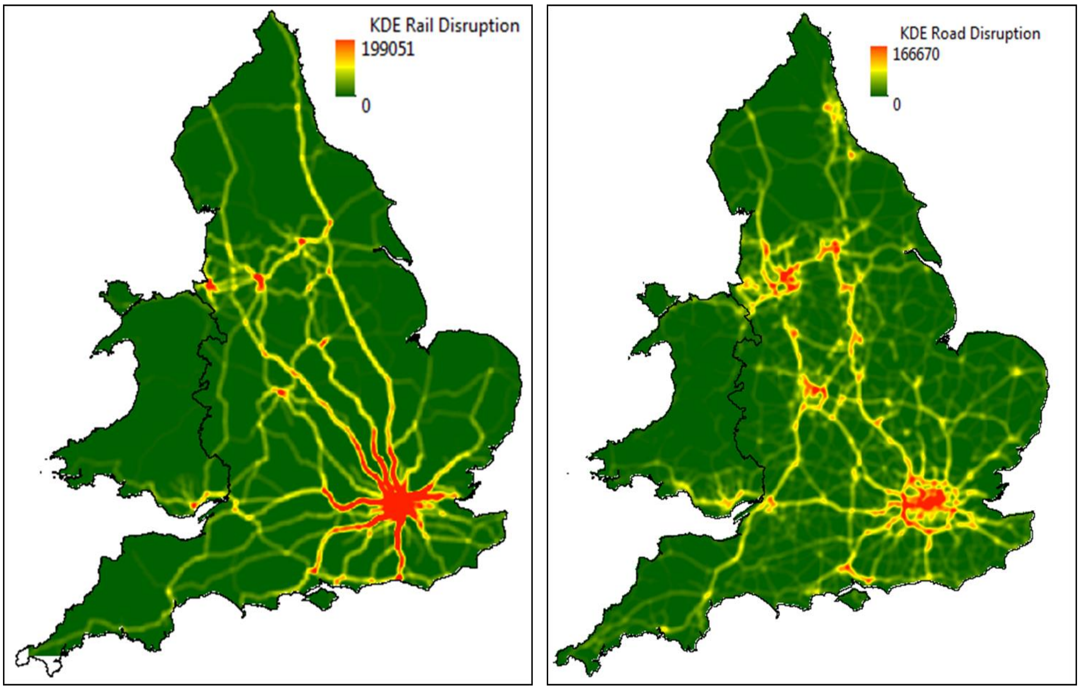
(a) (b)

Figure 5.8: (a) London's electricity infrastructure asset user demand hotspots at a 99% significance level (Z-score > 2.56). (a) Electricity infrastructure asset user demand hotspots at a 99% significance level (Z-score > 2.56) for South and West Yorkshire.

5.4.2 Transportation asset criticality

For transportation asset criticality KDE results Figure 5.9 (a) show that there are only a small number noticeable hotspots of criticality outside London. In the case of London, disruption radially propagates along the mainline rail connections into the south-east. The result is a large hotspot for London and the mainline rail corridors connecting it, with only four other much smaller (both spatially and in terms of magnitude) hotspots occurring at Liverpool, Greater Manchester, Birmingham and Leeds.

A slightly more complex relationship exists between road assets and related criticality compared to rail. Larger more significant densities of criticality are also found outside London Figure 5.9 (b). Resulting hotspots of criticality are focused around principal motorways, in particular the M25, M1, M6 and the local motorways of Greater Manchester and Leeds, including the M62.

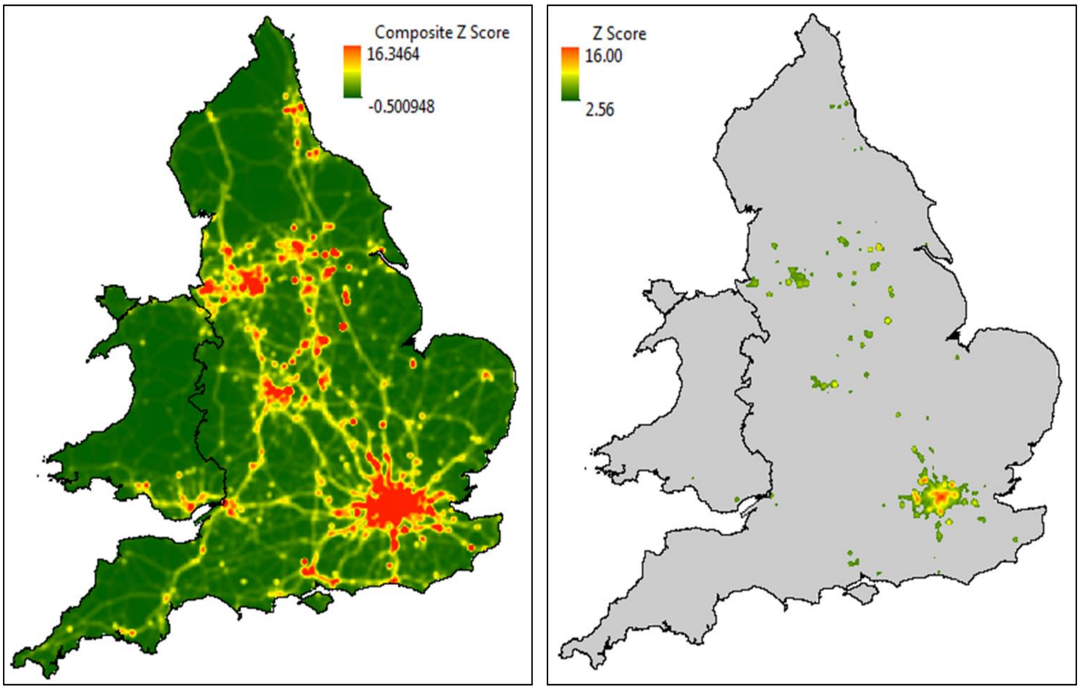


(a) (b)

Figure 5.9: (a) Kernel density estimated rail disruption (stations and track). (b) Kernel density estimated road network disruption on the basis of passengers

5.4.3 Composite asset criticality

The composite criticality hotspots analysis Figure 5.10 (a) and Figure 5.10 (b) shows the major role that the large urban areas of England and Wales have both in terms of the demand for infrastructure services and also in terms of spatially accommodating these. The composite analysis (combination of criticality for individual assets, interdependence with the electricity network and transport disruption) shows that London is a major focus of criticality; it has a spatially continuous hotspot with multiple peaks that covers a spatial extent of approximately 2,331 sq-km 63 km west-to-east and 37 km north-to-south; Other composite hotspot locations are found in or around Greater Manchester, Liverpool, Leeds and Birmingham. However, the magnitude of these is lower than the London and the spatial extent significantly smaller (e.g., the largest hotspots are 256 sq-km Manchester, 115 sq-km Liverpool, 110 sq-km Leeds and 153 sq-km Birmingham. A cluster of smaller hotspots (between approximately 8 and 26 sq-km) are found in the Sheffield, Derbyshire and Nottinghamshire, and Humberside areas which are a result of the strong hotspots previously noted in these regions relating to electricity assets meeting user demand.



(a) (b)

Figure 5.10: (a) Composite Z scores of user demand and disruption of assets, electric network, rail and road (b) Statistically significant composite hotspots at a 99% significance level (Z-score > 2.56).

5.5 Conclusions

In this study we have developed methodology that incorporates both physical and geographic infrastructure interdependencies to identify infrastructure criticality hotspots. The methodology has been applied at the national scale for a range of infrastructure types in England and Wales.

Through application of the methodology to a real-world system we were able to highlight areas of infrastructure criticality in England and Wales that can be targeted for investment to reduce risks and enhance resilience. Results highlight the importance of evaluating criticality as a function of direct and indirect infrastructure users, rather than infrastructure asset concentrations. Although many locations rather intuitively correspond to areas of high user density, other, non-intuitive locations are also highlighted. These typically exist on the peripheries of cities where dependence is focused onto a small selection of infrastructures located outside of urban areas.

The general methodology developed in this paper is not only applicable to different geographic areas, but also to a broad range of infrastructure types, providing a means to explore the relationships that exist between different infrastructures at a variety of operational and spatial scales. There are many natural extensions to this work that include, (i) the development of methodology and applied analyses to incorporate logical and information interdependencies (Rinaldi et al. 2001) into a single framework with physical and geographic interdependencies; (ii) the development of risk assessment that integrates a mapping of infrastructure criticality with a spatial representation of hazard likelihood and quantification of the consequences of failure in economic or other terms; (iii) The incorporation of hotspots into a decision making framework designed to inform prioritization of investment in system resilience.

Assembling the data for such an analysis represents a significant challenge. This is not only because of the variety of data needed from different sectors, but also because information on infrastructure users are often restricted due to matters relating to privacy, security or commercial sensitivity. Due to these complexities, where data have not been available, we have adopted an approach that allocates users to assets through Voronoi decomposition and network path based assignments. A physics-based approach for estimating users would be a valuable extension to this work, though the data and computation requirements to facilitate such an analysis may prove prohibitive.

In conclusion, the methodology and analysis presented herein provides a range of decision makers with the ability to identify infrastructure criticality hotspots. Such an analysis provides useful evidence and insights for assessing the vulnerability of modern interconnected infrastructure systems.

6. Evaluating the Benefits of Adaptation of Critical Infrastructures to Hydrometeorological Risks

Abstract:

Infrastructure adaptation measures provide a practical way to reduce the risk from extreme hydrometeorological hazards, such as floods and windstorms. The benefit of adapting infrastructure assets is evaluated as the reduction in risk relative to the 'do nothing' case. However, evaluating the full benefits of risk reduction is challenging because of the complexity of the systems, the scarcity of the data and the uncertainty of future climatic changes. We address this challenge by integrating methods from the study of climate adaptation, infrastructure systems and complex networks. In doing so, we outline an infrastructure risk assessment that incorporates interdependence, user demands and potential failure-related economic losses. Individual infrastructure assets are intersected with probabilistic hazard maps to calculate expected annual damages. Protection measure costs are integrated to calculate risk reduction and associated discounted benefits, which are used to explore the business case for investment in adaptation. A demonstration of the methodology is provided for flood protection of major electricity substations in England and Wales. We conclude that the on going adaptation programme for major electricity assets is highly cost-beneficial.

6.1 Introduction

Critical national infrastructures (CNIs) support society by facilitating the distribution of essential services such as electricity, gas, transportation, information, water and waste. In recent years a number of extreme hydrometeorological hazard events have caused the failure of CNIs, resulting in large customer disruptions and economic damages. Examples include: The 2007 United Kingdom (UK) summer floods (Pitt, 2008), the 2011 Queensland floods (Queensland Government, 2011), Hurricane Sandy that hit the East Coast of the United States in 2012 (RAND, 2014) and the UK winter storms of 2013-2014 (Met Office, 2014). The IPCC (IPCC, 2014) suggest that, in the future, the hazards to which infrastructure systems are exposed are set to grow with increasing extreme event risks caused by climate change. For example, In the UK, the proportion of infrastructure exposed to flooding is projected to increase in all sectors by 2050 (CCC, 2014). Given these historic events and the threats posed by a changing climate, characterization of the current and future risks of failure of the UKs CNI to climate hazards become a national priority (CST, 2009; POST, 2010; Cabinet Office, 2010; Cabinet Office, 2011; DEFRA, 2011). This has resulted in coordinated governmental efforts to understand the severity of risks and target adaptation interventions, (Environment Agency, 2009; DEFRA, 2012; DEFRA, 2013).

To support this effort, a number of recent studies have highlighted the large impacts that climate hazards are likely to have on infrastructure systems in the future (e.g., Kirshen et al. 2008; Hunt and Watkiss, 2011; McColl et al. 2012; van Vliet et al. 2012). Despite the contributions made by these studies, the current body of adaptation research does not adequately account for the interconnections within and between different infrastructures (Bollinger et al. 2013). In a review of the literature on adaptations of infrastructures to climate change, Chappin and van der Lei (2014) identify that interdependencies are primarily presented in qualitative, descriptive terms and that explicit interconnections are not dealt with. The failure to incorporate infrastructure interdependencies, as defined by Rinaldi et al. (2001), may result in the full impacts of cascading failures not being accounted for (DEFRA, 2013). Underestimation of the risks of failure of CNI may therefore lead to the underestimation of the true benefits of investing in infrastructure adaptation.

