Water infrastructure vulnerability due to dependency on third party infrastructure sectors

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Abstract

Society is critically dependent on water networks to provide a safe and reliable supply of clean water. Water companies must balance the requirement for very high levels of reliability with the need to protect the customer from excessive bills. This, in turn, requires them to assess the entire range of risks including low probability, high impact events.

Water companies are confident when estimating the risk of failure due to natural hazards affecting their own systems but they are less certain assessing how failures in third party infrastructure could affect their services. For example, 1 500 homes in Cumbria lost their water supply in 2005 due to power cuts caused by flooding and strong winds. This highlights the need for better methods to help water companies assess these risks and their options for managing them.

Current risk assessments rely heavily on the expertise, experience and intuition of companies' employees. However, the interactions between different infrastructure networks create complex systems which can behave unpredictably and leave customers vulnerable to unanticipated consequences. Previous academic studies have been hampered by limited data and therefore have mainly used coarse resolution models which simulate only the high-level performance of idealized networks. This thesis has improved on this situation by developing more realistic models of water systems and their dependencies. Two real-world case studies have been used to explore their potential as aids to inform better decision making.

The first model assesses the likelihood and consequence of third party infrastructure failures causing water supply interruptions. It draws on catastrophe modelling techniques used in the insurance industry and is composed of three elements: i) a hazard model producing synthetic but realistic time series of wind, temperature and rainfall; ii) a suite of fragility curves describing the susceptibility of highways, electricity, telecommunications and water facilities to these hazards; and iii) a set of network models to explore the impact of individual facility failures on the availability of water supplies.

The model is implemented for a real-water distribution network where dependence on external infrastructure systems was found to cause an expected loss of 9.9 minutes per property per year. In isolation, electricity, telecommunications and transport respectively make up 75%, 11% and 0% of the total risk. The remaining 14% results from interactions between these sectors. It is argued that these failure modes are unlikely to be identified using existing risk assessment methods.

While the first model provides a quantitative and probabilistic risk assessment, its complicated nature makes interpreting the results challenging and limits the number of scenarios that can be investigated. The second model takes a different approach and focuses upon identifying low probability, high impact events. The hazard model and fragility curves are replaced by the UK Cabinet Office's 'reasonable worst case scenarios', and a simpler stocks and flow model takes the place of the hydraulic network models but maintains the representation of the network structure and components.

The results provide insight into how, where and why water supplies are vulnerable to failures in third party sectors. They show that dependencies can dramatically increase vulnerability (in one case the loss of power to an emergency pumping station causes 6 million property hours without supply). Equally, an inland flooding scenario shows that simple solutions such as installing a connection for a mobile generator can significantly reduce vulnerabilities.

The methods developed in this research make a significant contribution to closing the gap between existing theoretical studies of dependency and the requirements of infrastructure providers to improve the resilience of real systems. The first model provides a probabilistic assessment of risk that enables infrastructure providers to prioritise investment. The second model identifies the full range of vulnerabilities and investigates the sensitivity of the outputs to model parameters and inputs.

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Definitions and Abbreviations

Definitions

Deadband – A range around a company's performance commitment. If performance is within this band then they will receive neither a penalty nor reward.

Facility – The sponsors have a defined asset hierarchy to avoid confusion over what constitutes an asset, process stage, site etc. This thesis will operate at the facility scale which corresponds to most of the definitions used for regulatory asset planning e.g. water treatment work, pumping station etc.

Infrastructure – This term is used in its general sense i.e. the systems which transmit goods, energy and/or information from where they are available to where they are needed. This thesis does not differentiate between the specific water industry definitions of infrastructure and non-infrastructure.

Performance commitment – The level of service which water companies will aim to provide. Under-performance or outperformance may result in a financial penalty or reward.

Price review – The five yearly process in which Ofwat sets the prices water companies can charge their customers. Individual review are abbreviated to PR followed by the year of the review e.g. PR09 , PR14 etc.

Resilience – "Resilience is the ability of assets, networks, and systems to anticipate, absorb, adapt to and / or rapidly recover from a disruptive event" (Cabinet Office 2011, p15). The adoption of this definition is discussed in Chapter 2.

Rezone – To reconfigure a water or other infrastructure network so customers may be fed from a different source.

Vulnerability – where 'relatively small damage leads to disproportionately large consequences' (Agarwal et al. 2003, p263).

Water industry / water company – The industry / company which provides water and wastewater services to customers. Elsewhere the term ‘water’ is used to refer to the potable water supply and excludes the wastewater sub-sector.

Abbreviations

ARMA	Autoregressive moving average
DMA	District Metered Area. The second smallest level of the water network hierarchy, equivalent to a neighbourhood.
DMZ	Demand Monitoring Zone. The second largest level of the water network hierarchy typically used for asset planning.
DNO	Distribution Network Operator. Regional electricity distribution companies in England and Wales
DWI	The Drinking Water Inspectorate. Regulates drinking water quality in England and Wales.
FMEA	Failure modes and effects analysis
FMECA	Failures modes, effects and criticality analysis
GIS	Geographic Information System
HAZOP	Hazard and operability study
IEEE	Institute of Electrical and Electronics Engineers
KPI	Key performance indicator
PR	Price Review, normally followed by a number indicating the year of the final determination (e.g. PR09, PR14 etc.)
SD	System Dynamics
WTW	Water treatment works

Chapter 1. Introduction

1.1 Context and research gap

Infrastructure is critically important. It underpins national economies and provides the vital services needed for daily lives (Cabinet Office 2011a, HM Treasury & Infrastructure UK 2014). The potentially catastrophic impacts of failure make it imperative that these services are reliable (Commission of the European Communities 2004).

The initial impact of Hurricane Sandy – which hit the north-eastern US in 2012 – was substantial: it destroyed or damaged 650 000 homes, flooded eight tunnels and directly caused 72 deaths (Hurricane Sandy Rebuilding Task Force 2013). However, its impact was increased and prolonged by the damage to infrastructure. 25% of cell phone transmitters were lost across 10 states and commuting times doubled in some parts of New York (ibid.). Figure 1.1 shows that the loss of power to 8.5 million customers accounted for almost a third of all fatalities caused by the hurricane (Blake et al. 2013).

Other international examples of critical infrastructure failures include Hurricane Katrina and the 9/11 terrorist attacks (Moteff 2014), the European Blackouts of 2003 and 2006 (Lewis et al. 2013) and 2011 East Japan earthquake (Norio et al. 2011, Sagara & Ishiwatari 2012).

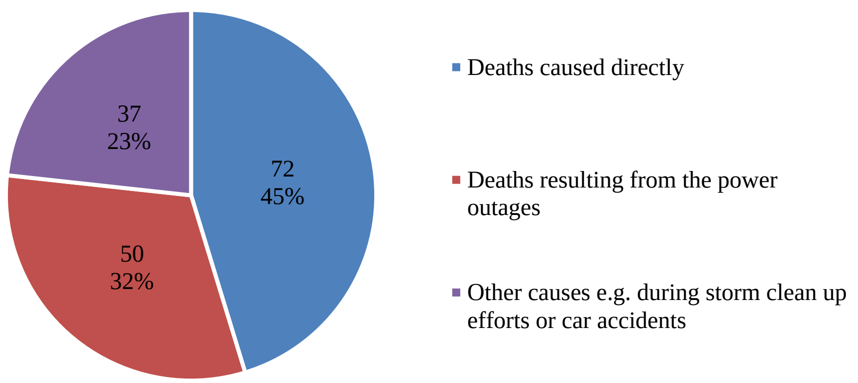


Figure 1.1 Causes of Hurricane Sandy fatalities (after Blake et al. 2013)

From a UK perspective, it was the 2007 Summer Floods which highlighted the vulnerability of the nation's critical infrastructure and the potential impacts of its failure:

- 10 000 people were stranded in cars on the M5 (Pitt 2008).
- 82 000 people lost power due to flooding at Neepsend and Castle Meads substations (Pitt 2008).
- 350 000 customers were without water for up to 17 days due to the flooding of the Mythe water treatment works (Figure 1.2b) (Severn Trent Water 2007).
- Severn Trent Water estimate the event cost them £25-£35 million, of which only £10-£20 million was recoverable through insurance (Severn Trent Water 2007). The total cost ran into billions of pounds (Pitt 2008).

The subsequent Pitt Review (2008) made a number of recommendations about assessing the risks to critical infrastructure and protecting essential services. This has triggered a renewed focus on infrastructure resilience among policy makers and regulators (Ofwat 2010, Cabinet Office 2011a, Defra 2012) and this attention has been replicated on a global scale as the importance of reliable infrastructure is realised (e.g. Commission of the European Communities 2006, Australian Government 2010).

The Summer 2007 floods also reportedly came within inches of closing Walham substation which would have cut off power to 500 000 customers (McMaster & Baber 2008, Pitt 2008). The Pitt Review noted that:

> *"The failure of supply on that scale … would have caused chaos and, almost certainly, loss of life" (Pitt 2008 p238)*

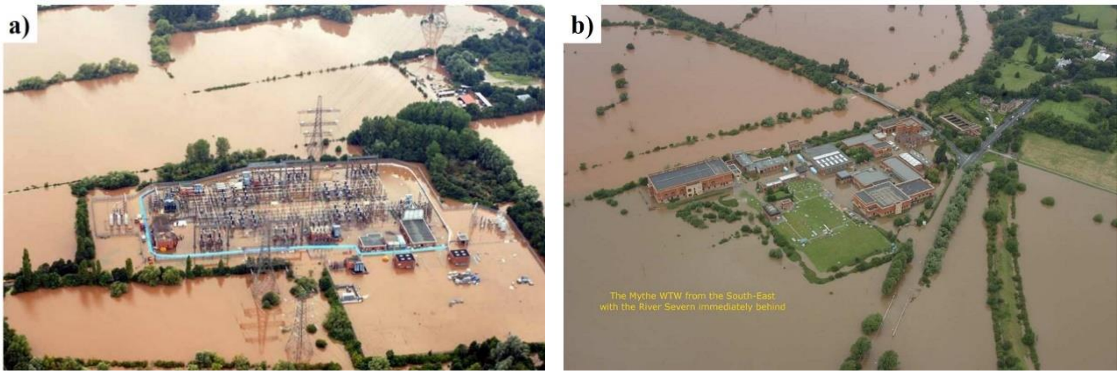


Figure 1.2 a) Castle Meads substation in the 2007 floods (Western Power Distribution 2007). b) Flooding of Mythe WTW in July 2007 (from Severn Trent Water 2007)

More importantly in the context of this research, this near miss and others elsewhere in the summer of 2007 highlighted the dependencies between different infrastructure sectors. Pitt argues that critical infrastructure are interdependent systems where failures in one network can cascade into another, potentially undermining what would otherwise be a resilient system. This is echoed by the Institution of Civil Engineers in their 2009 *State of the nation* report:

> *"A single failure can cascade across the network of critical infrastructure, rendering otherwise unaffected sectors inoperable. … The UK's current infrastructure defence system fails to recognise this vital interdependency." (ICE 2009, p8)*

The realisation of interdependency's importance has led to a further shift in policy and regulation. Every Sector Resilience Plan produced by the Government since 2011 has specifically noted interdependence as a threat (Cabinet Office 2011b, 2012, 2013a, 2014). Equally, Ofwat's new 'principles for resilience planning' (2012) include engaging with third parties to help understand interdependency.

United Utilities, one of the sponsors of this research, were already acutely aware of their vulnerability to failures in other sectors following the combination of heavy rain and high winds which hit Cumbria in January 2005. Many critical infrastructure assets were flooded, including civic buildings, railway lines, major road links, electricity substations, water and wastewater treatment works (Figure 1.3a) (Cox 2005, Environment Agency 2006, Horsfall et al. 2005, McDonald & Yerkess 2005). Strong winds simultaneously damaged structures (including one water treatment works), blocked roads with debris and caused around 1 440 faults in the electricity distribution network (Figure 1.3b) (Horsfall et al. 2005, Cox 2005).

Figure 1.3 a) Flooding of Carlisle Police Station & Civic Centre, January 2005 (Environment Agency 2006). b) Wind damage to power lines in Cumbria, January 2005 (Cox 2005)

The effects of these infrastructure failures were amplified by cascading failures in the networks which depended upon them. From the water company's perspective:

- 23 potable water and up to 41 wastewater facilities lost power (Horsfall et al. 2005, McDonald & Yerkess 2005).
- The inspection and recovery of sites was slowed by damage to access routes: some wastewater sites were inaccessible for over 72 hours and police assistance was needed to deliver emergency generators to Carlisle wastewater treatment works (McDonald & Yerkess 2005).
- The public switched telephone network failed and the batteries sustaining mobile telephone transmitters were depleted. This not only restricted communications between staff but also caused reservoirs to empty as telemetry signals were lost (Horsfall et al. 2005, McDonald & Yerkess 2005).

Whilst the impact on water company customers was relatively small – only four potable water facility failures resulted in a loss of potable water supply and wastewater facilities were returned to service before the floods receded – the financial costs to the company were significant (Horsfall et al. 2005, McDonald & Yerkess 2005).

These impacts, combined with the policy and regulatory focus on resilience, mean that the water companies require effective methods for assessing the risks posed by their dependence on third party infrastructure networks. Moreover, it is important to demonstrate that these methods are robust in order to justify investment in reducing any unacceptable risks (Keil 2008).

In spite of this need, a survey of the water companies in England and Wales identified the lack of data on interdependencies and difficulty of assessing interdependencies as a barrier to effective resilience planning (Ofwat 2012). Equally, both the Pitt Review and the ICE's *State of the nation* report suggest that the management of interdependent infrastructure is fragmented (Pitt 2008, ICE 2009). The existing risk assessment methods fail because they focus on breaking systems down into isolated sub-systems and do not capture the risks arising from interactions between these systems (Rinaldi et al. 2001, Haimes et al. 2008).

Infrastructure interdependency is an area of intense research activity but the focus has either been theoretical work on abstracted topological networks (e.g. Holmgren 2006, Buldyrev et al. 2010) or large scale impact assessments which only provide information for national level strategic decision makers (e.g. Bush et al. 2005, Pant et al. 2014). The perspective of this project's sponsors is quite different: they require methods which can assess the risks to specific, real-world systems at a tactical level. This research gap is addressed by this thesis through the development of two separate models for assessing risk at this level. These models are then applied to two separate case studies to assess their effectiveness.

1.2 Aims, objectives and scope

1.2.1 Industrial sponsorship

The goal of an Engineering Doctorate is to deliver novel and innovative research which has value for the project's industrial sponsors. Therefore their requirements and priorities guide the aims, objectives and scope of the project.

Initial discussions identified that infrastructure providers require methods which:

i. Provide quantitative information which decision makers can use to make evidence based decisions.

ii. Identify where their systems are vulnerable and hence where to direct efforts to reduce risk.

iii. Are practical to implement in an industrial context.

The Stream Industrial Doctorate programme, supported by EPSRC, which funded this research requires researchers to be embedded within the sponsors for at least 75% of the project. This close relationship with the sponsors has had an important influence on the direction of the project and provided significant opportunities. Access to their databases reduces some of the issues around data availability and allows the methods to be tested on real-world case studies. Two separate case studies are produced to reflect the contributions and satisfy the requirements of the different sponsors. Because they are real networks any geographic information which may identify them has been removed.

1.2.2 Aim and objectives

The aim of this thesis is to develop methods which can assess the vulnerability of water networks to failures in other interconnected critical infrastructure systems, and to assess whether this information can be used to improve the resilience of the water networks.

To achieve this aim five objectives and eight research questions have been established.

1) Understand the government policies and regulatory frameworks relevant to water companies and the information they must produce to demonstrate compliance.

The water companies require these methods to support their decision making over whether and how to invest in more resilient services. For the project to deliver useful outputs it is essential to understand the context in which these decisions are made. This is particularly important in the context of the water industry because each water company holds a natural monopoly and there is a complex regulatory framework in place to guide, control and scrutinise their decisions.

Research Question 1a. How has the impact of the 2007 floods and subsequent Pitt Review been reflected in UK Government policies on infrastructure resilience?

Research Question 1b. How do regulators influence water companies to achieve the correct levels of resilience, and how can water companies influence the regulator's decisions?

2) Identify the most relevant threats to UK infrastructure and obtain or produce hazard models to represent them.

The regulators require water companies to provide robust evidence to support their plans. Infrastructure systems are exposed to a wide range of threats and it is not possible for this research to address every one so a defined set of the most critical threats will be identified. They will then be characterised in a way which allows the vulnerability of the infrastructure to be assessed:

Research Question 2a. Which hazards pose a significant threat to UK infrastructure and can be represented with enough precision to allow a quantitative risk assessment?

Research Question 2b. Are there existing sources of information / models for these hazard and, if not, can hazard models be created to represent them?

3) ***Characterise how these hazards affect UK infrastructure facilities.***

Experiences in the 2005 and 2007 floods show that different infrastructure facilities will respond differently to different hazards. Moreover, the probability of facility failure is likely to increase with increasing hazard intensity. Understanding the nature of these relationships will be central to understanding the resilience of the wider infrastructure networks.

Research Question 3a. Can a set of relationships between hazard intensity and impacts on UK infrastructure be developed?

4) ***Develop system models of infrastructure networks to simulate the impact of damage to facilities and the effects of dependencies between sectors.***

Redundancy in infrastructure systems means that the failure of individual components and the impact on customers is unlikely to be proportional. Some critical facilities (e.g. Mythe WTW and Walham substation) may have a disproportionately large impact whilst, equally, some groups of properties may experience more frequent disruption than others. Therefore it is important to model the impact of facility failures on service delivery to customers in a way which allows specific vulnerabilities to be identified. This will be demonstrated through the application of the methods to two real-world case studies identified through discussions with the project sponsors.

Research Question 4a. What methods are available to reveal how damage to infrastructure facilities affects the function of the overall network?