Risk based decision-making, such as required to inform the targeting of investments to reduce CNI failure risks and enhance system resilience, uses evidence of risks to inform choices that affect the future (Hall and Borgomeo, 2013). Risk, in the broadest sense, can be defined as a function of the probability of an unwanted event and the severity of the consequences of the event (Kaplan and Garrick, 1981). Thus in the context of extreme climate events impacting CNIs, evidence of risks constitutes an understanding of the probability of a climate event impacting an infrastructure system and the magnitude of consequences. To develop this understanding, methodology is required that recognizes the interrelationship between hazards, infrastructure exposure and vulnerability, and potential societal and economic impacts (Hall et al., 2003a,b).

Using a risk based approach, we produce methodology and applied analyses for evaluating the benefits of investment in adaptation of interdependent critical infrastructure to reduce hydrometeorological hazard risks. Evaluation is resolved at the scale of individual assets, the scale at which decisions are made by owners and operators of utility companies. In order to address the limitations of previous adaptation studies, we integrate explicit representations of CNI systems that represent the complex interconnectivity, interdependence and functionality found in real-world counterparts. To do this we represent the CNI as a spatial, interdependent network, as described by Lewis (2006), Lewis (2011) and D'Agostino and Scala, (2014). The disruptive impacts of failure within and between infrastructures are computed using network-based methods that replicate the most salient properties of real infrastructure systems to estimate failure-related user service disconnections, as demonstrated in Johansson and Hassel (2010) and Thacker et al. (2014). Economic losses are calculated by summing the direct asset damages associate with the hazard and the indirect economic flow losses. To calculate these indirect losses we make use of economic input-output modelling, as proposed by Leontief (1986) and demonstrated for calculating climate disaster loss (e.g Okuyama, 2004; Hallegatte, 2008) and infrastructure network disruption loss (e.g Cho et al. 2001; Li et al.,2013).

The benefits of adaptation are evaluated in terms of avoided expected annual damages that are resolved by intersecting network asset locations with probabilistic hydrometeorological hazard data. To assess these benefits we make use of cost-benefit analysis (CBA), which is a well-established technique for comparing the benefits of a project or policy with its corresponding costs of implementation (Pearce et al. 2006). In the context of infrastructure, assessing the costs and benefits of adaptation options is important in assisting adaptation planners and practitioners to identify the most appropriate interventions to reduce vulnerability, enhance adaptive capacity and build resilience (CIRIA, 2010). To support the methodological development we present a comprehensive national-scale application for the investment in flood protection measure adaptation for major electricity substations in England and Wales, which are used to support not only users of electricity, but also of air, port and railway transportation, waste water, water and telecommunications.

The remainder of this paper is organized as follows: Section 6.2 introduces the methodological framework for the study. Section 6.3 provides the details for a demonstration of the methodology for major electricity assets in England and Wales facing a risk of flooding. In Section 6.4 we provide the results from the demonstration, highlighting the business case for investment in protection-measure based adaptation. Finally, Section 6.5 offers conclusions from the study.

6.2 Methodology

6.2.1 Overview of the methodology

Figure 6.1 provides an overview of the methodology developed for the purpose of evaluating the benefits of adapting infrastructures to reduce hydrometeorological risks. This includes an interdependent infrastructure risk assessment that incorporates representation of hydrometeorological hazards, interdependent infrastructure networks, user demands and the structure of the macro-economy to calculate the expected annual damages that may result from the failure of the asset. The business case for investment in adaptation measures to reduce these potential damages is evaluated using cost benefit analysis techniques. The following subsections of this paper provide a mathematical description of each element within the figure. Information on real-world infrastructures has been incorporated alongside notation to provide a more complete description of the methodology and applicability for real-world studies.

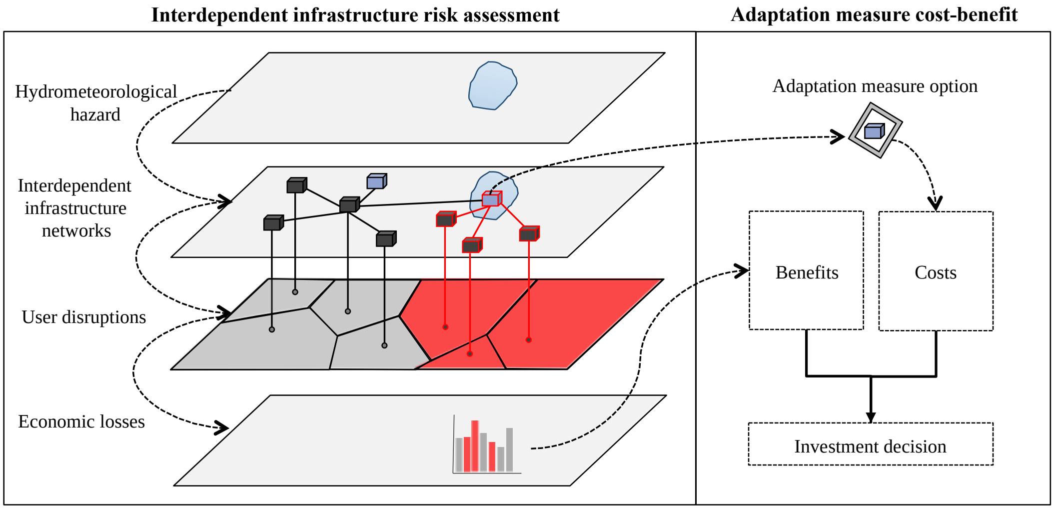


Figure 6.1: Overview of the methodology for evaluating the benefits of investment in interdependent infrastructure adaptations to reduce hydrometeorological risks: comprising an interdependent infrastructure risk assessment and an adaptation measure cost benefit analysis.

6.2.2 Hazard representation

Unlike deliberate terrorist or cyber attacks, hydrometeorological hazards, such as a flood, windstorm or heat wave can be characterized by a coherent hazard footprint which can be thought of as a random field. We represent a continuous spatial hazard using the multivariate spatially random field $f_{\mathbf{Y}}(\mathbf{y})$. From this distribution a sample hazard $\mathbf{y} = \{y_1, \dots, y_d\}$ is generated, where $y_k = y(\mathbf{x}_k)$ denotes the hazard measure (flood depth, wind velocity, air temperature etc.) at point location $\mathbf{x}_k$. The probability of the hazard occurring for a given year is given by the exceedance probability $P_e(\boldsymbol{y})$.

6.2.3 Interdependent infrastructure network systems

We represent the set of all coordinates that denote the spatial extent of a geographic area such as a country as $Q \subset \mathbb{R}^2$. Located with Q is a population of users who consume a variety of essential services that include water, electricity and gas. Supporting the delivery of services to users is the CNI that is made up of the collection of physical infrastructure assets that include water pumps, electricity sub-stations and gas terminals. The collection of n infrastructure assets that form the CNI are given by the set $A = \{a_1, \dots, a_n\}$. We collect assets belonging to a specific infrastructure sector (water, electricity, gas etc.) to form the set $A^k \subseteq A$. The number of users S dependent on a single infrastructure system A^k is given as $S^k \subseteq S$.

In order to efficiently perform this function, CNIs have evolved through time from single assets to large, spatially distributed network systems, characterized by their complex interconnectivity. Assets within this complex arrangement can be described as performing specific functions to fulfil the function of the CNI as a whole. For this purpose, assets are classified as either sources – where services originate; sinks – where services are distributed to users and intermediate – which function to transmit the flow of services between source and sink assets.

For all m sink nodes within A^k we construct a geographic user asset footprint by partitioning Q into disjoint partitions $\{Q_1, \dots, Q_m\}$. Denoting the number of users associated with the sink node of infrastructure A^k serving the area Q_l as S_l^k, we can construct the sets of all unique subsets of users $\{S_1^k, \dots, S_m^k\}$ on the infrastructure A^k. The number of users that place demand on the intermediate and source assets is a function of a variety of factors that includes: which sinks they are connected to, the connectivity of the network in which the assets are embedded, the capacity of other assets in the system and other functional constraints of the system.

6.2.4 Infrastructure asset reliability

For each individual infrastructure asset a_i we associate the function r_i to describe its state. Within the scope of this paper we assume assets states to be binary, therefore when $r_i = 0$ then asset a_i is in a 'failed' state, defined as having a loss of functionality, and when $r_i = 1$ then asset a_i is in a 'non-failed' state. In the context of an infrastructure asset failure through exposure to a hazard, the conditional failure probability is given by the fragility function $L(r_i|y_i) = \mathbb{P}[r_i = 0|y_i]$. The unconditional failure probability or reliability is calculated by integrating the product of the asset fragility and hazard probability distribution, given below in Equation 6.1.

$$P(r_i = 0) = \int_{y_i} L(r_i|y_i) f_{\mathbf{Y}}(y_i) dy_i = L(r_i|y_i) F_{\mathbf{Y}}(y_i) \tag{6.1}$$

6.2.5 Infrastructure disruption estimation

Given the networked and interdependent nature of the CNI the failure of a single asset can result in a cascade of failures, resulting in disruptions to users from multiple sectors. As such, we are interested in understanding the disruptions that can result due to the failure of the single asset. For any give asset (source, intermediate or sink) a_i we can assemble the set D^k of all sink assets from a particular infrastructure sector that it is supplying to through network functionality. So for example, and electricity asset not only supports users of electricity but also, indirectly through interdependencies, supports users of water, gas and telecommunications. The number of users from a given sector dependent on a_i is given by $S_i^k = f(\bigcup_{\forall a_l \in D^k} S_l^k)$, where the function f depends upon the capacity of the asset to serve the total demand $\bigcup_{\forall a_l \in D^k} S_l^k$ of all sinks in the set D^k.

We collect all the disruptions that can occur from the failure of a single asset with the disruption vector $\boldsymbol{S}_i = \{S_i^1, \dots, S_i^z\}$ for z sets of infrastructure users associated with different infrastructure sectors that would be affected by the asset, if it were to fail. We assume that failures are static in nature and that failure-related disruptions remain for a given duration of time. Asset disruption ΔS, is given as $\Delta S = S - \boldsymbol{S}_i$ where (S) is the pre-disruption service delivery.

6.2.6 Economic loss estimation

Two forms of economic loss are considered in this methodology: (i) the direct costs associated with the restoration of the asset following failure after exposure to the hazard. This is given by the function of each $K(r_i) \equiv K(r_i = 0)$ and relates to the component restoration or replacement costs following failure; and (ii) economic flow losses that occur due to the loss of service associated with the failure of the asset. To calculate this we use the Leontief economic input output model, given in vector form as, $\mathbf{q} = \mathbf{Aq} + \mathbf{c}$, where sector outputs ($\mathbf{q} \in \mathbb{R}^{n\times 1}$) are distributed to meet inter-industry economic flows (intermediate demand sales) ($\mathbf{Aq} \in \mathbb{R}^{n\times n} \times \mathbb{R}^{n\times 1}$) and final demand sales ($\mathbf{c} \in \mathbb{R}^{n\times 1}$) for n sectors in the macroeconomic system (Leontief 1986). To compute the total (direct and indirect) propagation of losses through the macro economy, we assume that, for a given infrastructure sector l, the ratio between the economic loss ($\Delta c_l(r_i)$) and cost of pre-disruption service delivery (c_l) is same as the ratio between amount of service disrupted ($\Delta S_l(r_i)$) and pre-disruption service delivery (S_l), i.e. $\Delta c_l(r_i) =$

$\frac{\Delta s_l(r_i)}{s_l} c_l$. Using the demand loss vector $\Delta\mathbf{c}$, the total service related economic losses are derived by solving the system $\Delta\mathbf{q}(r_i) = [\mathbf{I} - \mathbf{A}]^{-1}[\Delta\mathbf{c}(r_i)]$. Finally, the total economic losses incurred during failure of the infrastructure asset are given by:

$$D(r_i) = K(r_i) + \sum_{i=1}^{n} q_i(r_i) \qquad (6.2)$$

6.2.7 Infrastructure asset adaptation cost-benefit characterization

The expected annual damages associated with the asset a_i for a given hazard type is given by $EAD_i = D(r_i)P(r_i)$. Given the threat posed by current and future hazards, we have the possibility of investing in different adaptation options, for example, flood defences to protect an asset against flooding. Such options are used to reduce the impacts of disruptions that might arise from an asset failure. An example of an adaptation measure is the installation of a flood defence around the asset. The benefits of the measure would be the reduction in expected average annual damages from the flood hazard, calculated previously as: EAD_i measured against the 'do nothing' case. The costs C_i would be the investment costs for installing the flood measure. Given the time value of money, benefits and costs are given as Net Present Values (NPVs) calculated using a discount rate ρ. The NPV for a project is calculated as

$$NPV_i = \sum_{t=t_0}^{t_z} \frac{EAD_i^t - C_i^t}{(1+\rho)^t} \qquad (6.3)$$

Where the project start year is given by t_0 and end year t_z the costs and benefits of the project at time t are given by C_i^t, EAD_i^t respectively. Projects with a positive NPV_i value are considered favourable for investment.