Research Question 4b. Can more realistic models be developed which better reflect infrastructure provider's requirements?

5) ***Assess the effectiveness of these models in providing useful data for decision makers.***

The intention of this project is to develop methods which are compatible with the processes which water companies use to define and justify a proportionate level of resilience. To determine the success of the models, and identify whether they should be developed further, it is important to assess whether they deliver useful information for decision makers.

Research Question 5a. Do the model outputs deliver useful information to support decision making by the project sponsors and other infrastructure providers?

1.2.3 Outline and scope of thesis

This thesis is presented in 7 chapters; Figure 1.4 outlines how these and their subsections relate to the research questions.

Chapter 2 reviews the context in which the water companies make decisions about the resilience of their services and how this influences what is required from risk assessment methods. It is not possible to consider all threats to infrastructure, all infrastructure sectors and all facets of infrastructure interdependence and resilience. Therefore the scope of this research is limited to meteorological hazards which develop and dissipate over a few days. The sectors considered are limited to the water sector and its dependence upon three principal networks: electricity, telecommunications and highways. These boundaries are discussed and justified in the context of the existing literature in Chapter 3.

Chapter 4 develops a catastrophe modelling / performance based design approach to produce a probabilistic assessment of the risks to water networks from their dependency on the three external infrastructure sectors. In Chapter 5 this is applied to a real-world case study to evaluate its usefulness to infrastructure providers.

Building upon the first model, Chapter 6 develops an alternative model which focuses upon exploring the potential impacts of interdependency and identifying vulnerabilities to low probability, high impact events. This is applied to a further real-world case study to test its effectiveness.

Finally, Chapter 7 assesses the potential of this work to aid infrastructure providers' decision making and identifies pathways to improve it further

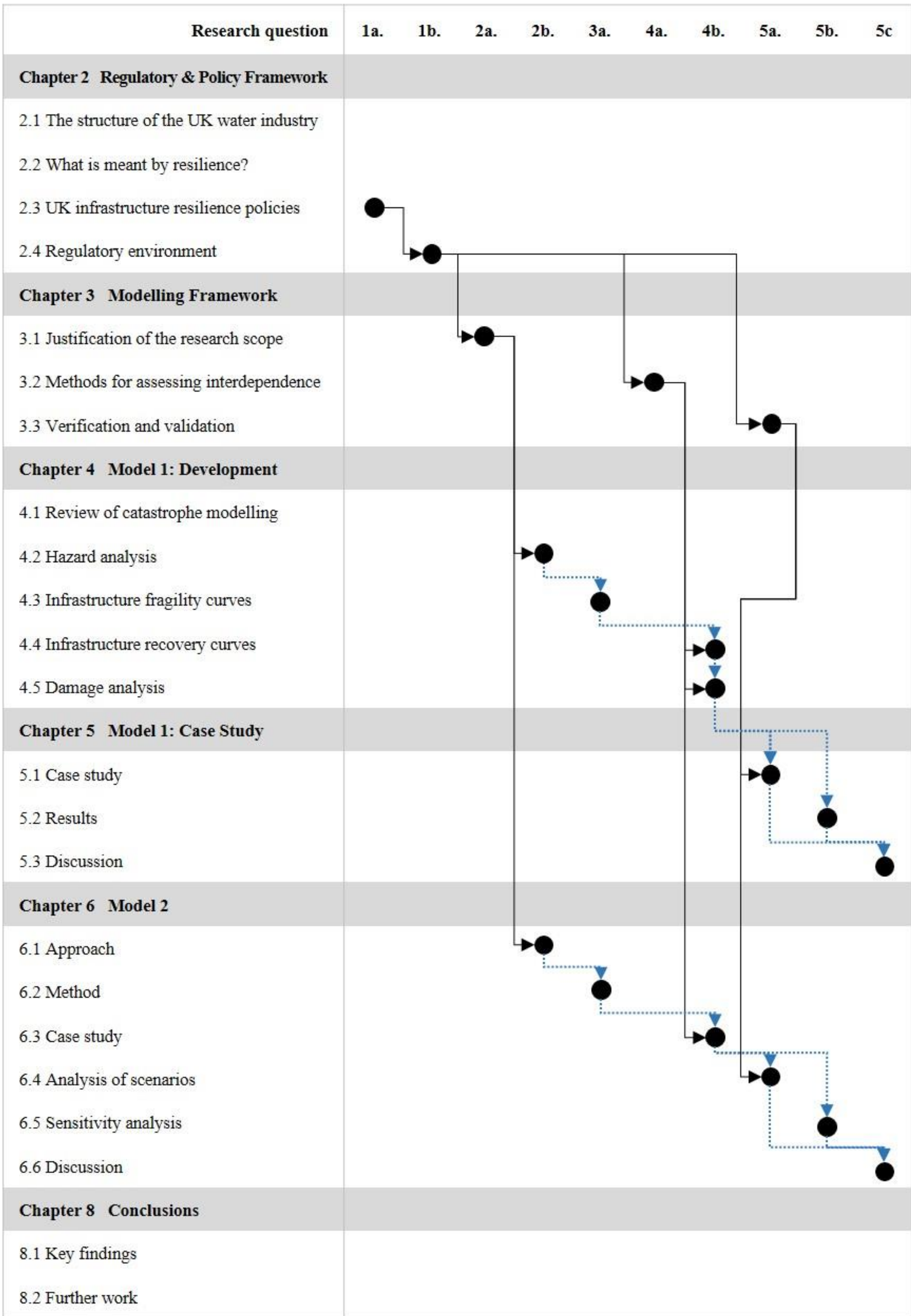


Figure 1.4 The relationship between objectives, research questions and thesis structure. Solid lines represent the influence of literature on research methods and dotted lines represent the flow of information through the individual models.

Chapter 2. Regulatory and Policy Framework

Privatised utilities form natural monopolies. The essential nature of the services that they provides requires them to be governed by a strict regulatory framework guided by government policies. This framework defines how water companies set their goals, view their business and make decisions. Therefore understanding it is essential for developing models which provide the outputs necessary for decision makers.

This chapter reviews the current policies and regulations that govern the water sector. As part of this the structure of the water industry and the concept of resilience are also briefly outlined. The chapter concludes that there are large reputational and financial incentives for providing a reliable service, but resilience strategies must be proportionate and cost effective.

2.1 The structure of the UK water industry

The current structure of the English and Welsh water industry emerged when it was privatised in 1989. The 10 existing Regional Water Authorities became the 10 large water and sewerage companies alongside 33 smaller water only companies (Pollitt & Steer 2012). Figure 2.1 shows that the 10 water and sewerage companies have remained largely unchanged in 2014, but mergers have reduced the number of water only companies to nine.

Three regulators were established to counterbalance the private companies' focus on generating value for their owners or shareholders (Byatt 2013):

- The Environment Agency (the National River Authority prior to 1994) regulates water quality in the environment.
- The Drinking Water Inspectorate (DWI) regulates drinking water quality.
- Ofwat are responsible for regulating the economics of the new system, including price controls and new entrants into the markets.

Water only companies

AFW	Affinity Water
BRL	Bristol Water
CHL	Cholderton & District Water
DVW	Dee Valley Water
PRT	Portsmouth Water
SBW	Sembcorp Bournemouth Water
SES	Sutton & East Surrey Water
SEW	South East Water
SSC	South Staffs Water

Water only companies run by water and sewerage companies

ESK	Essex & Suffolk (Northumbrian Water)
HPL	Hartlepool (Anglian Water)

Figure 2.1 Water companies in England and Wales (Ofwat 2015)

The close regulation of the water industry reflects the many externalities which are inherent to the sector (Schouten & Van Dijk 2010):

i. Chapter 1 discussed how critical infrastructure is defined by its importance to society and the national economy. This is one of the primary arguments for public ownership (Helm 2001) and in a privatized industry this ownership is replaced by regulation (Helm 1994).

ii. UN Resolution 64/292 recognised safe and clean drinking water and sanitation as a human right. Regulation is important to protect people's health from unsafe water or sanitation.

iii. Water companies have a direct and delicate interface with the natural environment; they abstract raw water and collect, transport and treat wastewater. Regulation protects the environment and the people which rely on or enjoy it.

iv. The cost of the water infrastructure leads to the regional monopolies shown in Figure 2.1. Since customers are unable to choose their provider the regulator is needed to ensure they are charged a fair price (Beecher & Kalmbach 2013).

The relationship with regulators is crucial to water companies (Ogden & Watson 1999, Reynaud & Thomas 2013). On one hand the regulators have a direct influence on their profitability because they can impose financial penalties for poor performance. In addition, the perception of the regulatory relationship is also important because one of the central tenets of the UK Regulators Code is that regulation should be targeted according to risk (Department for Business, Innovation & Skills 2014). Companies with a healthy regulatory relationship can expect less onerous regulation, a principle which is reflected in both Ofwat's 'risk-based review' of the PR14 business plans and the enforcement policies of the Environment Agency and DWI (Ofwat 2014a, Environment Agency 2014a, DWI 2009a).

Equally, as economic regulator, Ofwat also defines how much the companies can charge their customers, and therefore how much they can invest in the resilience of their infrastructure. If water companies can present a business case based on solid evidence they are more likely to secure the investment they require. Robust and accountable risk assessment methods are therefore essential.

Softer regulatory mechanisms, predominantly through central government, are also influential. Whilst some are legal requirements (for example the requirements of the Civil Contingencies Act and the Security and Emergency Measures Direction), much of their weight is carried through the potentially negative impacts on the companies' reputation if they do not follow the guidance.

2.2 What is meant by resilience?

The majority of the literature, particularly in the policy and regulatory spheres, refers to infrastructure resilience. Therefore it is worthwhile to establish a consistent definition of what this means before considering the literature.

The basic notion of resilience is simple; the ability to perform well in and recover from adverse circumstances. It neatly integrates into one term the many aspects which keep complex systems – such as people, ecosystems and infrastructure – functioning. However, because it is so multi-faceted, defining resilience more precisely is difficult and there are many subtly different definitions and taxonomies (Lhomme et al. 2013). This thesis does not add to this already congested space – for comprehensive and up-to-date reviews see

Zhou et al. (2010), Carhart & Rosenburg (2014) or Bocchini et al. (2014) - but adopts the definition from the Cabinet Office's guide to '*Keeping the Country Running'*:

> *"Resilience is the ability of assets, networks, and systems to anticipate, absorb, adapt to and / or rapidly recover from a disruptive event" (2011a, p15)*

The principal advantage of this definition is its relevance to the project's industrial sponsors as the guide sets out the UK Government's perspective on how they should address infrastructure resilience (further discussed in Section 2.3.4).

Vulnerability, in general terms, is understood to be the opposite of resilience. This thesis adopts the definition given by Agarwal et al. (2003, 2014); a system is vulnerable if the initial, typically small, perturbation has disproportionate impacts.

It is important at this point to note the distinction made by Wreathall (2006) & Park et al. (2013) between resilience and risk analysis. They argue that risk analysis is concerned with the identification of specific hazards, exploration of root causes and quantification of their probability. This is very different from the all-encompassing definitions of resilience which describe more generally the ability of a system to perform well in adversity.

Wreathall (2006) and Park et al. (2013) describe a number of limitations of risk assessments in assessing resilience:

i. They only consider hazards which can be identified. This is a problem in complex systems where unforeseen hazards are likely (i.e. black swan events as popularized by Taleb 2007) (Park et al. 2013).

ii. They require the quantification of probabilities which may be incalculable, either due to the joint probability of combined events or their interest in extremes where empirical data is scarce (Park et al. 2013).

iii. They account for the physical and logical causes of accidents but rarely consider the equally important social and organisational factors (Wreathall 2006).

Notwithstanding these limitations, this thesis will concentrate on the development of risk assessment methods. The view is taken that assessments of risk and resilience are complementary – Park et al. argue both are essential to any organisation. Infrastructure providers, policy makers and regulators are all aiming for greater resilience but they also recognise that this must be balanced by the need to limit the cost to consumers. Therefore methods which assess risks in quantitative terms are essential.

However, it is recognised that the risk assessment will not capture the full resilience of the system. Indeed, it is questionable whether resilience can ever be analysed completely given the complex factors which determine it and the inherent unpredictability which is well illustrated by Figure 2.2 (see Hollnagel et al. (2006) for an in depth discussion on resilience and engineering).

The following section discusses how the UK Government's policies reflect the desire for a greater understanding of infrastructure resilience which arose out of the 2007 floods and how this impacts upon the shape of risk assessments.

Figure 2.2 Lorton Bridge following the 2009 Cumbrian floods. The severed water mains (right) have been temporarily replaced by pipes hung from trees (left). (Lingaard 2010)

2.3 UK infrastructure resilience policies

2.3.1 Prior to 2007

There are two important piece of legislation which predate the 2007 floods. These are outlined briefly below.

The Civil Contingencies Act 2004

The Act establishes the principles for Government agencies and other stakeholders' joint response to events which threaten serious damage to human welfare or the environment. Water companies and other utility providers are listed as Category 2 responders meaning that they have a legal duty to co-operate and share information with the Category 1 responders leading the response (Cabinet Office 2011a). Local Resilience Forums, typically at a county or police force level, act as the main platforms for the development of multi-agency plans and agreements, and also co-ordinate training exercises to practice emergency responses (Cabinet Office 2010).

The Security and Emergency Measures Direction (SEMD)

This direction requires that water companies have sufficient plans in place to supply safe and wholesome water in 'any event' (Defra 2009, Cabinet Office 2010). In general, SEMD breaks down into two parts:

i. In an emergency, regardless of the situation, water companies have a legal duty to provide customers with 10 litres of water a day, rising to 20 litres per day if the incident lasts longer than 5 days.

ii. Defra's Security Advisor has guided companies on ensuring that their assets are sufficiently protected against terrorism. The actions companies have taken remain confidential, but some have sought to increase the redundancy in their systems instead of focusing solely on the hardening of assets.

Each company's plan is assessed by a certifier who confirms they have appropriate plans in place. There are no defined penalties for non-compliance but it carries very significant reputational consequences, especially if an event were to occur.

2.3.2 The Pitt review

"The floods of last year caused the country's largest peacetime emergency since the Second World War" (Pitt 2008, p.vii).

Frequently a single major event acts as a catalyst for action. For critical infrastructure in the UK this was the Summer 2007 floods which, as Chapter 1 outlined, left thousands of people variously stranded on roads, without power and without water. The Pitt Review was commissioned by the UK Government to examine what lessons could be learned and its recommendations have been a driving force behind infrastructure resilience in the past seven years.

The Pitt Review was not directly critical of infrastructure owners and operators. The focus was on the Government's role of enabling resilience and the inherent vulnerability of infrastructure. The weaknesses it identified revolved around four themes:

i. The Government's approach to mitigating risks from natural hazards was uncoordinated, reactive and lacked a central understanding of infrastructure's vulnerability.

ii. There were no consistent emergency plans in case of failure.

iii. There was a shortage of information available to local responders about the location, vulnerability, significance and dependencies of critical sites.

iv. Civil Contingencies Act Category 2 responders, including utility providers, had not been involved in the Gold Command groups which were leading the response to the event.

A recurrent theme was Pitt's concern that a lack of understanding around the vulnerability of infrastructure was inhibiting our ability to reduce risk. He also saw a need for national coordination to drive the creation of more resilient infrastructure, led by central government but also enabled by key regulators.

Both of these concerns reinforce the rationale for this project. Firstly, effective methods for assessing risk due to dependence on other infrastructure sectors will address one of the key gaps in our understanding of infrastructure vulnerability. Secondly, having this information will enable more constructive dialogue with Government and regulators about the most effective ways of increasing resilience.

In addition, the defence that these events are unprecedented no longer stands. Whilst Severn Trent Water's customers were prosaic about the company's performance under rare and challenging circumstances, they were also unequivocal that the situation should not happen again, anywhere in the country (Accent 2007).

The focus of Pitt's concerns are reflected in the six of his 92 recommendations which have particular relevance to infrastructure resilience and interdependence:

Recommendation 50: The Government should urgently begin its systematic programme to reduce the disruption of essential services resulting from natural hazards by publishing a national framework and policy statement setting out the process, timescales and expectations.

Recommendation 51: Relevant government departments and the Environment Agency should work with infrastructure operators to identify the vulnerability and risk of assets to flooding and a summary of the analysis should be published in Sector Resilience Plans.

Recommendation 52: In the short term, the Government and infrastructure operators should work together to build a level of resilience into critical infrastructure assets that ensures continuity during a worst-case flood event.

Recommendation 53: A specific duty should be placed on economic regulators to build resilience in the critical infrastructure.

Recommendation 55: The Government should strengthen and enforce the duty on Category 2 responders to share information on the risks to their infrastructure assets, enabling more effective emergency planning within Local Resilience Forums.

Recommendation 56: The Government should issue clear guidance on expected levels of Category 2 responders' engagement in planning, exercising and response and consider the case for strengthening enforcement arrangements.

Each of these recommendations is being implemented in some form by the Government (Defra 2012):

- Recommendations 55 and 56 relate directly to the implementation of the Civil Contingencies Act discussed in Section 2.3.1 above
- Recommendation 51 has resulted in the National Risk Register and Sector Resilience Plans outlined in Section 2.3.3 below.
- Recommendation 53 is reflected in the Cabinet Office's *Interim Guidance to the Economic Regulated Sectors* (Cabinet Office 2011a). This has largely been superseded by *Keeping the Country Running* so is not discussed in detail here.
- Section 2.3.4 examines the Cabinet Office's *Keeping the Country Running* document in response to Recommendations 50 and 52.

2.3.3 The national risk register & sector resilience plans

One of Pitt's criticisms was that the Government's critical infrastructure protection programme prior to 2007 overlooked natural hazards and focused primarily on terrorism. Moreover, there is the natural tendency to focus attention on the risk which has most recently been realized, for example winter preparedness in 2010 (Quarmby et al. 2010) or flooding in 2014 (Department for Communities and Local Government 2014).