6.2.8 Implementation of the methodology

Figure 6.2 provides a framework for the implementation of the methodology outlined in the previous sub-sections of this paper.

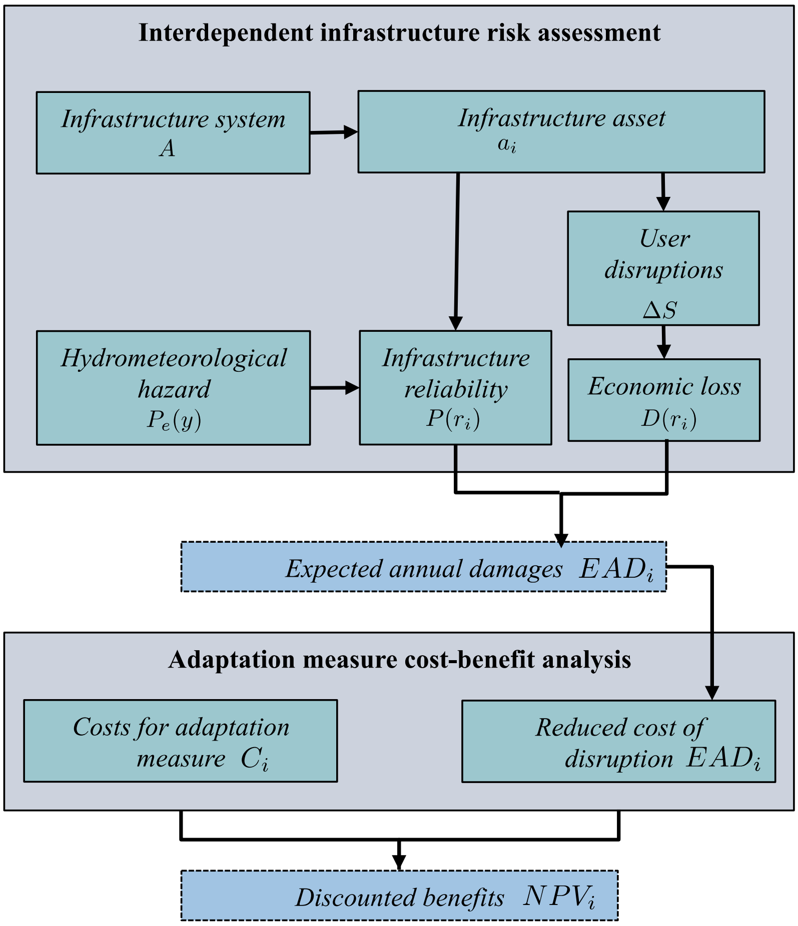


Figure 6.2: Framework from implementation of the methodology for the evaluation of the benefits of adapting interdependent infrastructure systems to reduce hydrometeorological hazard risks.

6.3 Adapting key electricity substations in England and Wales to reduce flood hazard risks

6.3.1 Overview of the system

Despite the UK's national electricity transmission system being built with considerable redundancies, security requirements do not provide for the complete loss of a grid substation, in such circumstance, customers may suffer a loss of supply (Energy Networks Association, 2011). This vulnerability has been highlighted on several occasions over the last decade, including: In 2005 when a major flood event in Carlisle in the UK caused the failure of the Willowholme electricity transmission substation, which resulted in power loss to 60,000 homes and caused disruption to mobile phone systems (Convery and Baily, 2008). During the summer of 2007, widespread flooding in the Midlands, South Yorkshire and Gloucestershire resulted in multiple electricity failure and near miss events. This included: the flooding and failure of Neepsend substation which resulted in service disruption to 40,000 people spread over for 5 days; the forced shut-down of Castle Meads substation with power loss to 42,000 people for up to 24 hours and the near miss flood event at Walham substation, where the deployment of temporary defences helped protect power supply for 500,000 people (Pitt, 2008). The disruptive potential of power loss has also been highlighted by the failure of other infrastructures that have a critical dependency on it. Examples include in 2011 when the loss of electrical power to major exchange in Birmingham resulted in the loss of broadband connection to hundreds of thousands of customers across the UK (BBC, 2011) and in 2013 flooding of local electricity substations resulted in power losses at Gatwick airport, contributing to the disruption of 13,000 airline customers (McMillan, 2014).

As a direct result of the 2005 and 2007 flood events, a collective initiative between government and industry resulted in the development of the guidance document: ETR 138 – Resilience of flooding of primary and grid substations (Energy Networks Association, 2009). The document sets out guidance for the adaptation of substations to protect against flood risk. The Energy Network association (ENA) recommends, that major electricity assets (from the National transmission systems) be resilient to the level of flooding that may occur in a 1:1,000 year flood contour. Following the release of this guidance document, the transmission network owner (National Grid plc.) has identified assets at risk and has begun the process of adaptation measure installation.

Within the following sections of this study we provide a flood risk assessment for major (transmission) electricity substations within England and Wales and use this information to explore the business case for adaptation to reduce flood risks. The explicit representation of network interconnectivity and infrastructure interdependence within the analysis is used to ensure that the cascading consequences of disruption and hence the true benefits of adaptation are incorporated. We calculate the benefits that have already been achieved, and that are still to be achieved, due to the implementation of ETR 138.

6.3.2 Infrastructure network hazard risk assessment

To estimate flood risks we have used the National Flood Risk Assessment (NaFRA) flood likelihood map data (Environment Agency, 2012) illustrated in Figure 6.4(a). The map data provides information on the actual likelihood of flooding to areas of land within the flood plain of an extreme flood (0.1 per cent or 1 in 1000 chance of both fluvial and tidal flooding in any year). The likelihood of flooding is estimated based on assessments undertaken for 85 river catchments and coastal cells (50m x 50m), taking in account the probability that the flood defences will overtop or breach, and the distance of the impact cell from the river or the sea. The results of the analysis are presented for three flood likelihood risk categories (exceedance probability) as (i) low: $P_e = 0.004$, (ii) moderate: $P_e = 0.01$, and (iii) significant: $P_e = 0.014$.

Table 6.1 presents asset data from the energy, transport, water, waste and communications sectors that have been used in the analysis. At the centre of the analysis and hence CNI network is a representation of the integrated electricity network for England and Wales. The network integrates data from the transmission system that is owned and operated by the National Grid and from six Distribution Network Operators (DNOs) who manage the sub-transmission and distribution networks. Electricity generators are embedded at different voltage levels of the integrated network. Domestic electricity users are supplied with electricity via a connection to electricity distribution sub-stations, supplied at 11kV. Figure 6.3 provides a representation of this network.

Table 6.1: List of assets included in the spatial criticality analysis. Detailing the data sources used to complete the spatial topological network representations and the capacity and demand data used to estimate the functional path set and assign customer demands.

Sector	Spatial and Topological Attributes	Capacity and Demand Attributes
Electricity generation • Owners: Multiple • Nodes: 207	Generator node locations derived using DECC 2012 DUKES data (DECC, 2012)	Individual generator capacity values derived using DECC 2012 DUKES data (DECC, 2012)
Electricity transmission • Owners: National Grid • Nodes: 437	Transmission network derived from National Grid maps (National Grid, 2012), using spatial network recreation (Barr et	User demands derived using capacity constrained location allocation – detailed in paper, based on Thacker et al. (2014)

	al. 2013)	
Electricity sub-transmission • Owners: Multiple DNOs • Nodes: 4798	Sub-transmission network derived from OS MasterMap topography layer node and edge data (Ordnance Survey, 2015), using spatial network recreation (Barr et al. 2013)	User demands derived using capacity constrained location allocation – detailed in paper, based on Thacker et al. (2014)
Electricity Distribution • Owners: Multiple DNOs • Nodes: 164,069	Distribution network derived using OS MasterMap topography layer node and edge data (Ordnance Survey, 2015), using spatial network recreation (Barr et al. 2013)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)
Airports • Owners: Multiple • Nodes: 32	Airport locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived from CAA 2010 flight statistics (CAA, 2010)
Water towers • Owners: multiple • Nodes: 2566	Water tower locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)
Waste-water treatment • Owners: multiple • Nodes: 1563	Waste-water treatment locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)
Telecom masts • Owners: multiple • Nodes: 5226	Telecom mast locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)

Table 6.1 also highlights a number of point asset dataset's that are used to represent the location of airports, ports, railway stations, water towers, wastewater treatment plants and telecommunication towers. Each asset of these specific types is dependent on electricity for its operation. In many cases, the nature of the physical connection between the dependent asset and its supporting electricity asset is unknown. We complete our CNI representation by building a dependency edge between the asset and its nearest (geographically closest) electricity asset of

appropriate voltage. Figure 6.3 provides a mapping that describes the voltage level at which the different infrastructures typically connect.

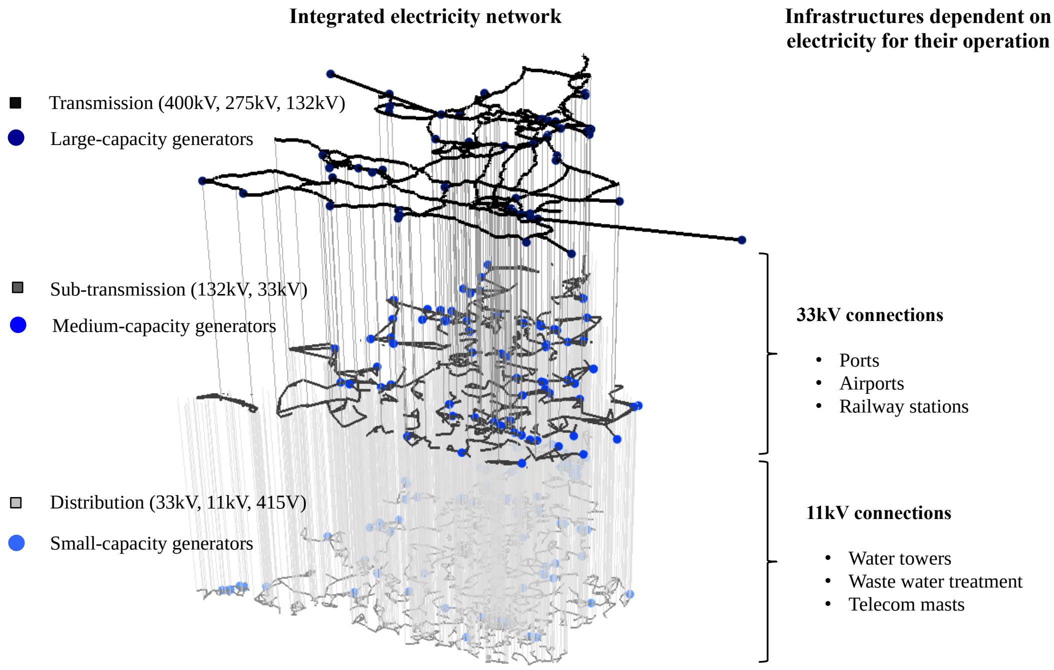


Figure 6.3: A representation of the integrated electricity network for England and wales; consisting of the electricity power generation, transmission, sub-transmission, distribution sub-systems. Highlighted on the figure are the voltage-level dependency mappings for a number of connected assets: Airports; ports, railway stations; water towers; wastewater treatment works and telecom masts.

Electricity networks support the transmission and distribution of electricity from generators to electricity users who are connected at the distribution sub-station level of the integrated electricity network. Electricity is also supplied to a range of dependent infrastructures that are connected to sink assets that are distributed throughout the integrated electricity network, as given in Figure 6.3. Due to issues relating to commercial and customer constraints, user data is not available for this study. To estimate user demands on electricity transmission assets from a range of customers, a functional network algorithm as demonstrated in Thacker et al. (2014) is used to estimate user numbers across sectors. The algorithm is based of the assumption that electricity flows through the network from sources (electricity generators) to sinks (electricity distribution substations) through a path of least resistance within capacity constraints. To apply this principle we use a capacity constrained location-allocation optimization algorithm to estimate user counts S_i^k for a range of sectors to derive the total disruption vector $\boldsymbol{S}_i$.

The impacts of failure are measured in terms of the potential economic losses that could result if the substation were to fail. To calculate these losses we translate the user disruption estimates using economic input output analysis. To do this, matrix $\mathbf{A}$, which represents structure of the economy and effects on inter-industry relationships, is assembled using large-scale economics data sources (Yamano and Ahmad, 2006) for England and Wales, national-level statistics for 2009 (ONS, 2009).