The National Risk Register (NRR) creates consistency by drawing together information on the likelihood and potential impact of potential risks to the UK (Figure 2.3). The NRR allows risk managers to compare risks more easily and identify which they need to include in their planning processes (Cabinet Office 2008). Chapter 3.1 uses this information to define the scope of this research.

The Cabinet Office also publishes annual 'Sector Resilience Plans'. These Plans cover the nine sectors of the 'national infrastructure' (food, energy, water, communications, transport, health, emergency services, government, and finance), plus hazardous and civil nuclear sites. Unlike the top-down approach of the NRR, these reflect Recommendation 51 of the Pitt Review and are the result of a tripartite discussion between the operator, Government and regulators (Cabinet Office 2013a).

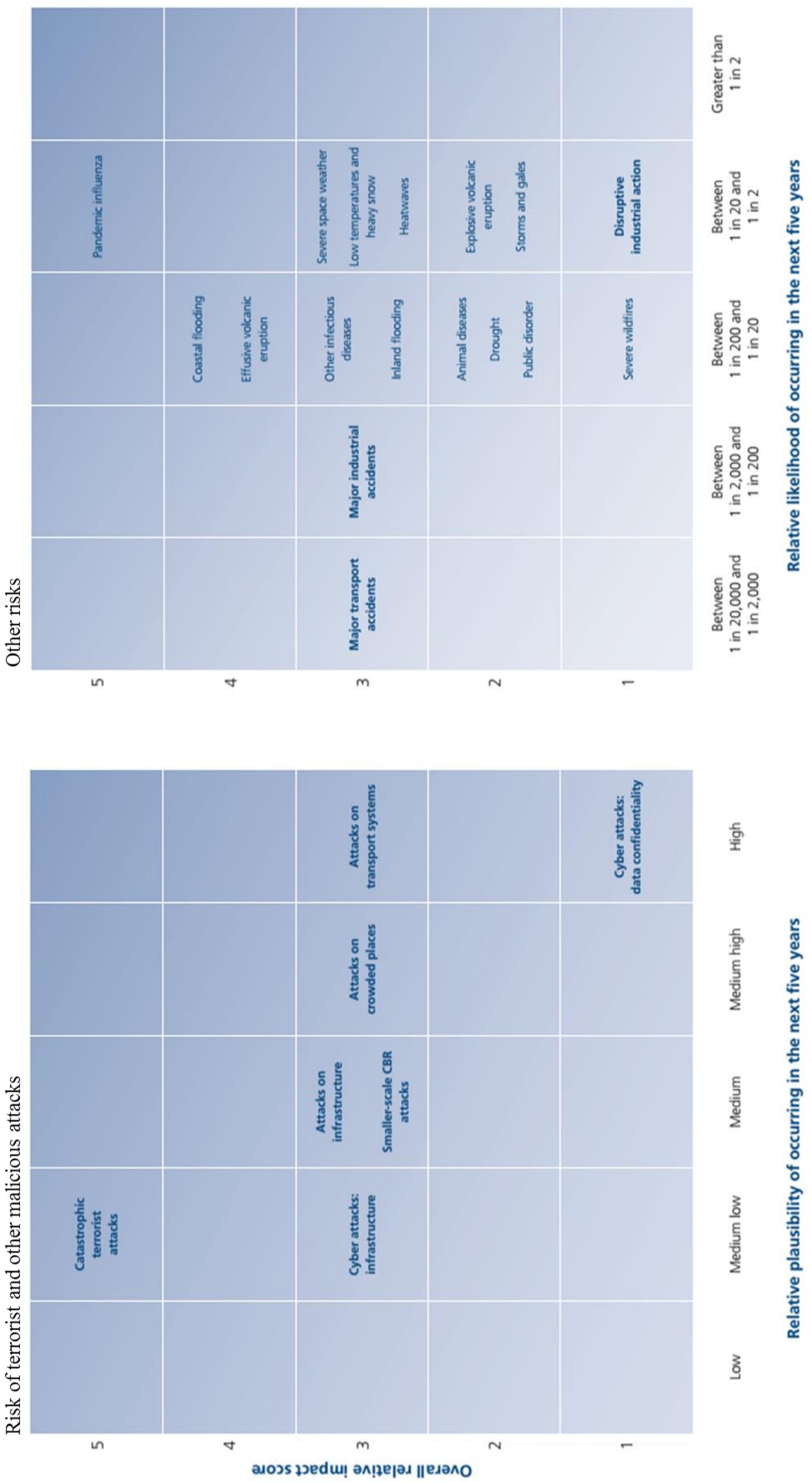


Figure 2.3 UK 2013 National Risk Register (Cabinet Office 2013b)

The full Sector Resilience Plans are classified but a brief one page summary for each sector is made public. The 2014 assessment of the water sector, which is largely unchanged from previous years, indicates that the sector is in strong position due a combination of the regulatory framework, mutual aid agreements and ongoing investment (Cabinet Office 2014). Since 2011, except for 2012 when drought was also included, the only risks mentioned specifically are vulnerabilities of the water sectors to disruption elsewhere. The importance of electricity and telecommunications has been raised every year and, following the heavy snowfall in the January 2010, they were joined in 2011 by the significance of road access (Cabinet Office 2011b). It is clear that the Sector Resilience Plans identify the dependence on other sectors which this research addresses as the most pressing concern for the resilience of water infrastructure.

2.3.4 Keeping the country running: natural hazards and infrastructure

At the centre of the Government's response to the Pitt Review's recommendations on infrastructure resilience is the 'guide to improving the resilience of critical infrastructure and essential services' produced by Civil Contingencies Secretariat in the Cabinet Office in 2011. The guide has already contributed the definition of resilience adopted in Section 2.2. The argument that resilience is secured through the four qualities shown in Figure 2.4 also forms the foundations for the methods used in this work.

Figure 2.4 'Components of Resilience' (Cabinet Office 2011a)

The idea of resilience as composed of multiple attributes is not unique to the Cabinet Office. Westrum (2006), for example, defines it as preventing, minimizing and recovering quickly from adverse consequences. Prior to adopting the Cabinet Office scheme in 2012, Ofwat broke it down into asset resilience, network resilience and emergency response (Ofwat 2010). Table 2.1 gives the Cabinet Office's definition for each of the four qualities.

Table 2.1 The Cabinet Office (2011a) components of resilience

Resistance	"the strength or protection to resist the hazard or its primary impact"
Reliability	"components are inherently designed to operate under a range of conditions and hence mitigate damage or loss"
Redundancy	"The availability of backup installations or spare capacity will enable operations to be switched or diverted to alternative parts of the network in the event of disruptions to ensure continuity of services"
Response & Recovery	"a fast and effective response to and recovery from disruptive events"

Some of the Cabinet Office descriptions are contentious. For example, Bruneau et al. (2003) and O'Rourke (2007) would describe the reliability as 'robustness' and use 'resourcefulness' to describe response and recovery. However, aside from a preference for words beginning with 'r', there is no consensus in the academic literature (see Bochinni et al. 2014). By contrast, the Cabinet Office terms are widely accepted in this project's industrial context. Notably Ofwat, in the principles for resilience planning they established in 2012, moved away from their 2010 approach and cite the Cabinet Office components. These definitions also feature in the UK Water Industry Research project to establish a common approach to resilience (UKWIR 2013).

Breaking resilience down into constituent parts can be viewed from two perspectives: i) a defence in depth and ii) the most efficient allocation of resources. The two perspectives are not contradictory but simply reflect different risk appetites.

Where safety is paramount (for example in air traffic control or the nuclear industry (Reason et al. 2006, Moller & Hansson 2008)) or an organisation has a specific responsibility to protect a particular receptor (for example the DWI and Environment Agency) then the defence in depth perspective is dominant because the risk appetite is very low.

The Cabinet Office and economic regulators such as Ofwat embody the other perspective. They are trying to strike a balance between attaining an acceptable level of resilience and the cost of achieving that level, seeking '*the most cost effective and proportionate risk management response*' (Cabinet Office 2011a, p14). They see a diversified approach as the most effective way for infrastructure to deal with the multiple hazards which it faces.

The underlying concept of the defence in depth approach is intuitive. If you have more barriers between a hazard and its potential consequence then the probability of the consequence occurring is lower. A commonly used metaphor, introduced by Reason in 1990, is of multiple slices of Swiss cheese (Figure 2.5). If all the holes in the cheese slices align then there is an uninterrupted path between the source and receptor.

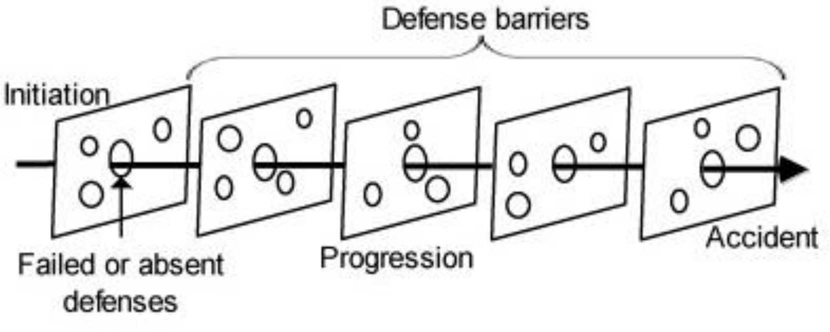


Figure 2.5 Reason's 'Swiss Cheese' model (from Mullai & Paulsson 2011)

Figure 2.6 shows the role of multiple defences in limiting the impact of the 2005 Cumbrian storms and floods. The initial impact, as discussed in Chapter 1, was large with many critical infrastructure assets flooded and wind damage to water treatment works and over 1 400 electricity lines. However, the ultimate impact on customer's potable water supply was relatively small with only 1 664 properties losing water supply for over 12 hours (McDonald & Yerkess 2005).

The different barriers acting to prevent the initial failures affecting customers are an excellent example of the defence in depth principle and can be mapped against the components of resilience described by the Cabinet Office. For example, providing bottled water and tankers pumping into the network are part of the response and recovery effort, whilst the ability to rezone customers onto different supplies is an example of redundancy.

In addition, the diversity of barriers also reflects the contrasting focus on proportionality. Firstly, the most critical water treatment works and booster pumping stations had standby generators installed to (theoretically) operate immediately when power was lost. Secondly, the less critical sites were restarted with mobile generators brought on to site. Thirdly, a tanker pumping into the network supplied a large group of properties who were cut off whilst smaller clusters of isolated properties were provided with bottled water.

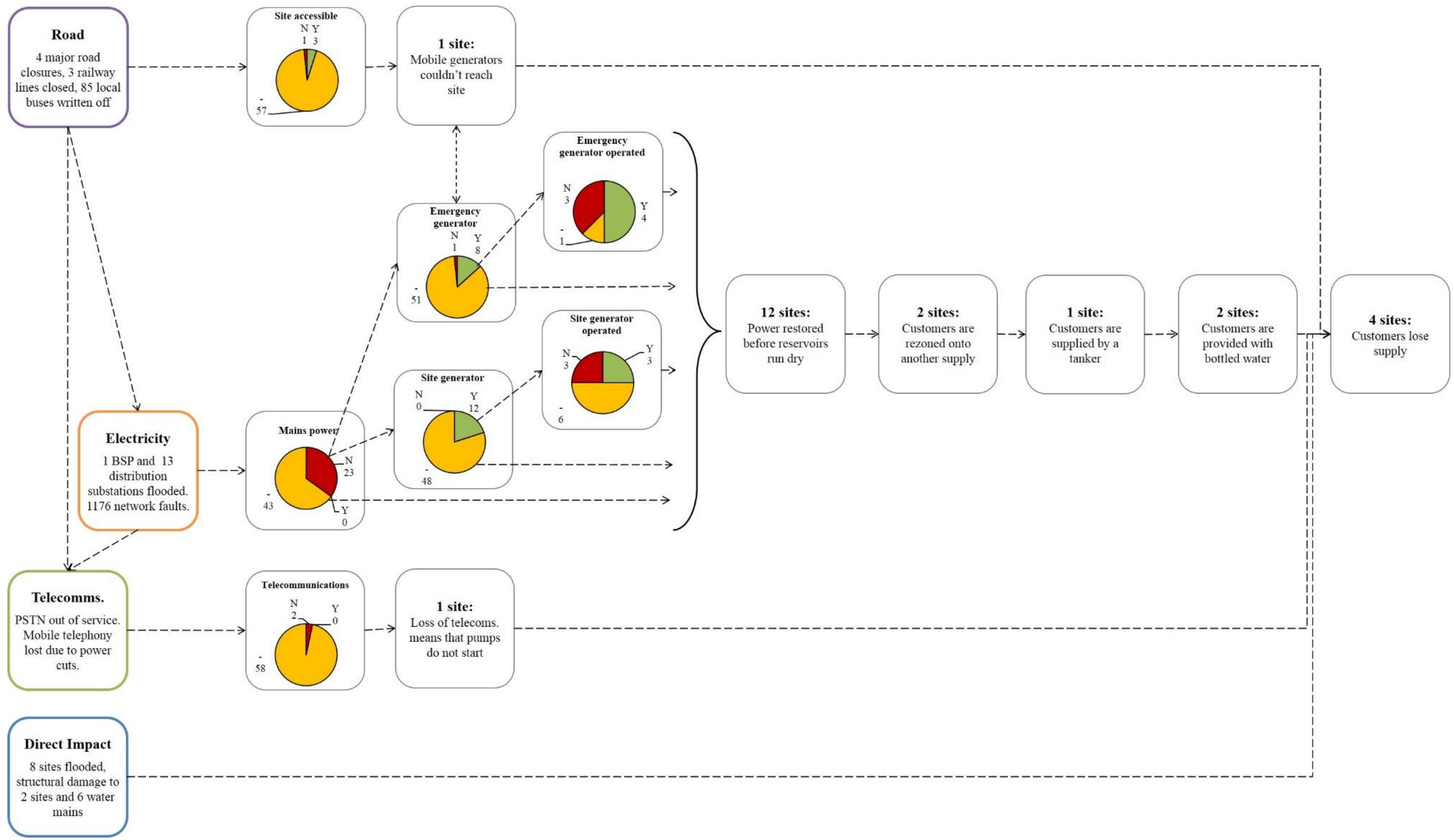


Figure 2.6 Direct and indirect impacts of the 2005 Cumbrian storm and floods on the potable water infrastructure. Data obtained from Cox (2005), Horsfall et al. (2005), McDonald & Yerkess (2005) & Environment Agency (2006).

The role of flexibility is further illustrated by the 12 sites where the power was restored before the water held in local service reservoirs was exhausted. The stored water created reliability within the water network since it continued to operate in adversity. Equally, the timely restoration of power supplies reflects the response and recovery efforts of the power company and their staff. The same result might have been achieved by focusing on each sector individually but this combination of both response and recovery and reliability is likely to be a more cost-efficient solution.

The Swiss Cheese metaphor also offers an insight into why accidents occur despite the manifold barriers. Reason (1990) argues that latent flaws in the later barriers are not revealed because the earlier barriers are effective. If the early barriers fail, the later barriers can turn out to be less effective than expected and the accidents still happen.

This is shown by the performance of standby generators following power cuts. Figure 2.6 shows how at least 25% of onsite generators and 38% of mobile generators failed to operate following the 2005 Cumbrian storm and floods. Similarly, Andrews (2006) claims that 50% of Thames Water's generators failed to start following storms in 1987.

Reason also builds on Perrow's (1984) Normal Accident Theory to explain why these flaws are not identified. Perrow emphasised two characteristics of complex systems:

i. Complex interactions: connections between system components are not easily understood so sequences of occurrences are unpredictable.

ii. Tight coupling: the buffers between system processes are small making it difficult to intercept cascading failures.

The argument is that a single person cannot hold a complete picture of a complex system and accidents, therefore, are inevitable. This is of particular relevance to interdependent infrastructure systems because they match Perrow's definition of complex systems. There are many interactions between facilities and varying degrees of coupling between them. Water companies and other stakeholders are concerned by their shortage of knowledge in this area, hence the requirement for the risk assessment methods developed in this research.

The 'Swiss Cheese' model provides a conceptual framework for assessing the risks to interdependent infrastructure and its barriers are reflected in the components of the model described in detail in Chapter 4.

The *Keeping the country running* guidance is also important because it includes a set of 'reasonable worst case scenarios'. Reinforcing the concept of proportionate resilience strategies, these define the size of event against which the UK government believes it is reasonable to expect infrastructure services to be protected. Considering these scenarios is an important part of infrastructure providers demonstrating their preparedness for potential disasters.

2.4 Regulatory environment

It has previously been discussed that the UK water industry has three principal regulators (Section 2.1). Two of these regulators, the DWI and Environment Agency, are focused on improving the quality of drinking water and the environment. The third, Ofwat, has a more complex role. Their duties, as defined in the 1991 and 2014 Water Acts, are to:

i. Protect the interests of customers.

ii. Ensure that water companies carry out their functions properly.

iii. Ensure that water companies are able to finance their operations

iv. To secure the 'long term resilience of the water and wastewater systems' with regards to environment pressures, population growth and changes in how customers behave.

The second duty is carried out through the penalties and incentives discussed in Section 2.4.2. The other duties are primarily achieved through the process outlined in the following section.

2.4.1 Price reviews

The amount that water companies can charge customers is set by Ofwat every five years through a process called a 'price review' (individual reviews are referred to as 'PR' followed by the year in which they took place, e.g. PR09, PR14 etc.). Each company produces a business plan detailing how much money they believe is needed to carry out their functions properly and invest in the long term health of their assets. Ofwat assess and challenges these plans to reach what they believe is a balance between protecting the bill-payer and ensuring that the companies are financially stable (Figure 2.7).