We assume that without adaptation (i.e. without installing a flood protection measure), that flooding in the location of the substation would result in its failure. The benefits of protecting the substation are evaluated in monetary terms by calculating the expected annual damages EAD_i at the site given the exceedance probability associated with the flood map that the asset intersects. Benefits are evaluated against the 'do nothing' where no adaptation is implemented i.e. no flood protection measure.

6.3.3 Adaptation measure cost benefit analysis

The possibility of a large concentration of consumers being disconnected in a single flood incident provides a substantive focus investment to improve resilience to flooding (Energy Networks Association, 2009). In accordance with this vision, the Energy Networks Association describes three categories of asset-level flood defence that can be used for flood adaptation risk reduction. This includes:

Permanent: Installing a permanent defensive wall; building an earth embankment; raising critical assets within the substation; relocation of the substation.

Demountable: Building demountable critical component protection; building demountable flood protection around site.

Temporary: Including the use of temporary barriers at the site.

During a trial of temporary and demountable flood defences, the Environment Agency (2011) found that such defences do not offer a large-scale alternative to permanent defences. This was mainly due to the large lead in time that is required to deploy and build temporary defences, particularly at times when resources are stretched. Coupled with the increased potential for disruption to transport infrastructure during flooding events, temporary defences thus are at risk of not being deployed. Given this evidence, the remainder of this study will consider permanent flood defence adaptation options only.

Within this study, flood risks are calculated and adaptation measures evaluated at individual transmission substations identified as being at risk of flooding. We assume that the adaptation measure provides complete protection of the asset and therefore we omit the calculation of residual risk. Table 6.2 provides typical costing's for three different permanent flood defence measures for standard electricity transmission substations that typically operate at 275kV-400kV, as set out in ETR 138. The Energy Networks Association recommends that all transmission substations be protected against a 1 in 1000 year event, with a target completion date for all planned works of 2022 (Energy Networks Association, 2009).

Table 6.2: Description and estimated cost of electricity substation permanent flood protection measures.

Permanent flood defence option	Cost C_i for a standard transmission substation operating at 275kV-400kV
Build protective wall (<1.2m)	£410,000
Raise elevation of substation (1.2m)	£14,500,000
Relocate substation	£45,000,000

The costs and benefits of installing flood defence adaptation measures are evaluated from a start date of $t_0 = 2015$ for an asset life of 45 years, giving an end date of $t_z = 2060$. This aligns with the planning horizon and risk evaluation planning of the main transmission electricity provider in the UK: National Grid (Met Office, 2006) and the average lifetime of an electricity transformer of 40 years (which is the largest capital expense in an electricity substation) (U.S Department of Energy, 2012). Initial substation repair and restoration costs that result from direct damage to the asset are given as $K(r_i) = £4{,}500{,}000$. This figure aligns with real flood-related damage estimates of similar assets, for example, £4,000,000 relating to Osgodby supply point in 2000 (Northern Powergrid, 2012); £5,000,000 relating to Willowholme substation in 2005 (Environment Agency, 2006) and a total of £9,000,000 relating to Neepsend and Castle Meads substations in 2007 (Environment Agency, 2010). In alignment with the historic flood events of 2005 and 2007, it is assumed that flood inundation of the substation will disrupt services for 3 days. In alignment with UK Treasury guidance, a discount rate of $\rho = 0.035$ has been chosen for the cost-benefit analysis (HM Treasury, 2014). Recognizing the uncertainty in these parameter values we accompany the initial NPV results with a sensitivity analysis.

6.4 Results

6.4.1 Key electricity asset flood risk

Figure 6.4 (b) presents a map that shows the location of transmission sub-station assets that are situated in either a low, moderate or significant flood likelihood risk areas. 43 assets were found to be at low risk of flooding, 32 at moderate risk of flooding and 32 at significant risk of flooding.

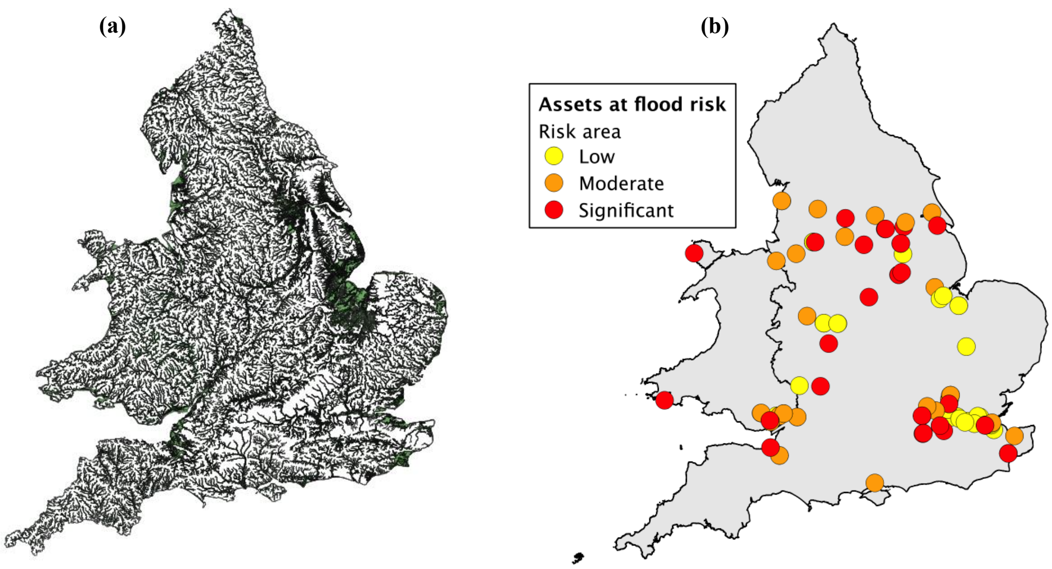


Figure 6.4: (a) NaFRA flood likelihood map for England and Wales (b) Highlights electricity transmission assets located in low, moderate or significant flood risk zones

Within the integrated electricity network, 169520 substation assets are represented from the transmission and sub-transmission and distribution sub-systems. Analysis reveals that 13348 assets (8% of all electricity assets) are involved in supporting dependent assets from other infrastructure sectors. Within the transmission network, 636 assets (99% of all transmission assets) are involved in supporting dependent assets. The magnitudes of impacts of failure for key electricity transmission substation assets measured in terms of the number of users disrupted are shown in Figure 6.5. The figure highlights the heterogeneous impacts that can results from asset failures for a range of different infrastructure service types. The results show that most of the electricity assets at the transmission level have the potential to impact a larger number on indirect non-electricity users compared to direct electricity users. In particular around (70%) of the major electricity substations could potentially indirectly affect, if they were to fail, at least three times as many users as they directly serve.

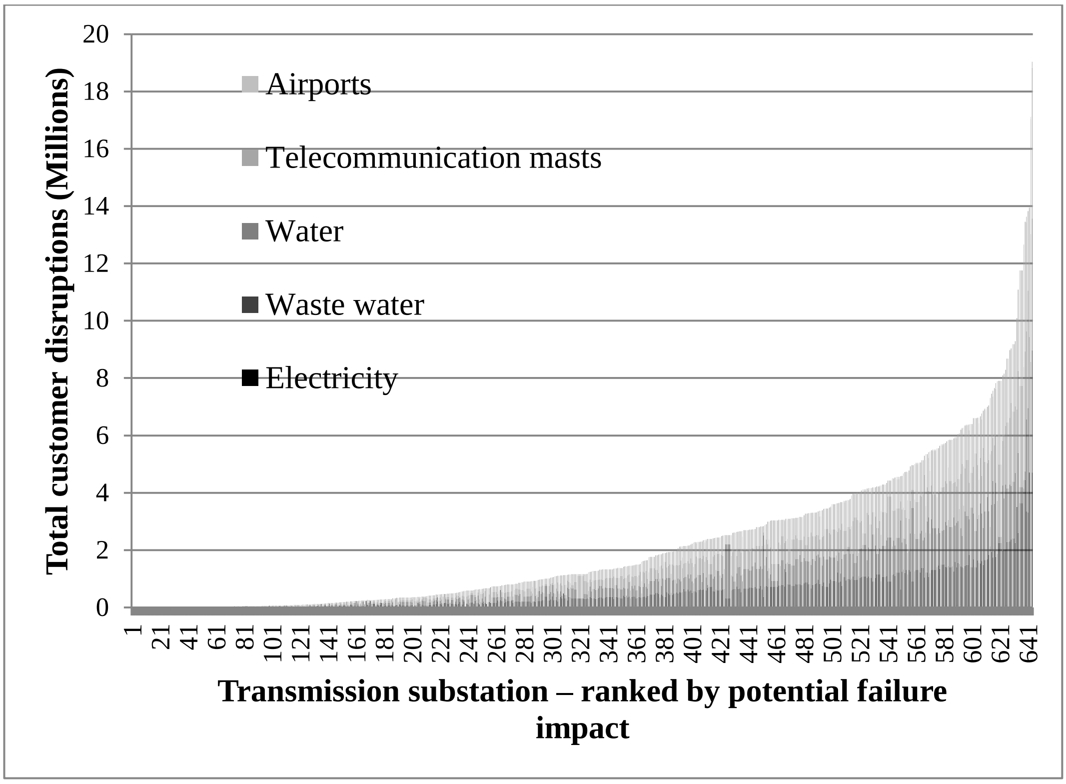


Figure 6.5: Transmission substations ranked by total potential customer disruptions for the electricity, telecommunications, water, wastewater and airport sectors.

6.4.2 Business case for adapting electricity assets to reduce flood risk

Figure 6.6 shows the NPV for the three different adaptation measures at 2060 (45 years asset life from implementation in 2015), assuming that the flood disrupt services for 3 days, that direct asset damages are £4,500,000 and that cash flows are discounted at a rate of 3.5%. Results highlight that for all 107 assets at risk of flood, the installation of a floodwall to protect against failure related losses results in a positive NPV, making the option favourable for investment. Under these 'most likely' parameter values, only 4 substation assets show a positive NPV for the substation raise option and no assets show a positive NPV for the substation relocation option. The ranked distribution of NPVs for individual substations provides guidance as to the most cost-effective targeting and prioritization of investment in protection. It is however recognized that adaptation through the installation of permanent measures, such as those suggested in this paper, may have local constraints such as planning permission issues that may ultimately limit any investment or physical work and hence protection.

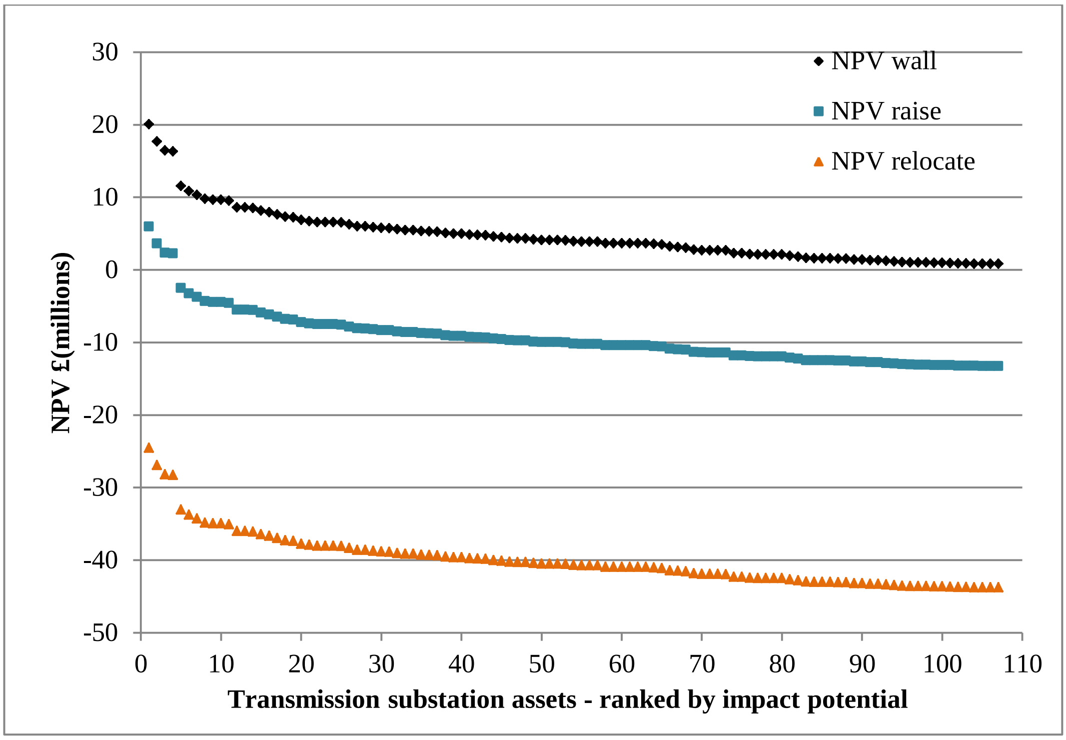


Figure 6.6: NPV cost benefit for 3 different adaptation measures using a 45 year asset life, disruptions that have a duration of 3 days, direct asset damages of £4,500,000 and a discount rate of 0.35.