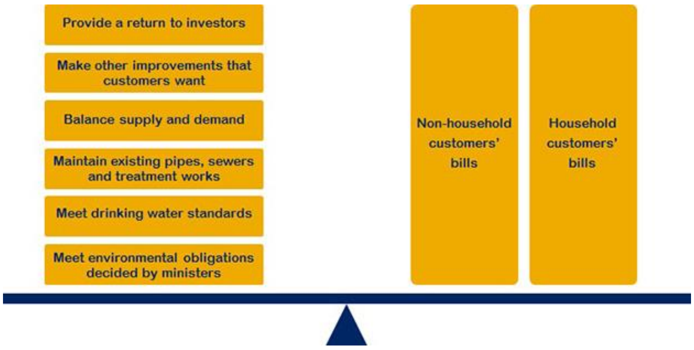


Figure 2.7 The Price Review Balance (Ofwat No Date)

The DWI, Environment Agency and, additionally, the Consumer Council for Water, are not directly involved in setting prices but can exert a strong influence on the process. Byatt (2013) notes that, as well as the risk of profiteering water companies, Ofwat have to protect customers from overeager regulators and Government departments pushing for disproportionate quality improvements.

The dialogue between regulators and companies is at the core of the process; this is evident in the draft and final determination documents published by Ofwat (2014b). Whilst it is a subjective decision (Ofwat's Chief Regulation Officer stressed in 2014 that *"constructive dialogue does not necessarily mean agreement"* (Brown 2014, p5)), robust evidence is essential (Ofwat 2010). Developing better methods for assessing the risks to water infrastructure will contribute to this dialogue and enable investment to be targeted more effectively.

Ofwat commissioned Mott MacDonald to publish *'Resilience: Outcomes Focused Regulation (Principles for Resilience Planning)'* as 'a contribution to thinking' on resilience (Ofwat 2012). Its nine principles develop on the Cabinet Office guidance:

1. An all-hazards approach to resilience planning.
2. Proportionate resilience strategies embedded into corporate governance.
3. Third party engagement.
4. Resilience planning focused on risk to service outcomes.
5. Customer preferences and environmental acceptability for different levels of resilience.
6. Broad consideration of intervention options for resilience.

7. Using cost-benefit analysis to support significant decisions.
8. Preparedness for response and recovery.
9. Continuous improvement in resilience planning.

These principles can be gathered into four themes relevant to this research:

i. Principles 3, 8, and 9 develop on the multi-agency planning which already exists through the Civil Contingencies Act and closely match the recommendations of the Pitt Review and the Cabinet Office in their *Interim guidance to the economic regulated sectors* and the *Keeping the country running* guide.

ii. The concept of all-hazards approaches promoted in principles 1 and 6 is to develop plans which span all the potential threats. The advantages of this approach are two-fold: i) they are more efficient because one intervention can treat multiple vulnerabilities, and ii) they account for situations where multiple hazards are occur simultaneously (Alexander 2005).

    An all-hazards approach matches the broad definition of resilience but a quantitative risk assessment necessitates a specific scenario or set of scenarios (Kaplan & Garrick 1984). This thesis will adopt an all hazard approach where possible by considering the likelihood of these hazards occurring together but the scope of the project is necessarily limited.

iii. The focus on proportionate strategies - Principle 2 - and cost benefit analysis - Principle 7 –recognizes that there must be a trade-off between cost and the level of protection. The risk assessment methods developed in this project are necessary to make these judgements about the proportionality of a strategy and analyse the benefits of interventions.

iv. Principles 4 and 5 mark Ofwat’s move away from detailed regulation of outputs (e.g. replacement of a certain length of pipe) to a risk based approach focusing on outcomes (e.g. a more reliable supply, less pollution etc.). Water companies are encouraged to think less in terms of asset failure and more in terms of how customers are affected. This is reflected in the incentives and penalties discussed below. It is important that the risk assessment methods and metrics used to measure failure capture the impact of failed infrastructure on customers.

Water companies which are able to articulate their investment requirements clearly, and support them with robust evidence, are more likely to gain Ofwat's support for their plans. This investment will make the companies less likely to receive the penalties for poor performance outlined below and increases the likelihood of outperformance.

2.4.2 Direct incentives and penalties

Each regulator has various mechanisms at their disposal to incentivise companies to deliver reliable service. It is worth noting that these mechanisms are potent but by no means predictable.

Environment Agency

The Environment Agency has a broad responsibility to protect the environment and regulate two water company activities; i) the abstraction of raw water for public supply, and ii) the return of sufficiently treated wastewater to the environment. If a company damages or endangers the environment then the Agency can take enforcement action to achieve the four outcomes shown in Figure 2.8.

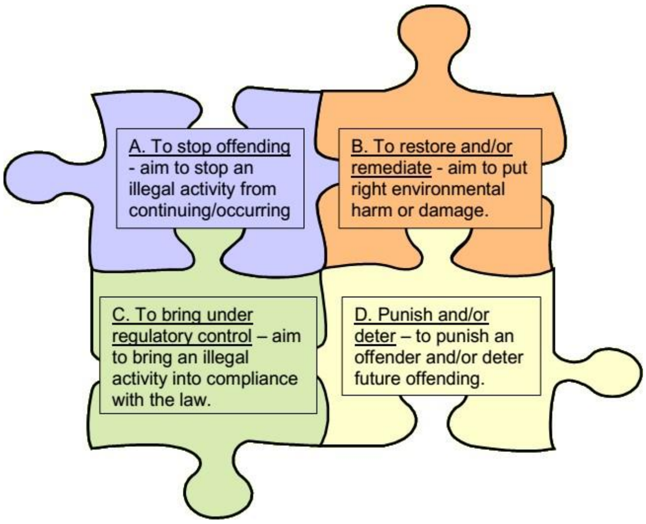


Figure 2.8 The outcomes sought by the Environment Agency's approach to enforcement (Environment Agency 2014b)

The Agency have a wide range of enforcement mechanisms at their disposal which are set out in their *Enforcement and Sanctions Guidance and Offence Response Options* (Environment Agency 2014b, 2014c). This section only considers those which are most relevant to water companies.

At the lowest level the Agency can issue warnings which have no immediate penalty but are recorded in case of future non-compliance. Similarly, formal cautions have no immediate penalty attached but require the offender to accept that they have committed an offence. If the caution is not accepted then the Agency will normally proceed with a prosecution in the normal way.

Prosecution is the most serious enforcement action that the Agency may take and, if successful, the maximum fine is unlimited (Sentencing Council 2014a). Stott (2009) calculates that the mean fine for water quality offences between the years 2000 and 2007 was £6 717 (he does not detail values for water resources offences but they appear to be of a similar magnitude). However, this does not capture the full picture on a number of fronts:

i. The financial means of an offender is considered when setting penalties. Stott (2009) notes that the average fine for an individual is around £5 500 compared to £8 000 for corporate offenders such as water companies.

ii. Mean values hide the range of potential penalties. Between 2011 and 2013 Southern Water, Thames Water and United Utilities all received fines in excess of £200 000 (BBC 2013a, Utility Week 2011, Crawford 2012).

iii. Prior to 2014 there was a perception that the penalties for offenders convicted of environmental offences were too low because magistrates were unfamiliar with the offences (Sentencing Council 2014b). In early 2014 the Sentencing Council published detailed guidelines which are expected to lead to larger fines (Eversheds 2014, Wilkinson 2014). Notably in the same year United Utilities received a fine for £400 000 and Southern Water were fined £500 000 (United Utilities 2014a, Environment Agency 2014d).

In lesser cases the Environment Agency also has powers under civil law. It can direct organisations to take actions to stop or remediate damage to the environment, or to change their practices to come into compliance with the regulatory requirements (Environment Agency 2014a). A company may also voluntarily enter into a legally binding enforcement undertaking where they agree to take action to remediate damage and prevent future failings. Both enforcement notices and enforcement undertakings are at the cost of the offender, which may have significant financial implications.

It is evident that enforcement is the subject of many different factors. The enforcement guidance includes 17 different public interest factors and considerations to be taken into account when choosing an appropriate response. Many individual consents also contain exclusions for extreme circumstances and failures caused by third parties – both of which are very relevant in this context. Therefore, whilst the enforcement powers of the Environment Agency are very significant, they are also highly unpredictable.

Drinking Water Inspectorate

The DWI has responsibility for both the quality and quantity of water received by customers, but its record of prosecutions and cautions indicates that it is almost entirely focused on the former (DWI 2014).

The enforcement options open to the DWI are almost identical to those available to the Environment Agency. They have civil powers to make companies take specific actions or they can use their criminal powers to issue cautions or proceed with a prosecution (DWI 2009a).

Their policy, however, is more clearly focused on encouraging companies to come into compliance with the regulations. For example, they issue 'Minded to Enforce' letters as an intermediate step to enforcement orders which encourage companies to enter into undertakings to remedy problems and prevent recurrence. Figure 2.9 shows that the fines issued upon convictions are also much smaller. It is important to note, however, that water companies place significant value on the health of their relationship with the DWI and its reputational importance.

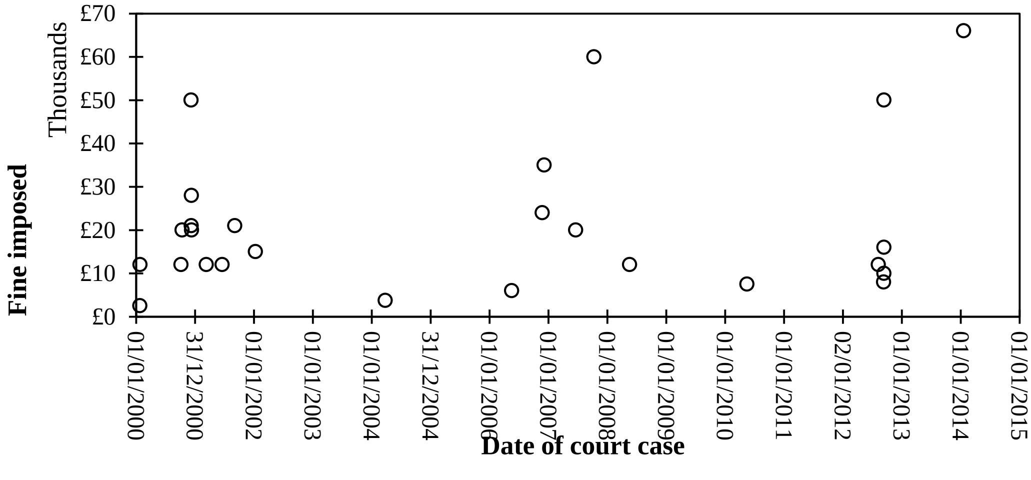


Figure 2.9 Fines imposed in drinking water quality prosecutions since 2000 (data from DWI 2014)

Ofwat

Ofwat have a number of performance measures which reflect the resilience of the company's services. The majority of this section focuses on the performance commitments which companies have made in their PR14 business plans but the Service Incentive Mechanism (SIM) is also significant. This mechanism assesses customer's experiences of contacting their water company (qualitative) and the number of contacts the company receives (quantitative) (Ofwat 2014b). The companies are ranked with the best performing company receiving a bonus of 0.5% of their revenue and the worst performing a penalty of 1% on their revenue. Resilience clearly has an effect on SIM performance since customers are more likely to be dissatisfied or contacting the company if their service is disrupted.

At the beginning of the latest price review process (PR14) water companies were asked to consult with their customers and develop their own performance measures which reflect their customers' interests (Ofwat 2011a). The metrics which have been proposed are not as varied as might have been expected; every water company has proposed measures regarding interruptions to supply. Moreover, the comparative analysis carried out by Ofwat (Table 2.2) indicates that the key performance indicators (KPIs) are also largely consistent, either because they were proposed as such or through Ofwat's intervention.

However, the actual level of service that each company proposed in their draft determinations varied significantly. For example Northumbrian Water's proposed performance level on supply interruptions by 2020 was five minutes per property per year, compared to 43 minutes per property per year for Welsh Water. Ofwat have resolved these discrepancies by adjusting the performance commitments of companies to match the upper quartile of performance recorded between 2011 and 2014 (Ofwat 2014c), with the exception of companies which had previously qualified as enhanced or were already proposing a better level of service.

Table 2.2 Outcomes of Ofwat's comparative analysis of proposed PR14 performance commitments (Ofwat 2014c)

Measure of success	**Standard KPI**	**Companies with standard KPI**	**Companies with comparable KPI**	**Companies with incomparable KPI**
Interruptions to supply	Number of hours lost due to water supply interruptions (including planned, unplanned, third party and overrun etc.) for three hours or longer, per property served.	15 Wessex Water and Sembcorp Bournemouth Water adopted the standard KPI after their draft determinations	2 Thames Water only count interruptions longer than 4 hours and Bristol Water include all interruptions regardless of duration	1 Affinity Water count unplanned interruptions over 12 hours. Ofwat did not intervene because Affinity's business plan was rated as enhanced.

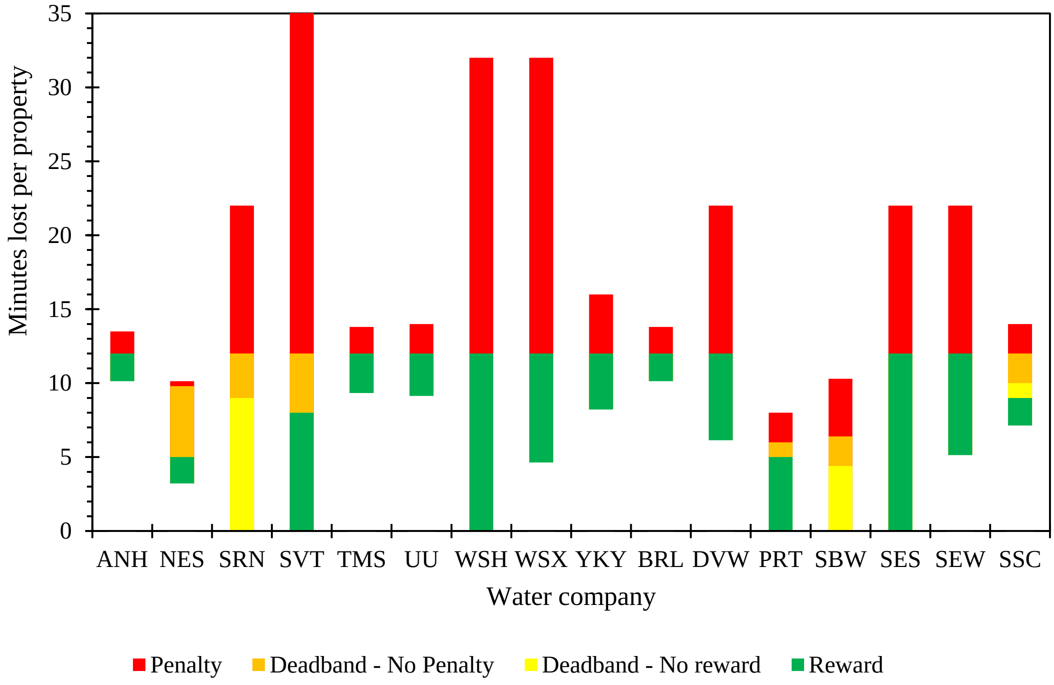


Figure 2.10 PR14 Penalties, deadbands and rewards for interruptions to supply (data from Ofwat 2014c)

ANH: Anglian Water (including Hartlepool), WSH: Dŵr Cymru / Welsh Water, NES: Northumbrian Water (including Essex and Suffolk Water), SVT: Severn Trent Water, SWT: South West Water, SRN: Southern Water, TMS: Thames Water, UU: United Utilities, WSX: Wessex Water, YKY: Yorkshire Water (including York), AFW: AffinityWater, BRL: Bristol Water, DVW: Dee Valley Water, PRT: Portsmouth Water, SBW: Sembcorp Bournemouth Water, SEW: South East Water, SSC: South Staffordshire Water (including Cambridge Water), SES: Sutton and East Surrey Water

For each measure of success the company can receive either a penalty or a reward. Additionally, there are often deadbands with no penalty and reward around each performance commitment, and caps and collars to ensure neither penalties nor rewards are excessive. Figure 2.10 shows that this is where the consistency ends. The size of the penalties and rewards also differ; Table 2.3 illustrates this with penalty and reward values for the three companies sponsoring this project.

Table 2.3 Penalties and rewards for industrial sponsors (Ofwat 2014b)

Company	**Interruptions to supply (£/minute/year)**	
	Penalty	**Reward**
Severn Trent Water	£1.1m	£1.1m
United Utilities	£5.2m	£4.0m
Yorkshire Water	£2.6m	£2.6m

It is important to note that there are many different balances between the size and probability of penalties. Seven Trent Water, for example, have much lower penalties but no upper cap. They may also have supplementary independent measures of success, for example Severn Treat Water have committed to reduce the number of customers with only one source of water.

Notwithstanding this complexity, three key principles emerge:

i. The potential penalties and rewards are significant. The Cumbrian floods and storms discussed previously caused 1 664 properties to lose supply for more than 12 hours. Making the very conservative assumption that all supplies were restored immediately at 12 hours this event would have added 24 seconds to the company's supply interruptions KPI for that year. Depending on the company's performance, this could equate to a £2.1 million penalty or cancel out a £1.6 million reward.[1]

ii. Many of the previous measures, for example the DG3 measure of customer interruptions, excluded events caused by third party failures. The new measures include all failures regardless of cause.

iii. The minutes lost per property measure matches the definition of resilience because they account for both the size of the impact and the speed of recovery (Figure 2.11). This is intuitive because customer disruption increases with longer interruptions. Therefore, this is a sensible metric for this project to adopt when measuring the performance of the potable water infrastructure.

[1] United Utilities billed 2 940 000 properties in 2007 (the closest available information) (Turner 2007).