To address the uncertainty inherent in the selection of the direct damages, disruption duration and discount rate parameter values, we provide the following sensitivity analysis. Undertaking such analysis provides the opportunity to test the business case for investment under a variety of possible parameter values, ensuring that decisions towards investment are robust under a range of possible futures.

Figure 6.7 shows the number of assets with a positive NPV (NPV greater > 0) for the three adaptation options with varying direct asset damages, set between £0 and the total asset cost £45,000,000, evaluated at 20 equal intervals. For this sensitivity analysis the asset life was fixed at 45 years, the duration of the disruption at 3 days and the discount rate equal to 0.035. The plot highlights the floodwall adaptation option displays a positive NPV for all 107 assets when direct asset damage is greater than £2,500,000 and a positive NPV for 79 assets when there is no asset damage. Progressively larger numbers of assets show a positive NPV for the substation raising option when direct damages exceed £10,000,000. This increase slows when direct damages exceed £20,000,000 until, at the total asset cost £45,000,000, 73 assets are favourable for investment. The relocation option shows no positive NPV assets until direct damages exceed 31,500,000. At total asset rebuild cost of £45,000,000; there is a business case to invest in relocating 16 assets.

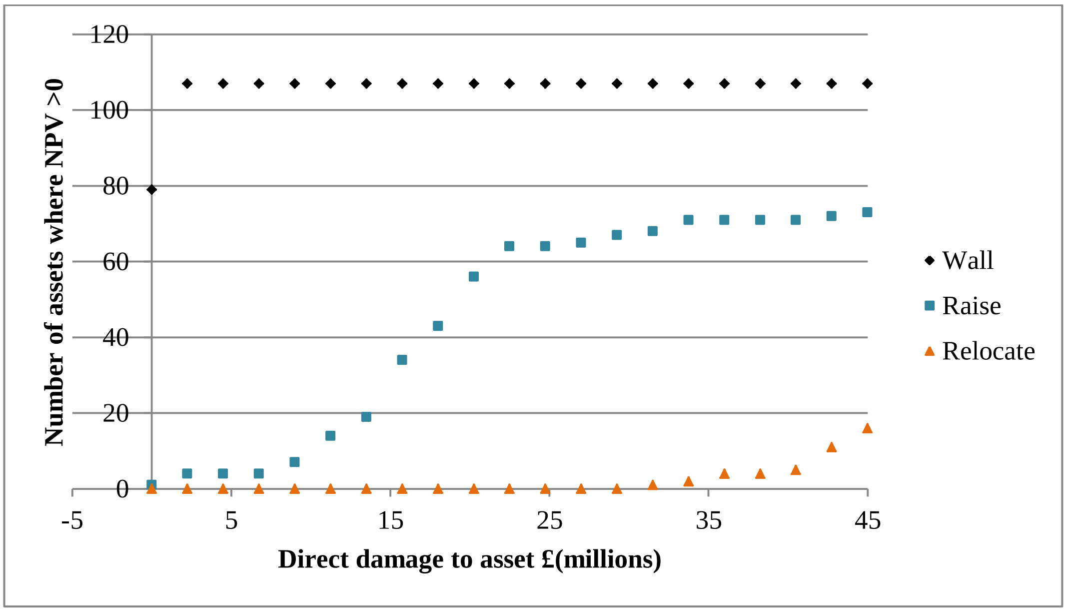


Figure 6.7: Sensitivity plot highlighting the number of assets that have a NPV > 0 for each of the three adaptation measures with varying direct damages. For these scenarios, the asset life was fixed at 45 years, the duration of the disruption 3 days and the discount rate 0.035.

Figure 6.8 shows the number of assets with a positive NPV (NPV greater > 0) for the three adaptation options with varying discount rate values, set between 0 and 20%, evaluated at 20 equal intervals. For this sensitivity analysis the asset life was fixed at 45 years, the duration of the disruption at 3 days and the direct damages set at £4,500,000. All 107 assets with the floodwall adaptation option show a positive NPV until the discount rate reaches 15% at which time a progressively smaller number of assets are favourable for investment. At the maximum discount rate of 20%, 88 assets show positive NPVs for this option. At a discount rate of 0, 20 substation assets show a positive NPV for the raise option. This number decreases steadily until no assets show a positive NPV at a discount rate of 6%. No substation assets are favourable for investment to be relocated under the range of tested discount rates and other stated scenario parameters.

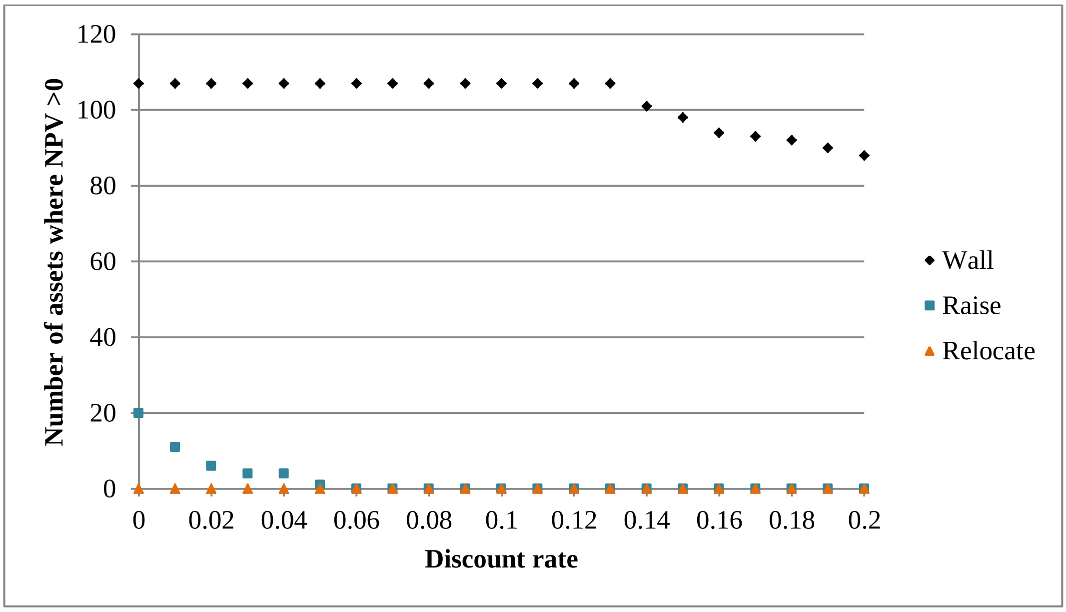


Figure 6.8: Sensitivity plot highlighting the number of assets that have a NPV > 0 for each of the three adaptation measures with varying discount rate. For these scenarios, the asset life was fixed at 45 years, the duration of the disruption 3 days and the direct damages £4,500,000.

Figure 6.9 shows the number of assets with a positive NPV (NPV greater > 0) for the three adaptation options with varying duration of disruption, set between 0 and 10 days, evaluated at 20 equal intervals. For this sensitivity analysis the asset life was fixed at 45 years, the duration of the direct damages set at £4,500,000 and the discount rate set at 0.035. The plot shows that with disruption duration of 0.5 days, 80 assets are showing a positive NPV for the floodwall option. In advance of 1.5 days disruption, all 107 assets are favourable for floodwall investment. Raising the substation shows a positive NPV when the disruption exceeds 2.5 days and increasing numbers of asset are positive as the maximum number of days is reached. At this maximum (10 days), 53 assets show a positive NPV for the raise option. Similarly, the relocate option is favourable for investment only when the disruption exceeds 7 days duration. At 10 days disruption, 4 substations show a positive NPV for the relocate option.

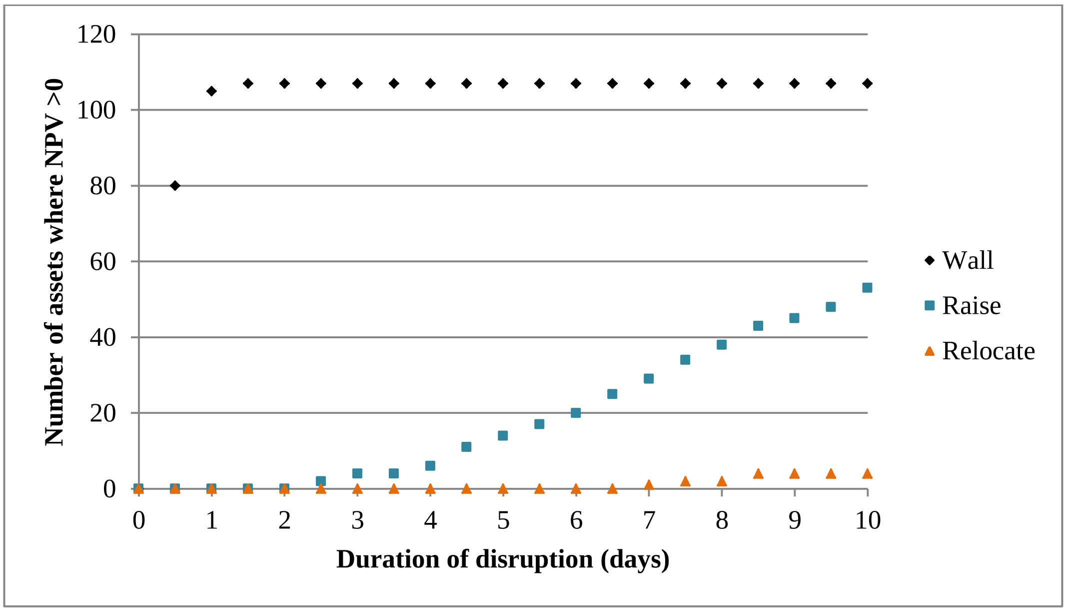


Figure 6.9: Sensitivity plot highlighting the number of assets that have a NPV > 0 for each of the three adaptation measures with varying days of disruption. For these scenarios, the asset life was fixed at 45 years, direct damages £4,500,000 and the discount rate 0.035.

6.4.3 Progress made to date: UK ETR 138

The Energy Networks Association has set National Grid a target of installing flood protection measures at all ‘at-risk’ substations before 2022. Table 6.3 gives the number of substations so far protected by National Grid. At the present time (2015), 7 assets at 1:100 risk of flooding and no assets at 1:200 or 1:1000 risk have been protected.

Given this information, the total expected annual losses avoided due to installing flood protection measures 7 years ahead of schedule (2015 instead of 2022), due to the adaptation plan established by the Energy Networks Association, is £14,600,000. This assumes that National Grid have targeted their investment at the assets likely to cause the largest disruptions (at risk of 1:100 year flooding), that the duration of disruption would last 3 days, that direct asset damages are £4,500,000 and with a discount rate of 0.035. Were National Grid to bring forward the remainder of the works, scheduled for 2022 to completion this year, and then this would result in an additional saving of £133,260,000 in avoided expected annual losses. Despite the financial incentive to proceed with adaptation, local planning may constrain implementation on this time scale.

Table 6.3: Progress made to date by National Grid on implementation of ETR 138.

Risk	Number of sites	Completed works	Remaining
1:100	11	7	4
1:200	26	0	26
1:1000	65	0	65

6.5 Conclusions

In this study we have provided methodology and applied analysis for evaluating the benefits of investment in adaptation of interdependent critical infrastructure to reduce hydrometeorological risks. A national scale demonstration is presented for investment in flood protection measures of major electricity substations in England and Wales.

Results show the large-magnitude impacts that can result from the failure of major electricity substations in England and Wales. Positive NPV values highlight the business case for adapting these substations through the installation of permanent flood protection walls to reduce hydrometeorological hazard risks. Using a sensitivity analysis it is shown that this options performs well under a range of future uncertainties, including the direct damages and the duration of disruption that are the most sensitive parameters in the analysis.