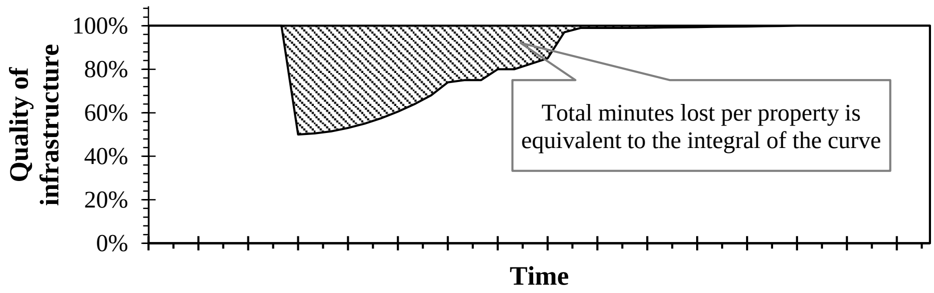


Figure 2.11 The correspondence between minutes lost per property and Bruneau et al.'s (2003) conceptual definition of resilience.

2.5 Summary

This chapter has outlined the drivers behind water companies' decisions and the information that they require to makes decisions about improving their resilience. These include their legal responsibilities under the Civil Contingencies Act and SEMD, the cascade of policy and regulatory documents which have followed the Pitt Review and the considerable financial penalties for failing to protect essential services.

The critical finding of this chapter is that there is a balance between i) protecting customers from high costs and ii) protecting them from infrastructure failures. This is mirrored in the regulatory regime: i) the companies must justify to Ofwat any extra investments that may be required to increase resilience and ii) a single major event could have severe financial and reputational consequences. The goal of this project is to help the companies achieve this balance by providing methods which assess the risk from dependence on other sectors.

Analysis of the policy and regulatory background also reveals factors which will influence the shape of the risk assessment methods. Firstly, the National Risk Register identifies the risks for which the water companies should be prepared and the sector resilience identify the infrastructure systems to be included in the assessment. This is discussed further in Section 3.1.3 of the following chapter. Secondly, the 'Swiss Cheese' metaphor and concept of resilience as a successive set of barriers between the hazard and its impact on customers will be used as a conceptual framework for the methods. Finally, the metrics used to measure risks will reflect the manner in which the failure affects customers; the property minutes without supply captures both the number of customers inconvenienced and the duration of this disruption.

Chapter 3. Establishment of a modelling framework

In the Chapter 1 it was established that the industrial sponsors, and infrastructure providers more generally, need methods which: i) provide quantitative information to support evidence based decisions; ii) identify where their systems are vulnerable and hence how to reduce risk; and iii) can be implemented in an industrial context. The central theme of this chapter is the balance between accuracy and complexity necessary to satisfy these three requirements.

The first section of chapter identifies all the necessary parameters that the risk assessment must consider to provide the information required by decision makers, including the relevant scales, sectors, hazards, and relationships between infrastructure components. The second part examines prospective methods and models for assessing risks before selecting the most appropriate for this research. The third and final section discusses the verification and validation of the risk assessments made in Chapters 5 and 6.

3.1 Parameters of the risk assessment

Hall et al. (2013) describe national infrastructure as systems-of-systems.

> *"Systems-of-systems are large scale, integrated, complex systems that can operate independently but are networked together for a common goal." (Hall et al. 2013, referencing Jamshidi 2008).*

As such, infrastructure has self-similar properties. At a low level, each asset in the infrastructure network is a system of its own components (motors, wiring, sensors etc.). Then each infrastructure network is its own system and, through its interdependencies, each network forms part of the wider system of national infrastructure. This national infrastructure then sits in the socio-political system of policy making and regulation described in the previous chapter. Given these many dimensions and scales it is essential to carefully define the boundaries of a risk assessment.

To define these boundaries in a systematic fashion this thesis uses the six dimensions of infrastructure interdependence defined by Rinaldi et al. (2001). These are shown in Figure 3.1; each of the subsections that follow corresponds to an arm of the diagram. The exception is the ‘infrastructure environment’ which has already been covered by the previous chapter.

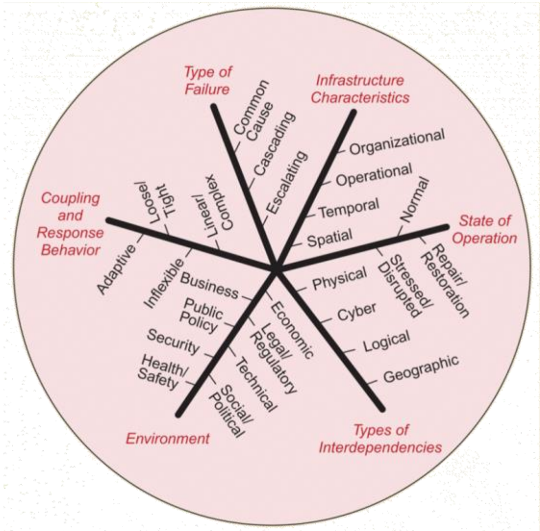


Figure 3.1 Dimensions for describing infrastructure interdependencies (Rinaldi et al. 2001)

3.1.1 *Infrastructure characteristics*

Spatial scales

Potable water networks operate at multiple and interconnected scales. Figure 3.2 shows the hierarchy used by the lead sponsor of this project to define different scales. This research will aim to deliver risk assessment methods which operate at the demand monitoring zone (DMZ) scale normally used by water companies for their asset management plans (United Utilities 2009).

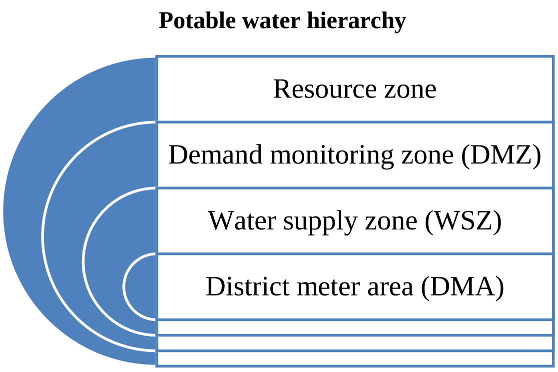


Figure 3.2 Water industry hierarchy of scales

Temporal range

It has previously been discussed that this research has adopted the Cabinet Office's definition of resilience (see Chapter 2.2). This definition refers to 'disruptive events', implying that the duration of the disruption is limited. Some academic definitions, such as Bruneau et al. (2003) and Greenberg et al. (2007), share this view and focus on shocks and events.

Others definitions, such as Holling's (1973) original ecological definition of resilience, refers to the ability to withstand disruption without change in the fundamental relationships and states. It therefore encompasses both the response to prolonged stresses and sharp shocks (Rose 2004). This perspective also appears in the policy and literature, with the phrase "resilient to climate change" occurring frequently (e.g. DEFRA 2011, Ofwat 2011b).

The risk assessment will be consistent with the adopted definition and focuses on short disruptions which develop and dissipate over a few days. Incidents which develop over weeks and months (e.g. drought and supply chain interruptions) are not considered.

Operational factors

These factors reflect the response and recovery component of resilience, including operational procedures, the training and motivation of staff and the effectiveness of contingency plans. These factors can be very significant, yet are difficult to model. This research focuses on the more predictable components of resilience, but the second case study brings elements of these operational factors into the analysis.

3.1.2 Types of interdependencies

Rinaldi et al. (2001) define four types of interdependency, the first three of which are within the scope of the research:

i. Physical – one system depends on the material output of another.

ii. Cyber – one system depends on information transmitted through another.

iii. Geographic – two systems can be affected by one local event.

iv. Logical – a dependency which is neither physical, cyber and geographic.

The concept of geographic interdependence is illustrated by Figure 3.3, an output from the 'hotspot analysis' conducted by the Infrastructure Transitions Research Consortium (ITRC). The concentrations of critical infrastructure suggest that hazards in some areas are likely to affect multiple systems.

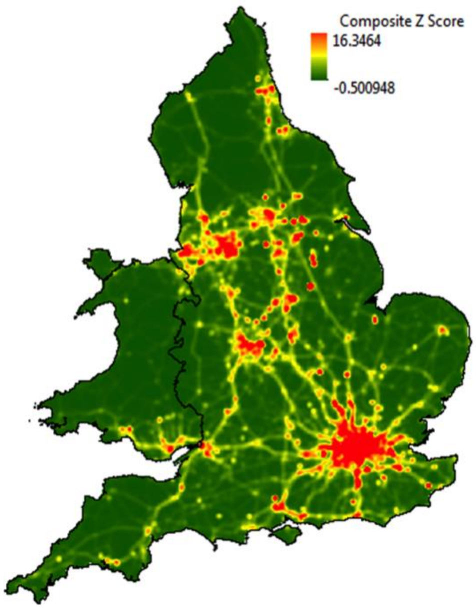


Figure 3.3 Criticality map from the ITRC critical infrastructure hotspot analysis (Hall 2014). Higher 'z' scores indicate concentrations of critical infrastructure.

Scale is clearly important to geographic interdependence. At a local scale, multiple systems may be affected by a single point of failure. For example, the damage to the Ulley Reservoir dam in 2007 endangered the M1 motorway, an electricity substation and gas network connection (Pitt 2008). At a regional or national scale a hazard across an area could simultaneously disable multiple systems, something which is evident in the 2005 Cumbrian floods and storm discussed in previous chapters.

This research will focus on the regional scale by assuming that the hazards occur uniformly across the area considered. In one respect this is a significant simplification because weather is affected by topography. However, micro scale hazard analysis is a developing science in its own right and beyond the scope of this project (see, for example, Blanc et al. 2012, Blenkinsop et al. 2012). The size of the DMZs and catchments means that the variability will not be large.

Geographic interdependency can exist regardless of the relationship between sectors but these connections become significant when considering physical and cyber dependencies. The UK Sector Resilience Plans identify nine national infrastructure sectors: food, energy, water, communications, transport, health, emergency services, government, and finance. This research focuses upon the three physical systems with which the water sector has physical and cyber dependencies: electricity, communications, and road transport.

The other sectors are potentially significant. For example, disruption to the health sector could affect staff availability or failures in the financial sector may prevent staff from buying essential equipment. In the 2005 Cumbrian floods the company's fuel cards were all held with one firm whose petrol stations were flooded. However, these are logical dependencies which are difficult to model systematically and outside the scope of this research.

3.1.3 Type of failure

Rinaldi et al. (2001) identify three types of interdependent failures:

i. *Cascading:* the loss of one infrastructure causes a failure in another.

ii. *Escalating:* a failure in one sector makes another failure in a different sector worse. For example repairs to flood damaged equipment can be delayed by a lack of access.

iii. *Common cause:* multiple networks are affected simultaneously. Most common cause failures are related to geographic interdependency but they can also be intermingled with cascading and escalating failures. For example the loss of power to any area may affect both water and telecommunications assets or transport disruption may delay the repairs of both failed electricity and telecommunications assets.

The remainder of this section defines which hazards will be considered by this research. The NRR includes 24 different hazards and it is beyond the scope of this project to consider them all. Beyond simply the number of hazards, the level of uncertainty over the likelihood and consequence of different hazards varies. This is illustrated by the New Zealand equivalent to the NRR, shown in Figure 3.4, which includes a representation of this uncertainty. Some threats (e.g. severe weather, financial crises and food safety scares) are relatively predictable but others (e.g. terrorism, human pandemic and large earthquakes) cover a very wide range. The scope of this research is limited to meteorological hazards as they are well understood.

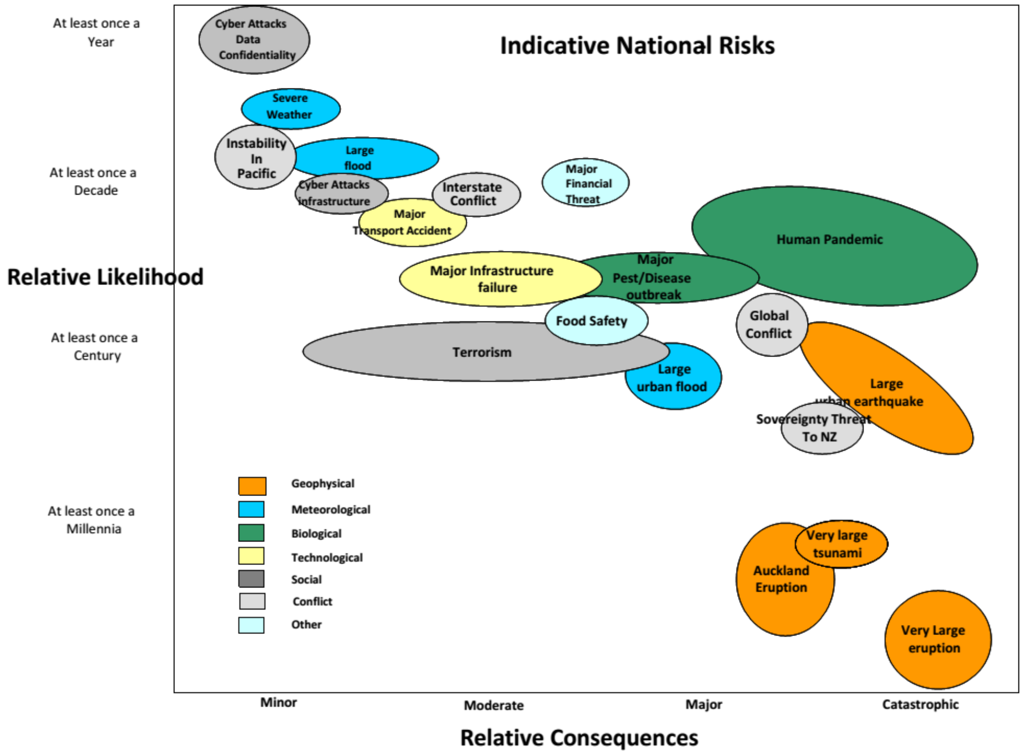


Figure 3.4 Indicative national risks to New Zealand (DPMC 2011). Like the UK equivalent the axes represent the likelihood and impact of the scenario, the size of the bubble provides additional information about the uncertainty around these estimates. Some (e.g. severe weather) can be predict be assessed with precision precisely, others (e.g. a human pandemic) are very uncertain.

Seven meteorological hazards are included in the UK NRR: coastal flooding; inland flooding; low temperatures and heavy snow; heatwaves; storms and gales; drought; and space weather. The Cabinet Office (2011a) also issues guidance which includes seven 'reasonable worst case scenarios'. Six of these match the NRR, but drought is omitted and land instability is included. These combined create a list of eight potential hazards. However the following three are excluded from the scope:

i. Space weather is an area of intense research interest and assessments of the probability of an event are starting to be formed (e.g. House of Commons Defence Committee 2012, Riley 2012). However, none are sufficiently detailed to perform a risk assessment comparable to the more conventional hazards.

ii. Land instability is a significant risk but the diversity of root causes and triggers (e.g. geomorphology, geology, antecedent rainfall) make it a difficult risk to assess across an area (van Westen 2006, Douglas 2007, Pellicani et al. 2014).

iii. Droughts develop outside of the short timescales to which the scope has already been limited.

Therefore, there are five hazards which are included within the scope: coastal flooding; inland flooding; low temperatures and heavy snow; heatwaves; and storms and gales.

3.1.4 Coupling and response behaviour

Coupling and response behaviour describes how the infrastructure sectors interact and determine the ease with which interdependencies can be diagnosed and managed. It has three facets:

i. The tightness of the coupling: how quickly do failures spread between sectors?

ii. The order of the coupling: does one sector depend directly on one another or do failures cascade through a number of sectors?

iii. Whether the coupling is linear or complex: is the dependency immediately obvious or the result of unpredictable interactions?

Tight or loose coupling

Loosely coupled dependencies give infrastructure providers time to diagnose and respond to failures. Tight coupling is more problematic because the impacts happen quicker and there is less time to organise an effective response. For example, the 2003 North American blackout, which affected an estimated 50 million people, was caused by a cascade of failures that occurred in quick succession (US-Canada Power System Outage Task Force 2004).

Whether coupling is tight or loose depends on the nature of the infrastructure. Electricity cannot be stored so a loss of supply causes an immediate loss of service. Interruptions of goods which can be stored more easily, such as water, gas and coal, may need to be longer in order to affect customer service. Gil & McCalley (2011) found that stored coal in the US bulk energy system made it resilient to major events such as the 2005 hurricanes. Similarly, in Britain, a simulation run by Chaudry et al. (2008) suggested that removing one storage facility increased the impact of losing a major gas terminal by 60%. In the water sector it has been estimated that, if the demand had not increased, there was enough water stored in the network to last for 36 hours after Mythe WTW had been shut down (Severn Trent 2007). It is essential that the scope includes the effect of storage to capture this resilience as not doing so could severely over-estimate the risk.

First or higher order coupling

First order dependencies are the most obvious and occur when there is a direct connection between two sectors. For example, a pump depends on power to operate and on telemetry to inform it when to turn on.

Higher order interdependencies occur where one sector is dependent on another through a third. For example, the telemetry system controlling a pump also requires electricity. Equally, crews repairing faults in the telemetry or electricity network are dependent upon the road network to reach the fault.

Linear or complex coupling

The distinction between linear and complex coupling was introduced by Perrow (1984), whose Normal Accident Theory was referenced in the previous discussion of the Swiss Cheese Model (Figure 2.5):

> *"Linear interactions are those in expected and familiar production or maintenance sequence, and those that are quite visible even if unplanned. ... Complex interactions are those of unfamiliar sequences, or unplanned and unexpected sequences, and either not visible or not immediately comprehensible." (Perrow 1984)*

Risks arising from linear interactions between components and sectors are the most obvious and must be addressed by the risk assessment processes developed through this research. With regards to unforeseen events, Pate-Cornell (2012) makes the distinction between two types:

i. 'Perfect storms': an unforeseen combination of circumstances.

ii. 'Black swans': events which only be explained and anticipated after they have occurred.

'Perfect Storms' are situations where a combination of hazards and failures given rise to an unexpectedly large consequence and are the target of this research. 'Black Swans' pose a more fundamental problem because, by definition, the impact of a scenario which cannot be anticipated cannot be assessed. These events therefore cannot be incorporated into a risk assessment and are outside the scope of this research.

3.1.5 State of operation

Demand

The relationship between natural hazards and demand is subject to many factors. Firstly, hazards have the potential to drive high levels of demand and therefore to cause widespread infrastructure outages. The demand for reactive power for air conditioning was a contributory factor in the 2003 North American blackout discussed above (US-Canada Power System Outage Task Force 2004). Equally high levels of leakage caused water shortages affecting around 450 000 Northern Ireland Water customers in the winter of 2010/2011 (Matthews et al. 2011).

Secondly, the threat of impending infrastructure failure can also drive exceptional demand. When Mythe WTW flooded in 2007 the major services reservoirs had enough water for more than 36 hours of normal demand. However Figure 3.5 shows how once the risk of interruptions was reported by the media (at 09:00 on the 22nd July) the demand for water more than doubled (Severn Trent Water 2007). The increased demand meant customers were losing water by 18:00 that evening and the reservoirs were empty by 21:15.

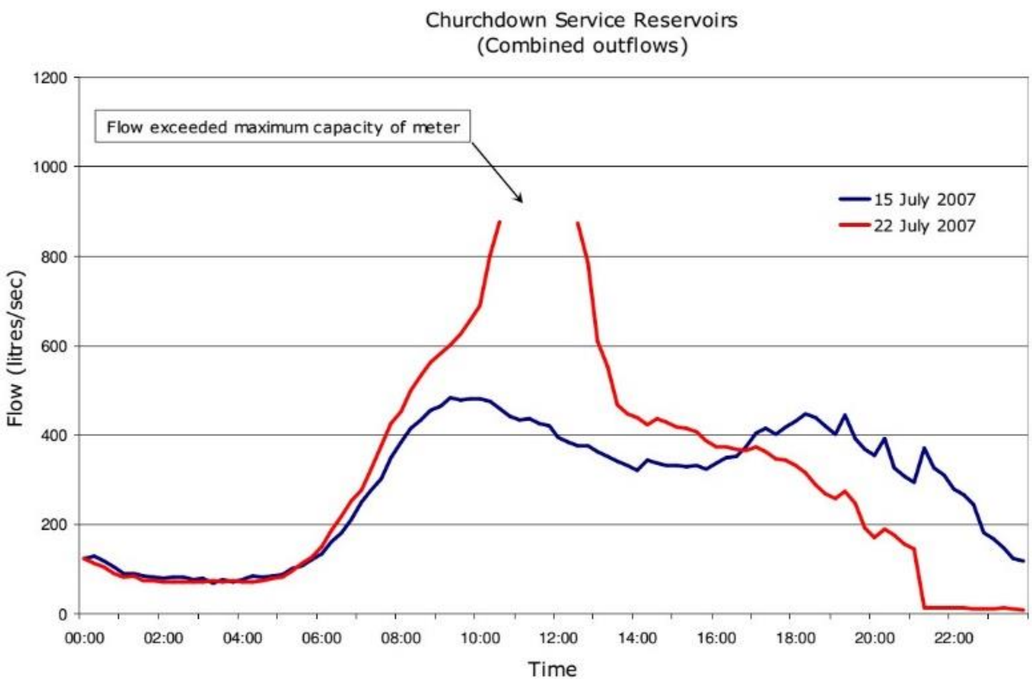


Figure 3.5 Combined outflows from the Churchdown service reservoirs prior to and during the 2007 flooding of Mythe WTW (Severn Trent Water 2007)

On the other hand, a natural disaster can reduce demand. For example, electricity companies do not protect the smallest (6.6 or 11kv) substations from flooding because the dependent properties are also likely to be flooded and therefore will not need power (Booth 2015 *pers. comm.*). Equally, Vugrin et al. (2011) use agent-based modelling to consider the chemical supply chains' exposure to two hurricane scenarios, one affecting Houston and the other New Orleans. They find that because Houston is a large producer of chemicals and New Orleans is a large consumer a hurricane affecting the latter will be less disruptive because demand will fall and the effect on production will be smaller.

Notwithstanding its significance, modelling demand is a complex exercise (Zio & Aven 2011). Introducing its dependency on hazards creates a complex joint probability problem so it is outside the scope of the first model developed in this research. However, it can be incorporated into the second model through the use of 'reasonable worst case scenarios'.

Degradation of service

The reliability component of resilience, as defined by the Cabinet Office (2011a), captures the idea that the operating state can be between the intended level and complete failure. This research will consider this dimension of resilience where justified by the balance of complexity, uncertainty and relevance.

Modelling reliability in the road network is simple as journey times can increase in response to a hazard. If the route is blocked the journey time can be set as infinite.

For electricity and telecommunications networks reliability is less relevant because the service these networks provide is largely binary. Power quality can be an issue (i.e. power 'blips') but water companies have protection in place which will cut the supply if there is a risk of their equipment being damaged (Booth 2015 *pers. comm.*). The question of whether systems restart automatically and correctly is outside the scope of this work.

The service provided by water networks can be degraded in two ways; i) reduced pressure or ii) lower quality of water. The former is not included because its impact does not warrant the extra complexity it would introduce; the customer can still perform the basic functions such as drinking and flushing toilets. Furthermore, the only regulatory incentives attached to low pressures is the SIM impact of the phone calls they may generate (see Section 2.4.2) because properties are only added to the low pressure register if the poor service persists or occurs frequently.

Poor quality drinking water is also omitted because of the difficulty of assessing water quality. This illustrated by the flooding of Mythe WTW where the Gloucestershire Primary Care Trust – responsible for public health – issued a blanket ‘Do Not Drink’ notice and did not allow water to be restored until customers received an information leaflet. The DWI, on the other hand, suggest that this was unnecessarily risk averse and contradicted the requirement to restore piped supply as soon as possible (DWI 2009b).

3.1.6 Summary of risk assessment parameters

This section has built upon the initial scope established in Chapter 1 and the regulatory and policy context discussed in Chapter 2 to set more detailed boundaries on the risk assessment methods developed through this research. These are summarised as follows:

i. The spatial scale will reflect the DMZs and catchments used by water companies for asset planning.

ii. The research will consider events which develop and dissipate within a few days.

iii. Geographical, cyber and physical interdependence will be considered. Logical interdependence is omitted.

iv. The research will explore water infrastructure’s dependence on electricity, telecommunications and roads.

v. Cascading, escalating and common cause failures will be included. The threats to infrastructure are limited to five meteorological hazards; coastal flooding; inland flooding; low temperatures and heavy snow; heatwaves; and storms and gales.

vi. The methods developed must recognise different levels of coupling between networks. They will also consider higher order and complex dependencies but will not consider entirely unforeseeable ‘black swan’ events.

vii. Changes in demand in response to hazards are recognised as a complex problem, therefore demand will be held constant in Case Study 1.

viii. Reliability (i.e. a reduced level of service rather than complete failure) is considered in the highways network. It is not relevant to electricity and telecommunications network, and omitted for the water and wastewater networks because the difficulty of assessing the risk outweighs the impact on the customer.

3.2 Methods for assessing interdependence

Infrastructure operators are not alone in wanting to assess the risk of failures in complex systems; the field of reliability engineering has grown around the desire to improve the reliability of complex and safety-critical systems such as oil rigs, nuclear reactors and aerospace.

In 2012 the UK Government Office for Science produced the *Blackett Review of High Impact Low Probability risks* which outlined three approaches to assessing risks:

i. *Heuristic:* a subjective score is given where there is little measurable information. This is the least preferable approach.

ii. *Deterministic:* evaluation of a single specific, frequently 'worst case', scenario.

iii. *Probabilistic:* evaluates different levels of impact from a range of possible events.

The methods for assessing risks outlined in the following section fall under these headings. The qualitative risk assessment techniques discussed in the first subsection belong to the heuristic category. The majority of the simulation methods for risk assessment outlined in the third section are deterministic but a small number of probabilistic examples are identified. Further probabilistic methods are discussed in the second section on the application of fault and event trees.

3.2.1 Qualitative expert elicitation

Many of the well-established methods apply a rigorous and exhaustive structure to the elicitation of knowledge from experts in the design and operation of the systems.

Hazard and operability (HAZOP) studies are one example of such approaches. An assembled team of experts follow a strict process using a set of guide words such as 'more', 'less', 'reverse', 'early' and 'before' to assess how the system would respond to deviations from its design conditions (Figure 3.6). As such they are able to deal with all the interdependence types discussed above and, in particular, different types of coupling. No studies have been found which use HAZOP to assess interdependent infrastructure, but it has been applied to supply chain risks (e.g. Adhitya et al. 2009) and is known to have been applied to a water company's SEMD capabilities.

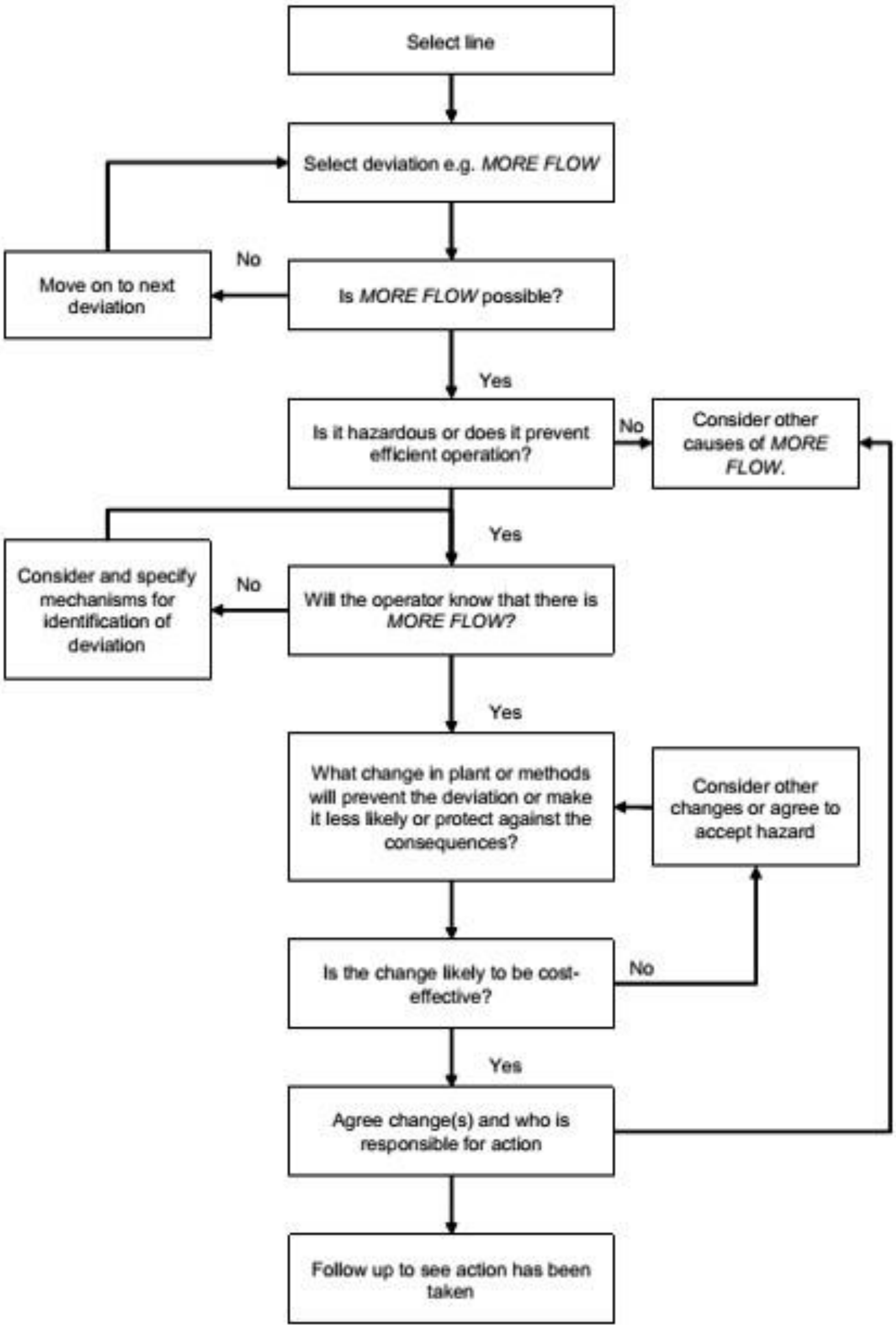


Figure 3.6 HAZOP procedure (NSW Planning Department 2008)

'Failure Mode Effects Analysis' (FMEA), or its extension 'Failure Mode, Effects and Criticality Analysis (FMECA), is similar to HAZOP but uses failure modes as the starting point for the analysis. The possible failure modes of each system component are listed along with potential causes and effects. Each combination is scored, typically between 1 and 10, according to its likelihood, severity and the chance of the failure being detected before impact. The product of these numbers is taken as the 'risk priority number' and used to prioritise risk control measures (McDermott et al. 2009).

A number of studies have successfully applied FMEA to critical infrastructure. For example, Bekkem et al. (2013) identified flood vulnerable stretches of the I-90/94 highway in Wisconsin which have now been added to the state's 'watch list'. Lhomme et al. (2011) extend FMEA to interdependent infrastructure. Notably they identify that, whilst faults in the electricity sector cause most failures, pumping stations are the most sensitive to failures. Therefore, they suggest, resilience strategies should focus on these vulnerable components.

One of the strengths of a qualitative approach is that the human mind has a more powerful imagination than a mathematical or computer model; the 'brainstorming' process which is central to FMEA and HAZOP studies may reveal previously unseen linkages. On the other hand, the rigid, meticulous structure of HAZOP or FMEA studies may inhibit this free thinking.

These approaches also have significant weaknesses. The meticulous, exhaustive structure of these approaches means that they are time consuming with fatigue and boredom increasing the chance of significant risks being missed (Baybutt 2013). The requirement to assess each component in turn limits their application, especially when considering large, complex, infrastructure networks with many components (Yusta et al. 2011). Methods founded on expert opinion are also limited by the inconsistency of human decision making, particularly when faced with uncertain information (Sterman 2001, French et al. 2009). Differences in opinion or, in the case of FMEA, the arbitrary scoring of risks can lead to drastically different results (Giacchero et al. 2013).

3.2.2 Fault and event trees

Fault and event trees are one way of moving from qualitative to quantitative assessment. The focal point of each is a particular undesirable system state known as a top event. A fault tree details the most credible faults, or combinations of faults, which could give rise to this top event (Figure 3.7). Combinations of faults are joined by logic gates; an AND gate identifies faults which must occur in union and an OR gate designates when only one of the faults would be sufficient (Vesely et al. 1981). The event tree works in the opposite direction; taking the top event as the starting point it identifies the potential consequences which may arise (Simpson et al. 2005).

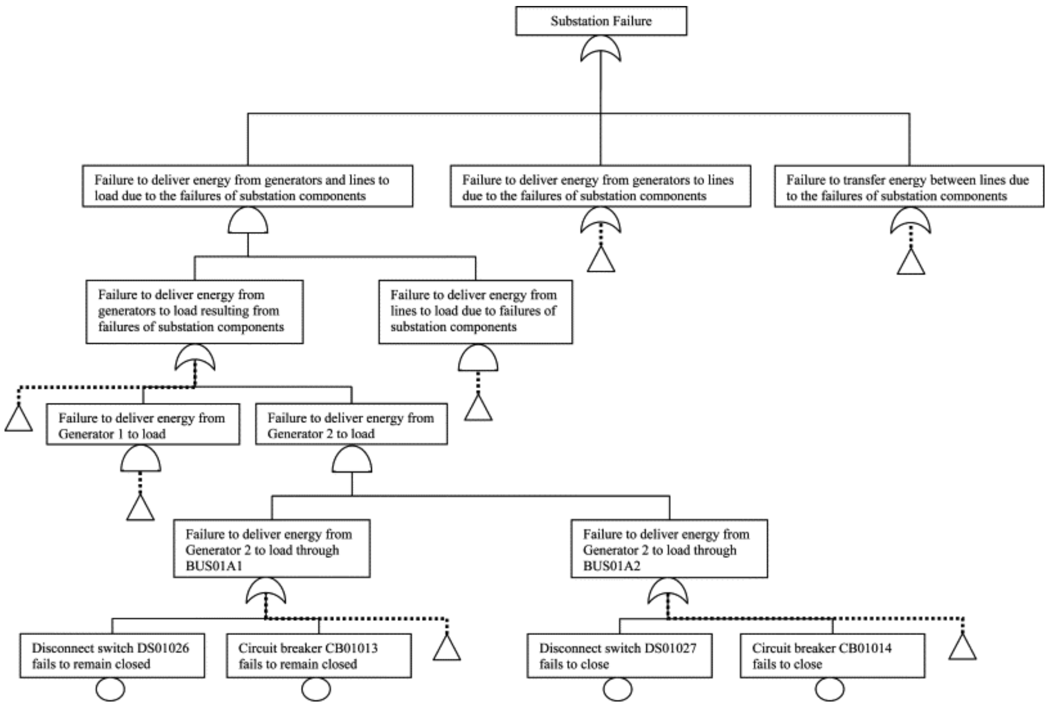


Figure 3.7 Simplified fault tree for a substation (Volkanovski et al. 2009)

When a fault tree and event tree for the same top event are combined they form a distinctive 'bow-tie' model (Figure 3.8). The origins of the bow-tie concept are uncertain but it developed and gained prominence when adopted by the Royal Dutch / Shell petrochemical group following the Piper Alpha disaster in 1988 (Blaauwgeers et al. 2013). The parallels with Reason's 'Swiss cheese' model (Figure 2.5) are striking with the 'systems resiliency barriers' in Figure 3.8 corresponding with the slices of holed cheese.