Investment in high cost adaptation options such as raising the substations and relocating the substation are cost-beneficial in only a limited number of cases. The business case for investment in such options may become more attractive when an asset is approaching the end of its life. Due to the inclusion of infrastructure interdependencies and indirect economic effects, the magnitude of the impacts of asset failures is discovered to be highly heterogeneous. Prioritization of adaptation investments using ranked impact provides the most cost effective way to develop a programme of risk reduction. Although, implementation of the ETR138 guidance has resulted in cost-effective risk reduction to flood hazards, we find that there is a significant benefit to bringing forward in time adaptation measure installations that are currently planned for coming years.

The general methodology presented within this paper has a broad applicability for a range of different infrastructures, interdependency types and geographic areas. Future developments of this work could include the incorporation of time-varying probabilistic hazard data that is capable of representing the changes expected to occur within the climate system over the coming decades. In addition to a changing climate, we can also expect that the technical infrastructure systems, the nature of interdependencies, the number of users and the economic activity reliant on them are set to change. Incorporation of these factors and the uncertainty that surround them would be a valuable extension of this research – ensuring that the benefits of adaptation decisions are robust under a range of possible futures. Incorporation of data on asset life cycles would further enhance this research, providing decision makers with additional information to optimally structure investments. Further research could also explore options for equitably distributing the costs of adaptation investments in a proportionate manner to the different owners of other infrastructures who benefit from indirect losses averted.

Collecting and assembling the high-resolution, national scale data for such an analysis represents a significant challenge. This is not only because of the variety of data needed from different infrastructure sectors, but also because local information on individual assets and their customer demands are often restricted due to matters relating to security, privacy and commercial sensitivity. Where data have not been available, we have utilized a number of existing techniques such as spatial analysis, network path-based techniques and economic input-output modelling to estimate asset-related user disruptions and economic losses. Despite the NaFRA dataset being the flood map of choice for most UK governmental departments (i.e. the EA), since the 2015 Cumbria floods, questions have been raised as to the accuracy and completeness of these datasets. This specifically relates to an underestimation of the return period of events that have occurred over the past decade. Interpretation of results from this analysis should therefore reflect this uncertainty. Uncertainty also exits in the estimation of indirect costs using the input-output methodology, more specifically in the derivation of economic losses using a fixed retail price. In reality this could be an underestimation, given customers increased willingness to pay when faced with a complete loss of power. The inclusion of a sensitivity analysis provides a means to explore inherent uncertainties within the analysis, including the selection of discount rate, the duration of disruption and the direct damages caused during the hazard event.

The critical national infrastructures upon which society and the economy depend face an increasing risk from hydrometeorological hazards. In order to reduce this risk, methodology and analysis is required to evaluate the business case for investment and efficiently target resources. Within this paper we address this need, providing evidence to inform risk-based decision making by highlighting the cost-beneficial nature of adaptation and the most efficient way to target and sequences adaptation investments. Despite recognized uncertainties, this study provides a number of important applied insights for decision makers concerned with the safe and reliable operation of the critical national infrastructure.

7. Conclusions

7.1 Summary of the Thesis

The overall aim of this thesis was to *develop methodology and analysis for understanding and reducing the risk of failure of national interdependent infrastructure network systems*. The content of the thesis provides evidence as to how this objective has been met; the substantive content falls within four first author peer-reviewed journal articles that have been presented in relation to the four research challenges and related sub-objectives, established in Section 1.2.

In summary, Chapter 3 (Paper I) provides methodology to produce synthetic representations of multi-level infrastructure network systems. These representations being necessary due to the lack of real-world infrastructure network data required to underpin network risk based studies. An application of the algorithm is performed to build a representation of the electricity network hierarchy within England and Wales.

Chapter 4 (Paper II) outlines methods to develop a system-of-systems based analysis to characterise failure propagation within physically interdependent infrastructures. This methodology was applied at the national-scale for England and Wales for the electricity network hierarchy (developed in Chapter 3) and domestic airline network. The analysis highlighted the magnitude of disruptions (to both electricity and airline customers) that could result from the failure of individual electricity assets. In doing so, it extends our understanding of the risks of failure of physically interdependent infrastructure.

Chapter 5 (Paper III) presents methodology to identify geographic hotspots of critical infrastructure, which incorporates the effect of physical and geographic interdependence. Supporting this methodology is a national-scale demonstration, incorporating asset-data from the energy (developed in Chapter 3), transportation, water, waste and digital communications sectors. The analysis produces a number of maps that provide evidence as to why the inclusion of data on customers and interdependencies is critical for accurately identifying failure risks.

Chapter 6 (Paper IV) presents methodology that integrates estimates of interdependent infrastructure failure impact (developed in Chapters 4 and 5) with probabilistic hazard risks and adaptation costs to identify the business case for infrastructure adaptation. With an application for major electricity transmission substations in England and Wales (developed in Chapter 3), investments were, on the whole, shown to be cost-beneficial to reduce risks. Chapter 6 of this thesis therefore gives a means to understand and reduce the risk of failure in an efficient and cost-beneficial way.

During the thesis, a high-resolution (asset-level), system-of-systems, network-based approach has been adopted. This has required large amounts of data from multiple sectors (energy, water, transportation, waste and digital communications sectors) on infrastructure location, connectivity, interdependence and usage to be assimilated in a coherent framework. There are a number of merits in following this approach. The first is that an ‘asset-level’ infrastructure representation is appropriate for analysis that is aimed at informing decision makers on the likely consequences of asset failures and thus the business case for investing in protection measures. This is particularly important due to the heterogeneous nature of infrastructure systems, and the variety of impacts that can arrive due to their failure.

In order to capture these heterogeneities we have adopted a systems-of-systems based approach that evaluates infrastructure performance as the collective function of physical infrastructures for the purpose of delivering services to society and the economy. Intuitively, the integration of data from different infrastructure sectors yields important new insights, particularly when considering the disparate nature under which these systems have evolved and are currently designed, operated, managed and regulated. The analysis also highlights the importance of incorporating information on different infrastructure sub-systems within a system that often have different owners, but however function collectively for a single purpose i.e. the provision of electricity. The multi-level network paradigm and description of these systems as a functional hierarchy, provides a useful conceptualisation for this approach.

The analysis shows that, due to network effects and interdependencies, the failure of 'smaller assets' (such as electricity sub-transmission assets), not usually the focus of applied studies, can have large-scale impacts (equivalent to the failure of 'large assets'). The omission of smaller assets from other studies is reflective of the poor availability of data. The development of the synthesis algorithm within this thesis provides a method for integrating these limited quantities of data to reproduce networks which preserve the most salient properties of the network infrastructure – opening up studies that were previously not possible. As well as providing new theoretical and applied insights, these methods can provide 'realistic' models that can be demonstrated to infrastructure owners and operators and used to leverage real-data for future studies.

It is found that the impacts of failure can be spatially widespread due to the function of networks of delivering resources from production sites to demand centres. As highlighted within the analysis, the inclusion of information on infrastructure usage and interdependence is key to correctly identify critical infrastructure geographic hotspot concentrations. Results highlight that data on population density and asset concentration density are not, in isolation, reflective of geographically critical areas. Rural areas and urban areas on the periphery of cities also play a key role in the delivery of infrastructure services and should be candidates for investment alongside population dense areas.

The analysis also highlights the cost-beneficial nature of adaptation of critical infrastructure to reduce the risks of failure – helping to adapt the national infrastructure to possible threats. Research within this thesis provides a closed loop: from the mapping of the national infrastructure, the development of methods for failure propagation, the identification of geographically critical areas and practical cost beneficial solutions for reducing the risks of failure. In doing so, the thesis provides novel research-based developments, and important evidence to inform decision-making in government and industry.

Assembling the data required to perform multi-sector, national scale analyses represents a significant challenge. This is not only because of the variety of data needed from different sectors, but also because information on infrastructure users are often restricted due to matters relating to privacy, security or commercial sensitivity. Due to these complexities, a variety of practical approaches have been demonstrated for synthesising and estimating data that has not been available. This includes the algorithm for producing synthetic network representations, and the allocation of users to assets through Voronoi decomposition and network path based assignments. A dynamic approach for estimating users would be a valuable extension to this work, though the data and computation requirements to facilitate such an analysis may prove prohibitive at the national-scale.

7.2 Main Research Contributions

This thesis provides methodology and national-scale applied analyses with real-world data to understand and reduce the risks of failure of interdependent national infrastructure network systems. In doing so, it not only extends the state-of-the-art research in the field, but also acts to provide evidence to a range of decision makers in government, business and industry. By employing a system-of-systems network approach, the analysis is able to transcend the sectorial and operational boundaries, providing important new insights into failure, disruption, criticality, vulnerability and risk. The main research contributions achieved with this thesis are as follows:

- A system-of-systems formulation for critical national infrastructure systems that represents infrastructure systems as multi-level networks that have characteristic functional behaviour at different operational scales.
- The development of an algorithm for producing synthetic representations of multi-level infrastructure network systems.
- Methods for estimating failure propagation and customer disruptions of critical national infrastructures.
- Definitions and methods for calculating infrastructure asset criticality and infrastructure criticality hotspots.
- Methods for appraising infrastructure adaptation measures using a system-of-systems disruption model.

- A variety of applied analyses that are performed on datasets from multiple sectors at the national scale.
- A number of practical applications that have helped to inform decision makers with government and industry.

7.3 Practical Applications of the Research

One of the overarching objectives of this thesis was to develop methodology and applied analyses that would be applicable and useful to a broad range of decision makers within government and industry. Through the presentation of three examples, the following subsections provide evidence as to how this objective was met.

7.3.1 Identifying Criticality Hotspots with HM Treasury

Chapter 5 of this thesis describes methodology and applied analysis to identify geographic hotspots of critical national infrastructure. This research was developed in response to a challenge set by Infrastructure UK (IUK) in HM Treasury, to identify spatial hotspot locations in England and Wales that took into account interdependencies and indirect network effects. Following interaction with IUK over several months, the research (and subsequent paper which is provided in this thesis) has already been put to use. In the first instance, by highlighting key national hotspots that were to be evaluated at more local scales for resilience planning, and secondly, as an exemplar as to the manifestation of physical and geographical interdependence and the need to incorporate this within applied analyses.

7.3.2 Infrastructure Flood Risk Assessment for SAGE

During the 2013-2014 winter storms, the Chief Scientific Officer and the Special Advisory Group for Emergencies (SAGE) used outputs from the physical interdependence model (described in Chapter 4) to identify the numbers of customers at risk of disconnection from essential services due to continued flooding in the Thames catchment. The research helped to evaluate the extent to which the local population could be disrupted and subsequently assisted in emergency preparedness.

7.3.3 Cyber Threat Risk to the South East of England

The physical interdependence model (described in Chapter 4) was also used in a study, commissioned by Lockheed Martin and the Cambridge Centre for Risk Studies, to examine risks posed to the population and economy of South East England due cyber hacking of the electricity power grid. Application of the model in this context allowed the characterisation of disruption of not only directly connected electricity customers but also indirect disruptions to other sectors (as described in Chapter 5).

7.4 Future Research Directions and Activities

Despite the contributions made in this thesis and by advances from other researchers around the world, the understanding of the risks of failure in interdependent infrastructure systems remains in its infancy. The following paragraphs provide a selection of future research directions and activities that will help to improve this understanding and ensure that theoretical insights have the best chance of making impact with decision makers who are charged with the safe and reliable operation of a multitude of infrastructure systems.

- The development of generalised theory and models that reproduce the salient transient behaviours of service flows that occur on infrastructure networks systems. This could include the transient response to shocks, for example, recovery from failures. Such models will contribute towards a more comprehensive understanding of infrastructure resilience.
- The development of methodology and applied analyses for assessing the risks of failure faced to future infrastructure network systems. For example, future electricity power systems that are expected to undergo transformative change over the coming decades e.g. through increasing levels of distributed generation and improved demand response.
- The development of methodology and applied analyses to explore and characterise the implications of cyber interdependencies that manifest through control process and digital communications infrastructure networks.
- To extend national infrastructure models to the global scale for the purpose of understanding risks that exists between nations due to interconnected supply and demand of infrastructure services.
- To develop methodology and tools that can be used to extract infrastructure network topology and service flow characteristics using ‘Big Data’. For example, using mobile phone datasets.
- The development of testing platforms and open datasets that can be used by researchers and industry to validate existing and future models of failure, disruption and recovery.

- The development of interactive simulation and visualisation tools that can be used to engage a variety of decision makers and the general public as to the risks of failure faced to interdependent infrastructures.
- The development of real-time models that can be used to characterise the ‘current’ risk to service losses etc. Using real-time infrastructure loading and hazard data (i.e. weather forecasts at different time scales).

Bibliography

Albert, R., Barabaśi, A. L. 1999. Emergence of scaling in random networks. Science 286 (5439).