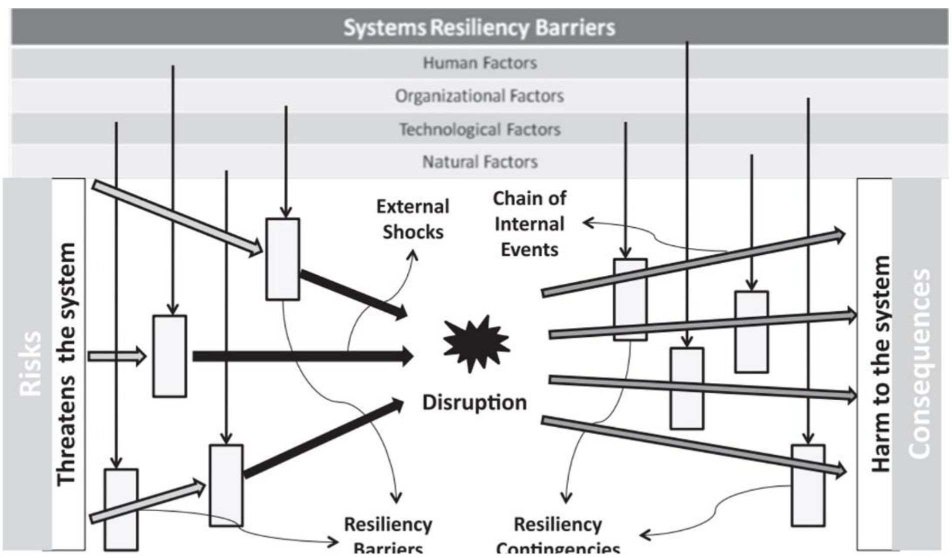


Figure 3.8 Bowtie model (Mansouri et al. 2010)

Like FMEA and HAZOP studies, fault and event can be used simply to identify and record vulnerabilities. ‘Cutsets’ can be defined which find the smallest combination of events likely to affect the system (Brown et al. 2006). More importantly, they provide a convenient way of introducing quantitative information as probabilities can be attached to each of the barriers (Vesely et al. 1981).

A number of studies have used fault trees to assess infrastructure components. For example, Volkanovski et al. (2009) and Cepin (2012) analyse electricity substations whilst WRc (2005) ran a collaborative water industry project to create a common approach to fault trees. Rahman et al. (2013) use fault trees to consider an entire, real-world, electricity distribution system and, by using distributions of recovery times, calculate the standard IEEE reliability indices. They show that, when the results are weighted by the customer impact, a fault tree analysis can closely match observed records.

However, the approach has limitations. Fault and event trees are capable of reproducing instantaneous physical and cyber dependencies because they describe the immediate consequences of a connection between components being lost. They are less well suited to modelling geographic and loosely coupled interdependencies.

Furthermore, as the redundancy within a system increases (and it nominally becomes more resilient) the importance of common cause failures, such as geographic interdependencies, also increases (Cepin 2010). The structure of fault and event trees naturally leans towards the analysis of independent events but there are various methods to consider common cause failures (e.g. alpha-factor, beta-factor and multiple Greek Letter (Cepin 2012)). The disadvantage is that considering common cause failures further increases the data requirements in situations where data is limited (Cepin 2010, 2012). Rahman et al. (2013) note that missing and insufficient data was a particular challenge in their work and ‘substantial effort’ was required to find the failure frequencies and downtimes of individual components.

Trees also grow rapidly as the number of components, consequences and dependencies increases; each triangle symbol in Figure 3.7 denotes an extension of the fault tree on another sheet. Rahman et al. (2013) suggest that for large systems the computational, and presumably cognitive, resources required for analysis of large trees quickly becomes unwieldy and a Monte Carlo simulation approach is often used instead.

The ability of fault and event trees to consider the temporal aspect of failures is limited to ‘PRIORITY AND’ gates specifying that faults must occur in sequence (Kontogiannis et al. 2000). In tightly coupled systems (e.g. electricity networks) this is not a problem, hence Rahman et al.’s (2013) use of recovery times to assess interruption durations. In loosely coupled systems (e.g. water networks) it is a more fundamental obstacle.

Ultimately, Eusgeld et al. (2008) argue that fault and event trees are not well suited to interconnected infrastructure systems with interdependencies, feedback loops and non-linear behaviour. Therefore more powerful methods are required.

3.2.3 Simulation

Simulation models are simplified representations which reduce the size, complexity or detail of their real-world counterparts (Gilbert & Troitzsch 2005). They are used for a number of reasons.

i. The nature of these real-world systems - large, complicated and interdependent – makes them difficult to understand. A model can highlight the dependencies which are most influential and hence drive the system behaviour.

ii. A model can bring together diverse sources of information into a single place. (Santella et al. 2009) and formalises a qualitative understanding of a system into a structure which is coherent, consistent and quantifiable (Gilbert & Troitzsch 2005). This understanding therefore takes on more validity because the underlying logic can be followed.

iii. Models are a low cost and low risk opportunity to experiment with interventions to improve systems (Sa Silva et al. 2010).

A number of comprehensive reviews by Pederson et al. (2006), Eusgeld et al. (2008), Yusta et al. (2011) and most recently Ouyang (2014) outline the many different methods for the modelling and simulation of interdependent infrastructure systems. The content of these reviews is not repeated in this thesis but the following section draws on this literature to establish the best approach for this research.

Sector models

System dynamics and input output models have been used to simulate disruption in multiple sectors. The progress of time is central to these models so they are well suited to modelling systems such as water networks with loose or variable coupling.

This is illustrated by Hallegate's use of input-output modelling to study the direct and indirect losses following Hurricane Katrina (Hallegate 2008, 2014). Basic input-output models use matrix describing how the outputs from one sector are the inputs of another and a sector's production must satisfy the requirements of other sectors and any external demand (Jiang & Haimes 2004). Hallegate develops this further to create an 'Adaptive Regional Input-Output' (ARIO) model which accounts for how sectors can stockpile resources and adapt following disruption. (Hallegatte 2008). Figure 3.9 shows the results from two sectors (agriculture and construction). Note how, in both cases, production drops six months after the event due to a shortage of resources but then recovers and capacity increases to meet the excess demand.

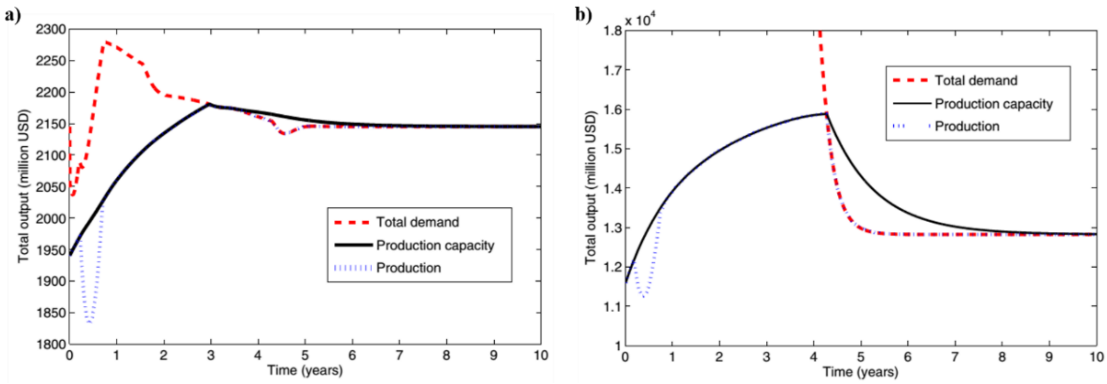


Figure 3.9 Hallegatte's modelling of production and demand in the a) agriculture and b) construction sector following Hurricane Katrina (Hallegatte 2014)

Another example is the CIP/DSS system dynamics model of interdependent infrastructure which has been developed by a group of the US National Laboratories. At their simplest, systems dynamics models have two types of components (Gilbert & Troitzsch 2005):

i. Levels – accumulations of items such as water in a reservoirs or patients in a hospital.

ii. Rates – flows into, from and between levels.

The relationships between these levels and rates define how the system operates. Figure 3.10 shows the CIP/DSS model of an infectious disease outbreak. Simulating these interactions can reveal the behaviour of complex systems responding to disruption. Pasqualini et al. (2006) apply CIP/DSS to contamination in the potable water network and show how the number of people who become ill steadily rises as the contaminant spreads through the system (Figure 3.11). They then trace the impact of this scenario through to other sectors, including the number of patients waiting in Accident and Emergency (Figure 3.12) and the total cost of the event (Figure 3.13).

The weakness of these approaches is that, because they address a broad set of sectors, they offer little information about the operation of individual networks and assets. Pasqualini et al. (2006) discuss how they break down a larger network into a tree structure to approximate local contamination and note that, once calibrated, the results compare well with results from a physically based model. However, they provide no information about how their model is calibrated. To help infrastructure providers identify how they make their specific systems more resilient it is apparent that the methods need to address the physical shape of the networks.

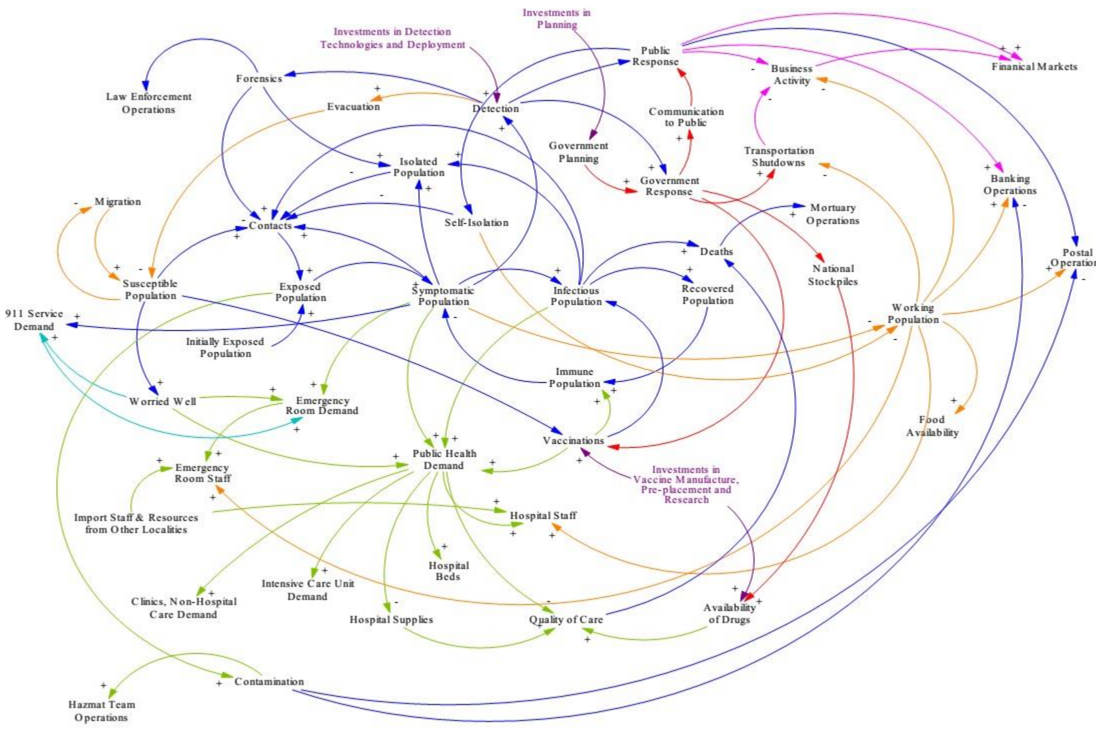


Figure 3.10 'Influence diagram' showing the CIP/DSS model of an outbreak of infectious disease (Bush et al. 2005)

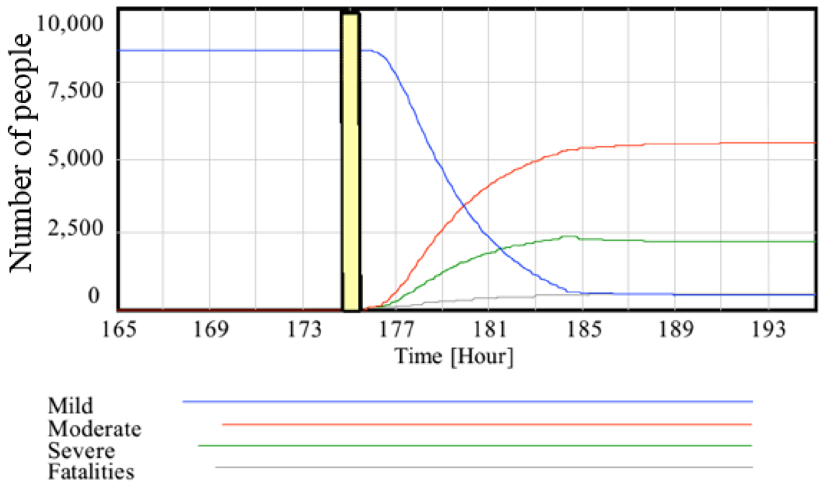


Figure 3.11 Modelled cumulative number of people affected by contamination and level of illness (Pasqualini et al. 2006). The yellow block indicates the contamination event but they do not explain why mild casualties occur before the contamination event.

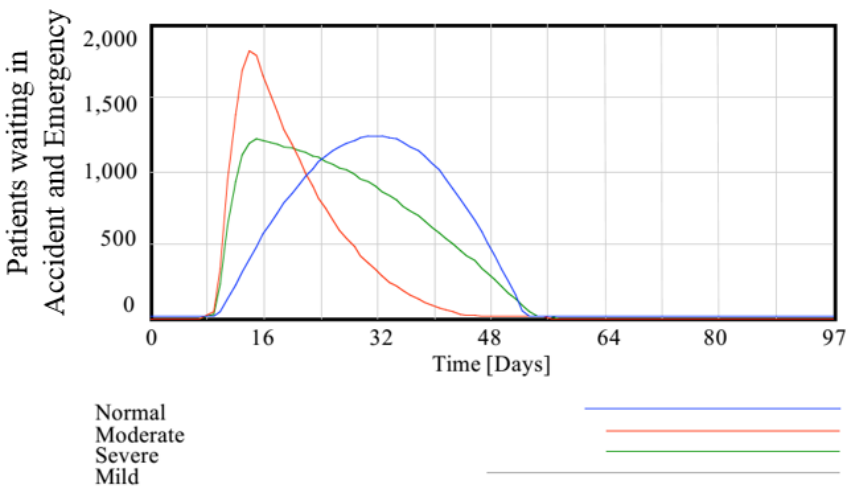


Figure 3.12 The results from coupling the contamination model to the health care model (Pasqualini et al. 2006). The blue line shows how patients attending A&E for other causes are affected by demand created by the contamination event.

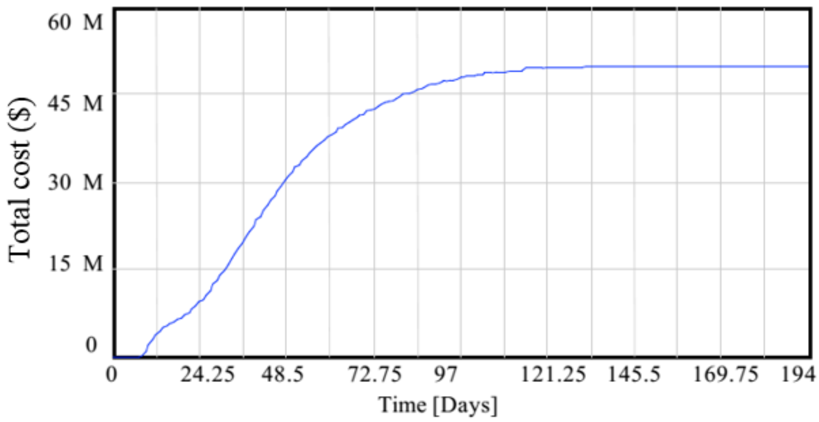


Figure 3.13 Total cost of the scenario (Pasqualini et al. 2006)

Topological models

Some studies make the topological structure of infrastructure networks their sole focus by simplifying them to sets of nodes and links. Failures are modelled by removing nodes or links and analysing how the connectivity or efficiency of the network is affected.

The principal advantage of these methods is their computational efficiency whilst still revealing information about the resilience of a network (Dunn et al. 2013). For example, Buldyrev et al. (2010) analyse how many nodes need to be removed before the network completely fragments into isolated clusters, with the assumption that only those in the largest cluster remain functional. Their key finding was that interdependence between two networks significantly reduced the threshold at which networks became completely fragmented (Figure 3.14).

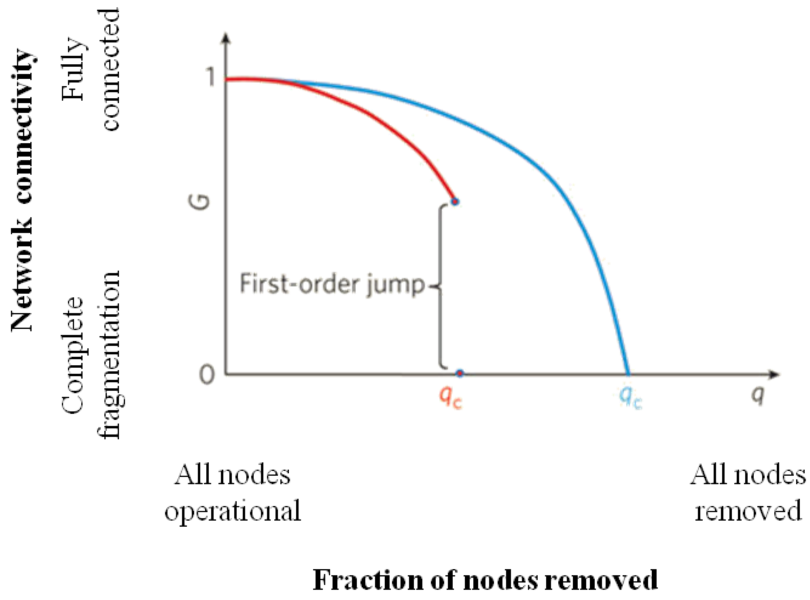


Figure 3.14 Breakdown of isolated (blue) and interconnected (red) networks (Vespignani 2010 – axis annotation added). In an isolated network there is a continuous curve describing the fragmentation of the network as nodes are removed. When networks are interdependent the transition occurs abruptly when fewer nodes have been removed.