Albert, R., Jeong, H., Barabaśi, A. L. 2000. Error and attack tolerance of complex networks. Nature, 406:378-382.

Aldous, D., Shun, J. 2010. Connected spatial networks over random points and a route length statistic. Statistical Science, 25:3:275-288.

Barabási, A. L. 2003. Linked: how everything is connected to everything else and what it means for business, science and everyday life. New York, NY: Plume.

Barr, S., Alderson, D., Robson, C., Otto, A., Hall, J.W., Thacker, S., Pant, P. 2013. "A National Scale Infrastructure Database and Modelling Environment for the UK". *International Symposium for Next Generation Infrastructure,* Australia , 2013.

Barthelemy, M. 2011. Spatial Networks. J.physrep. 499:1-101.

Bashan, A., Berezin, Y., Buldyrev, S. V., Havlin, S. 2013. The extreme vulnerability of interdependent spatially embedded networks. Nature Physics 9(10):667-672.

BBC. 2011. BT suffers huge broadband failure. Retrieved October 3rd 2011, from www.bbc.co.uk/news/technology-15154020 .

Bollinger, LA., Bogmans, CWJ., Chappin, EJL., Dijkema, GPJ., Huibregtse, JN., Maas, N., et al. 2013. Climate adaptation of interconnected infrastructures: a framework for supporting governance. Reg. Environ. Change, 14 (3):919–931.

Bondy, J. A., Murty, U. S. R. 2008. Graph Theory. Springer: Graduate texts in mathematics 244.

Brown, T., Beyeler, W. E., Barton, D. 2004. Assessing infrastructure interdependencies: the challenge of risk analysis for complex adaptive systems, International Journal of Critical Infrastructures, 1(1):108-117.

Brummitt, C. D., Hines, P. D. H., Dobson, I., Moore, C., D'Souza, R. M. 2013. Transdisciplinary electric power grid science. PNAS 110(30) 12159.

Buchholz, B, M., Styczynski, Z. 2014. Smart Grids – Fundamentals and Technologies in Electricity Networks. Springer.

Buldyrev, S. V., Parshani, R., Paul, G., Stanley, H. E., Havlin, S. 2010. Catastrophic cascade of failures in interdependent networks. Nature 464 (7291), 1025–1028.

Burt, G, M., Elders, I, M., Galloway, S, J., Kelly, N, J., Tumilty, R, M. 2008. Assessment of highly distributed power systems using an integrated simulation approach. Proceedings of the Institute of Mechanical engineers, Part A: Journal of Power and Energy 222: 657-668

Cabinet Office. 2010. Strategic framework and policy statement on improving the resilience of critical infrastructure to disruption from natural hazards. Cabinet Office, Whitehall, London.

Cabinet Office. 2011. Keeping the country running: natural hazards and infrastructure. Cabinet Office, Whitehall, London.

Casalicchio, E., Galli, E. 2008. Metrics for quantifying interdependencies. Critical Infrastructure Protection II. Chapter 16. Springer.

CCC. 2014. Managing climate risks to well-being and the economy. Adaptation Sub-Committee, progress report 2014. Committee on Climate Change Adaptation Sub-Committee.

Chang, S. E., McDaniels, T. L., Mikawoz, J., Peterson, K. 2007. Infrastructure failure interdependencies in extreme events: power outage consequences in the 1998 ice storm. Nat Hazards 41:337-358.

Chappin, EJL., van der Lei, T. 2014. Adaptation of interconnected infrastructures to climate change: A socio-technical systems perspective. Utilities Policy 31:10-17.

Chernick, H. 2005. Resilient city: the economic impact of 9/11. Russell Sage Foundation Publications.

Chou, C. C., Tseng, S. M. 2010. Collection and analysis of critical infrastructure interdependency relationships. Journal of computing in civil engineering. 24(6): 539-47.

Cho, S., Gordon, P., Moore, I., James, E., Richardson, H. W., Shinozuka, M., Chang, S., 2001. Integrating transportation network and regional economic models to estimate the costs of a large urban earthquake. Journal of Regional Science 41 (1):39–65.

Ciria. 2010. Flood resilience and resistance of critical infrastructure. Ciria C688.

Civil Aviation Authority (CAA). 2010. Civil Aviation Authority: UK Airport Statistics.

Convery, I., Bailey, C. 2008. After the flood: the health and social consequences of the 2005 Carlisle flood event. Journal of Flood Risk Management 1 100-109.

CST. 2009 A national infrastructure for the 21st century. Council for Science and Technology.

D'Agostino, G., Scala, A. 2014. Networks of Networks: The Last Frontier of Complexity Science. Springer.

Davis, G. 1999. The Auckland electricity supply disruption 1998: emergency management aspects. Australian journal of emergency management 13(4) 44-46.

Department of Energy and Climate Change (DECC). 2012. Digest of UK Energy Statistics (DUKES).

DEFRA. 2011. Climate resilient infrastructure: preparing for a changing climate. Department for Environment, Food and Rural Affairs.

DEFRA. 2012. UK Climate Change Risk Assessment: Government report. Department for Environment, Food & Rural Affairs.

DEFRA 2013. The national adaptation programme, making the country resilient to a changing climate. Department for Environment, Food & Rural Affairs.

Department for Transport (DfT). 2012a. UK Department for Transport: Maritime and Shipping Statistics.

Department for Transport (DfT). 2012b. Tag Unit 3.5.6 – Values of Time and Vehicle Operating Costs. London, UK.

Department for Transport (DfT). 2014. Road traffic statistics: http://www.dft.gov.uk/traffic-counts/

Dudenhoeffer DD, Permann MR, Manic M. 2006. CIMS: a framework for infrastructure interdependency modeling and analysis. In: Proceedings of the 2006 winter simulation conference 478–85.

Dueñas-Osorio, L., Craig, J. I, Goodno, B. J. 2007. Seismic response of critical interdependent networks. Earthquake Engineering and Structural Dynamics 36:285-306.

Energy Networks Association (ENA). 2009. ETR 138: Resilience to flooding of grid and primary substations. Energy Networks Association.

Energy Networks Association. 2011. Electricity Networks Association Climate Adaptation Report. Energy Networks Association.

Environment Agency. 2006. Cumbria floods technical report: Factual report on meteorology, hydrology and impacts of January 2005 flooding in Cumbria. Environment Agency.

Environment Agency. 2009. Flooding in England, A National Assessment of Flood Risk. Environment Agency.

Environment Agency. 2010. The costs of the 2007 summer floods in England. Environment Agency.

Environment Agency. 2011. Temporary and demountable flood protection guide. Environment Agency, Bristol, United Kingdom.

Environment Agency. 2012. NaFRA Spatial Flood Likelihood Category Grid Data Description. Environment Agency.

Erdös, P., Rényi, A. 1959. On Random Graphs. I. Publicationes Mathematicae 6: 290-297.

Eusgeld, I., Henzi, D., Kröger, W. 2008. Comparative Evaluation of Modeling and Simulation Techniques for Interdependent Critical Infrastructures: Scientific Report, Laboratory for Safety Analysis, Institute for Energy Technology, ETH Zûrich.

Eusgeld, I., Kröger, W., Sansavini, G., Schläpfer, M., Zio, E. 2009. The role of network theory and object-oriented modeling within a framework for the vulnerability analysis of critical infrastructures, Reliability Engineering & System Safety, 94:954-963.

Eusgeld, I., Nan, C., & Dietz, S. 2011. System-of-systems approach for interdependent critical infrastructures. Reliability Engineering & System Safety, 96(6):679–686.

Ferretti, L., Cortelezzi, M. 2011. Preferential attachment in growing spatial networks. Phys. Rev. E 84. 016103.

Forrester, J. W. 1961. Industrial dynamics. Cambridge, MA, MIT Press.

Fredman, M. L., Tarian, R. E. 1987. Fibonacci heaps and their uses in improved network optimization algorithms. Journal of the ACM (JACM), 34(3) 596-615.

Gao, J., Buldyrev, S. V., Havlin, S. & Stanley, H. E. 2011. Robustness of a network of networks. *Phys. Rev. Lett.* 107, 195701

Hagberg, A., Swart, P., Schult, D. 2008. Exploring network structure, dynamics, and function using NetworkX. In proceedings of the 7th Python in Science conference (Scipy 2008) Vol. 2008:11-16.

Haimes, Y. Y. 2006. On the definition of vulnerabilities in measuring risks to infrastructure. Risk analysis 26(2):293-296.

Hall, J., Dawson, R., Sayers, P., Rosu, C., Chatterton, J., Deakin, R., 2003a. A methodology for national-scale flood risk assessment. Proceedings of the ICE-Water and Maritime Engineering 156 (3):235–247.

Hall, J. W., Meadowcroft, I. C., Sayers, P. B., Bramley, M. E., 2003b. Integrated flood risk management in England and Wales. Natural Hazards Review 4 (3):126–135.

Hall, J. W., Borgomeo, E. 2013. Risk-based principles for defining and managing water security. Phil Trans R Soc A 371:20120407.

Hallegatte, S. 2008. An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina. Risk Analysis 28 (3):779–799.

Hernandez-Fajardo, I., Dueñas-Osorio, L. 2013. Probabilistic study of cascading failures in complex interdependent lifeline systems. Reliability Engineering & System Safety 111 (0):260 – 272.

Hines, P., Cotilla-Sanchez, E., Blumsack, S. 2010. Do topological models provide good information about electricity infrastructure vulnerability. CHAOS 20 033122.

HM Treasury. 2014. The green book: evaluation and appraisal in central government. HM Treasury.

Hunt A, Watkiss P. 2011. Climate change impacts and adaptation in cities: a review of the literature. Clim Chang 104(1):13–49.

IPCC. 2014. Summary for Policymakers: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the IPCC Fifth Assessment Report. United Nations Intergovernmental Panel on Climate Change.

Jenelius, E., Mattsson, L-G. 2008. The vulnerability of road networks under area-covering disruptions. In: proceedings of INFORMS annual meeting, Washington, DC.

Johansson, J., Hassel, H. 2010. An approach for modelling interdependent infrastructures in the context of vulnerability analysis. Reliability Engineering & System Safety 95 (12):1335–1344.

Kaegi, M., Mock, R., Kröger, W. 2009. Analysing maintenance strategies by agent-based simulations: a feasibility study. Reliability and systems safety 94: 1416-21

Kaplan, S., Garrick, B.J. 1981. On the quantitative definition of risk, Risk Analysis, 1 (1):11-27.

Kirshen P, Ruth M, Anderson W. 2008. Interdependencies of urban climate change impacts and adaptation strategies: a case study of metropolitan Boston USA. Clim Chang 86(1–2):105–122.

Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J. P., Moreno, Y., Porter, M. A. 2014. Multilayer networks. Journal of Complex Networks. 2 (3): 203-371.

Kröger, W. 2008. Critical infrastructures at risk: a need for a new conceptual approach and extended analytical tools. Reliability Engineering & System Safety, 93(12):1781–1787.

LaRocca, S., Johansson, J., Hassel, H., Guikema, S. 2015. Topological performance measures as surrogates for physical flow models for risk and vulnerability analysis for electricity power systems. Risk Analysis 35 (4):608-623.

Lee, E. E., Mitchell, J. E., & Wallace, W. A. 2007. Restoration of Services in Interdependent Infrastructure Systems: A Network Flows Approach. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, 37(6):1303-1317.

Leontief, W. 1986. Input output economics. Oxford University Press.

Lewis, T. G. 2006. Critical infrastructure protection in homeland security: defending a networked nation. Wiley.

Lewis, T. G. 2011. Network science: theory and applications. John Wiley & Sons.

Little, R. G. 2002. Controlling cascading failure: understanding the vulnerabilities of interconnected infrastructures. Journal of Urban Technology 9 (1):109–123.

Loggins, R. A., Wallace, W. A. 2015. Rapid assessment of hurricane damage and disruption to interdependent civil infrastructure systems. ASCE Journal of Infrastructure Systems 10.1061.

McColl, L., Palin, E. J., Thornton, H. E., Sexton, D. M., Betts, R., Mylne, K. 2012. Assessing the potential impact of climate change on the UK's electricity network. Climatic change 115 (3-4):821–835.

McDaniels T, Chang S, Peterson K, Mikawoz J, Reed D. Empirical framework for characterizing infrastructure failure interdependencies. Journal of Infra- structure Systems 2007;13(3):175–84.

McMillan, D. 2014. Disruptions at Gatwick airport – Christmas Eve 2013. Report by David McMillan to the Board of Gatwick Airport Limited.

Miller, J.D., Kjeldsen, T.R., Hannaford, J., Morris, D.G. 2013. A hydrological assessment of the November 2009 floods in Cumbria, UK.

Met Office. 2006. Scoping Study – Climate Change Impacts on the UK Energy Industry. Met Office, Exeter, United Kingdom.

Met Office. 2014. The recent storms and floods in the UK. Met Office.

Murray, A.T., Matisziw, T.C., Grubesic, T.H. 2008. A Methodological Overview of Network Vulnerability Analysis, Growth and Change, 39 (4):573- 592.

National Grid. 2012. Electricity Ten Year statement, UK electricity transmission. National Grid, UK.

Newman, M. 2003. The structure and function of complex networks. SIAM Review, (45):167-256.

Newman, M. E. J. 2004. Analysis of Weighted Networks. *Phys. Rev. E*70. *056131*

Newman, M. 2010. Networks: An introduction. Oxford University Press.

Northern Powergrid. 2012. IMP/001/012 – Code of practice for flood mitigation at operational premises. Northern Powergrid, UK

ONS. 2009. United Kingdom National Accounts: The Blue Book. J. Dye and J. Sosimi, eds., Palgrame Macmillan.

Office for National Statistics. 2011. Office for National Statistics, 2011 Census: Digitized boundary data (England and Wales) [computer file]. UK data services census support. Downloaded from http://edina.ac.uk/census

Okuyama, Y., 2004. Modeling spatial economic impacts of an earthquake: Input-output approaches. Disaster Prevention and Management 13 (4):297–306.

Openshaw, S. 1994. The Modifiable Areal Unit Problem. London, UK: Geo Books.

Ord, J. K., Getis, A. 1995. Local spatial autocorrelation statistics: distributional issues and an application. *Geographical Analysis* 24(3).

Ordnance Survey. 2015. OS MasterMap Topography. Ordnance Survey, UK.

Ouyang, M., Dueñas-Osorio, L. 2012. A three-stage resilience analysis framework for urban infrastructure systems. Structural Safety, 36-37:23-31

Ouyang, M. 2014. Review on modelling and simulation of interdependent critical infrastructure systems. Reliability Engineering & System Safety, 121:43-60.

Pant, R., Hall, J.W., Blainey, S. 2015. Vulnerability assessment framework for interdependent critical infrastructures: case study for Britain's rail network.

Special Issue on Climate Adaptation and Infrastructure of European Journal of Transport and Infrastructure Research. Accepted.

Patterson, S. A., Apostolakis, G. E. 2007. Identification of critical locations across multiple infrastructures for terrorist actions. Reliability Engineering and System Safety 92:1183-203.

Pearce, D., Atkinson, G., Mourato, S., 2006. Cost-benefit Analysis and the Environment: Recent Developments. ISBN: 92-64-01004-1, OECD.

Pedersen P, Dudenhoeffer D, Hartley S, Permann M. 2006. Critical Infrastructure Interdependency Modeling: A Survey of U.S. and International Research. Idaho National Laboratory.

Peerenboom, J. P., & Fisher, R. E. 2007. Analyzing cross-sector interdependencies. Proceeding of 40th Hawaii international conference on system sciences, Hawaii, USA.

Pitt, M. 2008. Learning lessons from the 2007 floods. Pitt Review.

Poljansek, K., Bono, F., Gutierrez, E. 2010. GIS-based method to assess seismic vulnerability of interconnected infrastructure: A case of EU gas and electricity networks. EU JRC 24275.

POST. 2010. Resilience of UK infrastructure. Parliamentary Office of Science and Technology POSTNOTE. Number 362. October 2010.

Prager, F., Beeler Asay, G. R., Lee, B., von Winterfeldt, D. 2011. Exploring reductions in London underground passenger journeys following the July 2005 bombings. Risk Analysis 31 (5), 773–786.

Prichard, O. G., Hallett, S. H., Farewell, T. S. 2013. Soil movement in the UK – Impacts on critical infrastructure. ITRC working paper series. http://www.itrc.org.uk/wordpress/wp-content/PDFs/Soil-movement-impacts-UK-infrastructure.pdf .

Queensland Government. 2011. Understanding floods: Questions and Answers. Queensland Government, the State of Queensland.

RAND. 2014. The Hurricane Sandy rebuilding task force’s infrastructure resilience guidelines. An initial assessment of implementation by federal agencies. RAND.

Rinaldi, S. M., Peerenboom, J. P., Kelly, T. K. 2001. Identifying, understanding, and analysing critical infrastructure interdependencies. Control Systems, IEEE 21 (6):11–25.

Rinaldi, S. M. 2004. Modelling and simulating critical infrastructures and their interdependencies. System sciences. Proceedings of the 37th annual Hawaii international conference on. IEEE.

Rose, A. 2004. Economic principles, issues, and research priorities in hazard loss estimation. In Okyuama, Y., Chang, S., editors. Modelling spatial and economic impacts of disasters. New York, Springer-Verlag p 13-36.

Sallam, A. A., Malik, O. P. 2011. Electricity distribution systems. (Vol.68). John Wiley & Sons.

Shekhtman, L. M., Berezin, Y., Danziger, M. M., Havlin, S. 2014. Robustness of a network formed of spatially embedded networks. Physical review E 90, 012809.

Silverman, B. W. 1986. Density estimation for statistics and data analysis. New York: Chapman and Hall.

Strogatz, S. H. 2001. Exploring complex networks. Nature 410 (6825):268–276.

Thacker, S. Pant, R., Hall, J. W. 2014. Characterizing the vulnerability of future configurations of Great Britain's electricity network infrastructure to climate-related hazards. Vulnerability, uncertainty and risk:648-657.

Tran, M., Hall, J. W., Hickford, A. J., Nicholls, R. J., Alderson, D., Barr, S., et al. 2014. National infrastructure assessment: analysis of options for infrastructure provision in Great Britain, interim results. Oxford, GB, Environmental Change Institute, University of Oxford, 104pp.

United States - Canada power system outage task force. 2004. Final report on the August 14th, 2003 blackout in the United States and Canada: causes and recommendations. United States Department of Energy and Canadian Department of Natural Resources.

U.S Department of Energy. 2012. Large Power Transformers and the U.S. Electric Grid. The U.S Department of Energy

UK Power Network Services. 2014. The Power Behind Airports.

Van Vliet MTH, Yearsley JR, Ludwig F, Vgele S, Lettenmaier DP, Kabat P. 2012. Vulnerability of US and European electricity supply to climate change. Nat Clim Chang 2(9):676–681.

Watts, D, J., Strogatz, S, H. 1998. Collective dynamics of 'small-world' networks. Nature, 393:440-442.

Wilkinson, S. M., Dunn, S., Ma, S. 2012. The vulnerability of European air traffic to spatial hazards. Natural hazards, 60(3):1027-1036.

Wilson, R. 2012. Using kernel density estimation to examine changes in voucher density over time. Cityscape: A journal of policy development and research Volume 14 Number 3.

Xiao, N., Sharman, N., Raj, R., Upadhyaya, S. 2008. Infrastructure Interdependencies Modeling and Analysis: A Review and Synthesis, Proceedings of Americas Conference on Information Systems (AMCIS).

Yamano, N., & Ahmad, N. 2006. The OECD input-output database: 2006 edition (No. 2006/8). OECD Publishing.

Zhang P, Peeta S. 2011. A generalized modeling framework to analyze interdependencies among infrastructure systems. Transportation Research part B: Methodological 45(3):553–79.

Zimmerman, R. 2001. Social implications of infrastructure network interactions. Journal of urban technology 8:97-119.

Zimmerman, R., Restrepo, C. E. 2006. The next step: quantifying infrastructure interdependencies to improve security. Int. J. Critical Infrastructures 2(2/3):215-230.

Zio, E., Sansavini, G. 2011. Modelling interdependent networks systems for identifying cascade-safe operating margins. IEEE transactions on reliability 60 (1):94-101.

Appendix A: Co-author Paper Contribution Statements

The following statements provide details of the contributions made by co-authors to papers included within this thesis:

Certificate of Authorship of Dissertation Work for Scott Thacker

To the Director of Graduate Studies: School of Geography and the Environment, University of Oxford.

I hereby certify that Scott Thacker carried out the majority of the work contained in the articles described below, which form part of his DPhil thesis:

- *Synthesis of multi-level infrastructure network systems*
- *System-of-systems formulation and disruption analysis for multi-scale critical national infrastructures*
- *Geographic hotspots of critical national infrastructure*
- *Evaluating the benefits of investment in the adaptation of interdependent critical infrastructures to reduce climate hazard risks*

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- *Synthesis of multi-level infrastructure network systems*
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- *Geographic hotspots of critical national infrastructure*
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Certificate of Authorship of Dissertation Work for Scott Thacker

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- *Geographic hotspots of critical national infrastructure*

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- *Evaluating the benefits of investment in the adaptation of interdependent critical infrastructures to reduce climate hazard risks*

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I hereby certify that Scott Thacker carried out the majority of the work contained in the article described below, which form part of his DPhil thesis:

- *Geographic hotspots of critical national infrastructure*

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Appendix B: Overview of Data and Tools

Table B.0.1: Infrastructure datasets used and developed in thesis

Sector	Spatial and Topological Attributes	Capacity and Demand Attributes	Papers used
Electricity generation • Owners: Multiple • Nodes: 207	Generator node locations derived using DECC 2012 DUKES data (DECC, 2012)	Individual generator capacity values derived using DECC 2012 DUKES data (DECC, 2012)	1, 2, 3 and 4
Electricity transmission • Owners: National Grid • Nodes: 437	Transmission network derived from National Grid maps (National Grid, 2012), using spatial network recreation (Barr et al. 2013)	User demands derived using capacity constrained location allocation – detailed in paper, based on Thacker et al. (2014)	1, 2, 3 and 4
Electricity sub-transmission • Owners: Multiple DNOs • Nodes: 4798	Sub-transmission network derived from OS MasterMap topography layer node and edge data (Ordnance Survey, 2015), using spatial network recreation (Barr et al. 2013)	User demands derived using capacity constrained location allocation – detailed in paper, based on Thacker et al. (2014)	1, 2, 3 and 4
Electricity Distribution • Owners: Multiple DNOs • Nodes: 164,069	Distribution network derived using OS MasterMap topography layer node and edge data (Ordnance Survey, 2015), using spatial network recreation (Barr et al. 2013)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)	1, 2, 3 and 4
Gas transmission • Owners: National Grid • Nodes: 625	Gas network derived from National Grid maps (National Grid, 2012)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)	3 and 4
Airports • Owners: Multiple • Nodes: 32	Airport locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived from CAA 2010 flight statistics (CAA, 2010)	2, 3 and 4
Ports • Owners: multiple • Nodes: 66	Port locations derived from OS MasterMap topography layer node data (Ordnance Survey,	User demands derived from DfT 2012 maritime statistics (DfT, 2012a)	3 and 4

	2015)		
Water towers • Owners: multiple • Nodes: 2566	Water tower locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)	3 and 4
Waste-water treatment • Owners: multiple • Nodes: 1563	Waste-water treatment locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)	3 and 4
Telecom masts • Owners: multiple • Nodes: 5226	Telecom mast locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	User demands derived using Voronoi decomposition – detailed in paper, based on Thacker et al. (2014)	3 and 4
Railways • Owners: multiple • Nodes: 3941	Railway locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	Passenger demands from a rail trip distribution model, documented in Pant et al. (2015)	3 and 4
Roads • Owners: multiple • Nodes: 24071	Road locations derived from OS MasterMap topography layer node data (Ordnance Survey, 2015)	Passenger demands from DfT AADF usage statistics (DfT, 2014) and DfT loading factors (DfT, 2012b)	3

Table B.0.2: Software and data processing tools used in the thesis

Tool name	**Tool type**	**Tool use within the thesis**	**Link to tool**
PostgreSQL	Spatial database	For data storage and geospatial functionality	http://www.postgresql.org
QGIS	GIS platform	For visualising database outputs	http://www.qgis.org/en/site/
ESRI-ArcGIS	GIS platform	For visualising database outputs and geo-spatial functionality	http://www.esri.com/software/arcgis
Python	Programming language	For general algorithm implementation and linkage (e.g. failure propagation algorithm)	https://www.python.org
Psycopg2	Python library	Package to establish link between Python algorithms and PostgreSQL database	http://initd.org/psycopg/
NetworkX	Python library	Package containing network	https://networkx.github.io

		functions (e.g. for path derivations)	
Gephi	Network visualisation	For visualising networks	http://gephi.github.io