A slightly less stylised approach is to use metrics from graph theory to assess the resilience and efficiency of networks. Seminal work by Albert, Barabasi and Yeung (Albert et al. 2000, Barabasi & Albert 2000) indicates that networks such as the internet and electricity networks grow through preferential attachment; critical nodes develop because new nodes attach to nodes which are already well connected. The resulting network is resilient to random failures because the chance of an important node being affected is small. However a failure at a critical node, perhaps due to a malicious attack, is potentially catastrophic. This is exemplified by the city of New York which has been affected by both a targeted attack – 9/11 – and a 'random'[1] disaster – Hurricane Sandy.

Yazdani & Jeffrey (2011) calculate a number of different graph theory measures for four real-world water distribution networks. The results question whether water networks follow the generic patterns identified in other networks by Albert, Barabasi and Yeung (Albert et al. 1999, Barabasi & Albert 2000). The constraints of the physical and urban environments (for example hills, rivers and roads) and capital cost of laying pipes mean that the draw of preferential attachment is weaker and the highly connected hubs do not form.

Yazdani and Jeffrey (2011) also note that connectivity is not the only criterion for identifying critical nodes. The position of a link in the network can make it more influential and critical links, or 'bridges', form between clusters meaning that removing a small number of links, a 'cut-set', can isolate large areas (Figure 3.15).

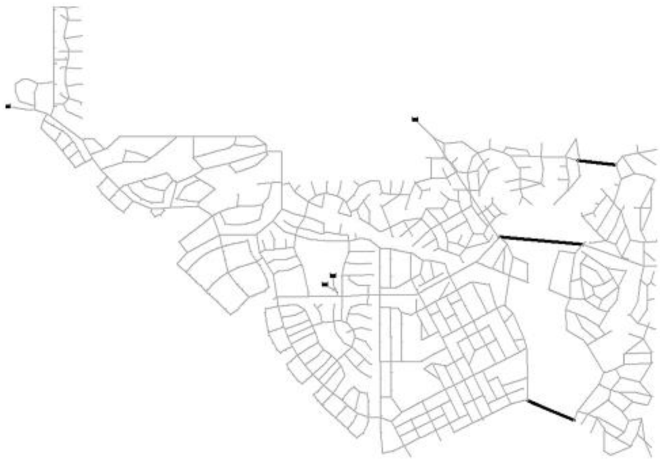


Figure 3.15 A region of the Colorado Springs network can be easily isolated by the removal of three links (Yazdani & Jeffrey 2011)

In later work they argue that the 'stark discrepancies' between the representation produced by the basic graph theory approaches methods and the actual network 'both limits the utility and compromises the plausibility of the analysis' (Yazdani & Jeffrey 2012, p9). They create a more informative representation by weighting nodes according

[1] It is worth noting that infrastructure networks are socio-technical systems so no event is 'random'; the social and economic value of New York's coastline led to its location and vulnerability to a storm surge.

to their demand and the diameter of the pipes which connect into them. They therefore account for the fact that treatment works, pumping stations and reservoirs, which are likely to be connected by large pipes, are more critical. This begins to close the gap between the graph theory approaches and real networks but there remain some critical omissions.

Firstly, topological methods assume that all dependencies are tightly coupled and they cannot account for the existence of storage or the increasing disruption caused by prolonged events. Therefore they are likely to overestimate the instantaneous impact of an event and underestimate its long term consequences.

Secondly, topological models assume that the existence of a connection allows customers to be supplied. In reality a water company's ability to rezone customers is limited by head losses in pipes and differences in elevation. This will further overestimate the impact of events.

Hines et al. (2010) benchmark two topological metrics against the output of a full power flow model. They find that the metrics are useful indications of general trends but reliance on them could lead to resources to improve resilience being wasted in the wrong places. They recommend that physically based models are more realistic and more useful.

Flow based models

The function of infrastructure networks is to transmit to a consumer something which they needed and it is natural to model them in terms of flows. This is most frequently achieved by using physically based models and there are numerous examples in the literature (see Yusta et al. 2011 and Ouyang 2014).

Ouyang's (2014) appraisal of different simulation methods for interdependent infrastructure supports the conclusion that flow based methods are the most versatile and realistic:

> *"In sum, flow-based methods capture the flow characteristics of interdependent CISs [critical infrastructures systems], and provide more realistic descriptions on their operation mechanisms. This type of methods can also identify critical CIS components, and provide emergency protection suggestions on CISs." (Ouyang 2014, p52)*

However the realism of these models comes at a cost; flow based approaches are computationally demanding and require large amounts of data. The computational cost is not trivial but this problem is more easily overcome; the rapid advance of computing power means that what was once prohibitive can quickly become possible.

The data requirements are the main weakness as more realistic models are computationally feasible but the information about how the infrastructure networks operate is difficult to acquire. This project has access to the industrial sponsor’s data and therefore a rare opportunity to create a realistic water model. For other infrastructure sectors it is dependent on publicly available data; in some sectors this information is quite extensive (e.g. roads are marked on maps and electricity information is available from network operators through their ‘Long Term Development Statements’), in others (e.g. telecommunications) less is available.

Notwithstanding the challenge of data availability, a flow based method is selected as the most appropriate for this study. Representing flow in networks is the most realistic way to recreate their operation and therefore inform infrastructure providers about the particular vulnerabilities of specific networks.

<u>Stochastic simulation</u>

A notable omission of studies using simulation methods is a consideration of how likely the hazard is to occur; they focus almost exclusively on the impact of a predetermined scenario. This is in contrast to expert based and fault / event tree methods which are explicitly include this dimension

Holden et al. (2013) are one exception, but they only use a very simple network (Figure 3.16) and sample capacities at random according to a hypothetical Beta distribution.

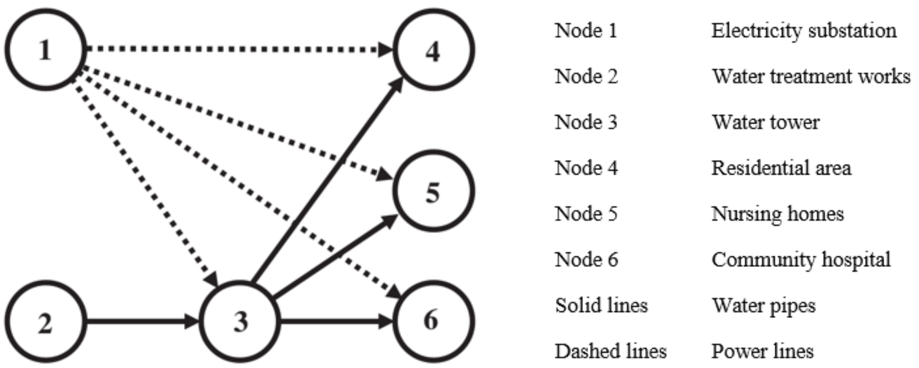


Figure 3.16 Simple network model used by Holden et al. (2013)

A more realistic approach taken is by Dueñas-Osorio and co-workers in their work on the vulnerability of interdependent infrastructure to seismic hazards (Dueñas-Osorio et al. 2007, Hernandez-Fajardo & Dueñas-Osorio 2013). They follow a process analogous with catastrophe modelling and performance based earthquake engineering, using fragility curves to describe the probability of an infrastructure component experiencing a certain level of damage given the intensity of the earthquake. They then use topological metrics as proxies for flow to assess the impact of lost nodes in simplified versions of real-world networks.

Figure 3.17 displays some of their results. Note how in the scenario where the networks operate independently (left hand column) the electricity network (top row) is markedly more vulnerable than the water network (bottom row). In the scenario where the networks are interdependent (right hand column) the vulnerability of the electricity network changes little but the vulnerability of the water network increases dramatically.

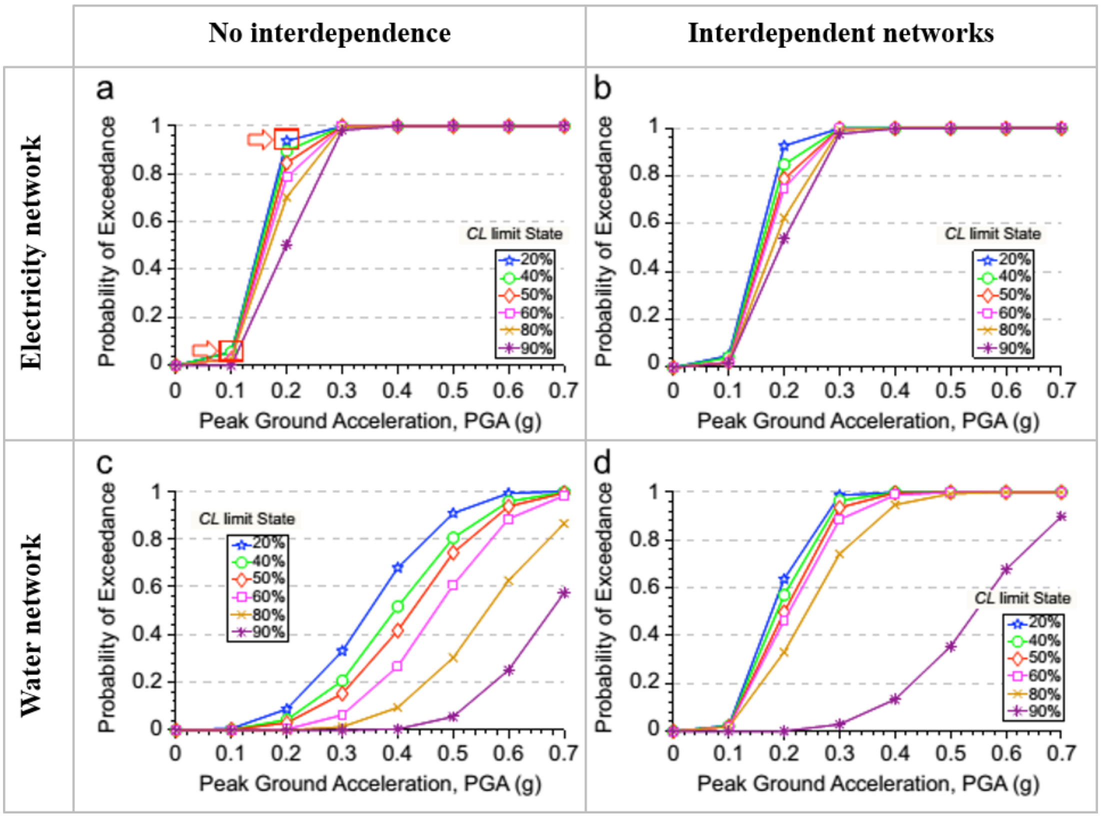


Figure 3.17 Interdependent systemic fragility plots from Hernandez-Fejardo & Duenas-Osorio (2013). The left hand column shows the responses of the two networks to earthquakes of increasing intensity when they are operating independently and the right hand column shows their response when interdependent. Peak ground acceleration (PGA) is a measure of earthquake intensity. The different colour lines represent different levels of connectivity loss (CL); the percentage reduction in the number of open paths from supply nodes to consumption nodes.

This approach is well suited to assessing the vulnerability of water systems in other sectors. The Swiss Cheese model of resilience outlined in Chapter 2 is reflected in the sequential structure which combines the generation of hazard intensities, description of component vulnerability through fragility curves and exploration of system response through network models. Furthermore, whilst the existing work is limited to one hazard and two infrastructure systems, its modular structure is well suited to the multi-hazard, multi-infrastructure scope established in the previous section. Developing models for different hazards and a library of fragility curves describing the response of different infrastructure facilities to these hazards will allow it to be generalized.

Importantly, the fragility curves permit the creation of a stochastic model which will consider the probability of failure in addition to potential impact. This is essential given the trade-off between level of service and cost to customers identified in Chapter 2.

A key shortcoming of the existing work is that only topological metrics are used to assess the system response. This section has identified that these models are not representative of true network operations and therefore their value to infrastructure operators and providers is limited. Replacing these topological metrics with more representative models will improve risk estimates by better representing the coupling within and between infrastructure sectors.

3.3 Verification and validation

In Chapter 1 it was discussed that the project sponsors require effective ways of assessing why and where their networks are vulnerable to interdependency. Furthermore, Chapter 2 established that their plans and processes are under intense scrutiny from regulators to ensure that they achieve the right balance between the level of service and cost to customers. To be successful this research must assess the accuracy of the outputs from the models which it develops. This will be achieved through verification and validation.

3.3.1 Verification

> *"The process of determining that a model or simulation implementation and its associated data accurately represent the developer's conceptual description and specifications." (US Department of Defense 2009)*

Verification is the first step towards demonstrating an output is accurate because it tests whether that the model is behaving in the way that it was intended. It is, nominally, a simple process and possible for any model; the simulation is run, the outputs are scrutinised, and any defects identified are fixed. This is repeated until the modeller is satisfied that, to the best of their knowledge, the model is running as they intended. Models of complex systems can never be verified completely - a new combination of occurrences may expose a new error (Carson 2005) - but the modeller can make an informed judgement based on their experience and knowledge of the model.

3.3.2 Validation

> *"The process of determining the degree to which a model or simulation and its associated data are an accurate representation of the real world from the perspective of the intended uses of the model." (US Department of Defense 2009)*

Validation is a more advanced test; it checks whether the model reflects reality rather than whether it reflects the modeller's intentions. In a classical modelling study this is achieved by comparing the outputs against a different set of observed data from that used to create the model. Yet, paradoxically, a shortage of empirical data is one of the reasons for using models to understand extreme events and this makes conventional validation difficult or impossible.

Gilbert and Troitzsch (2005) also argue that validation with empirical data is not authoritative proof that a model is an accurate representation of the target system for a number of reasons:

i. Random processes are likely to affect both the model and the target system so a perfect match is improbable.

ii. Model simulations are path-dependent and therefore sensitive to the precise conditions at the start of the period.

iii. The principle of equifinality means that a close match between the target and modelled results may be coincidental.

iv. The model may be correct and the data collected about the target incorrect.

An alternative is to consider the validity of individual components. Davis et al. (2007) argue that this is a credible approach if there is a clear and uncomplicated link between the model and empirical evidence:

> *"If this theory is based primarily on empirical evidence (e.g., field-based case studies and empirically grounded processes), then validation is less important, because the theory already has some external validity." (Davis et al. 2007, p494)*

If a model derives its overall validity from the validity of its individual component then it is essential that the construction of the model is clearly and carefully documented. This allows the reader to understand the connections between: i) the model and the target; ii) the variables and the outcome; and iii) the conclusions and the research questions.

Clarity and transparency is the first of the two recurrent themes through Gibbert et al.'s (2008) criteria for a rigorous study. The second theme is triangulation; using multiple perspectives and data sources to corroborate or disprove principles. If the individual components of the model are formulated in a clear, logical and precise way, drawing on all the available evidence, then the impact of being unable to validate the model in a conventional sense is reduced.

Comprehensive documentation of the modelling process also means that if errors are found then their impact can be more readily understood. However, this can be pre-empted by analysing the sensitivity of the model to changes in the model parameters.

The principal goal of a sensitivity analysis is to understand how much changes and, by extension, errors in the estimation of individual values affect the overall output (Gilbert & Troitzsch 2005). This information can be used to infer the robustness of conclusions drawn from the output and to direct future work towards the most significant sources of uncertainty.

The analysis also makes a useful contribution to the decision making process in its own right. Firstly, the process improves the modeller and decision maker's understanding of how system components interact (French et al. 2009). Secondly, it identifies where errors in the model or fundamental changes in the target system could affect the relative performance of different decisions.

Whilst it is the strongest form of validation, direct comparison with empirical data is impossible in this context. However, if each component is founded upon empirical evidence which has been triangulated with other data sources then the validity of these components is transferred onto the model as a whole. This must be supported by a coherent, logical framework connecting each component to the final output.

A secondary route to validating the outputs from probabilistic risk assessments is to use simpler deterministic scenarios. The Blackett Review (Government Office for Science 2012) notes that this approach is used by Lloyd's of London to 'stress-test' insurance portfolios against extreme events. This is the approach followed by this research. Chapter 4 and Chapter 5 respectively develop and apply a probabilistic model of infrastructure dependency which provides an estimate of the expected annual impact. Chapter 6 develops a deterministic model which can be used to test the plausible range of impacts and apply sensitivity analysis.

3.4 Summary

This chapter has set out how this thesis will meet the requirements of infrastructure providers. The parameters of the risk assessment are identified and a review of methods for assessing interdependency identifies that flow based models are the most useful for infrastructure providers. They offer a more realistic representation of how the networks operate, including accounting for storage and the physical constraints on the network, and therefore can inform the infrastructure providers about the vulnerability of specific real-world networks.

The review of methods also recognises the importance of assessing the likelihood of events alongside their impact. It identifies that the approach followed by Dueñas-Osorio et al. (2007) and Hernandez-Fajardo & Dueñas-Osorio (2013), which is analogous to catastrophe modelling and performance based engineering, as a means by which to assess this likelihood. This is developed further in the following chapter.

The final section of the chapter discusses the verification and validation of the results from the risk assessment. It establishes that direct validation of models of extreme events in complex systems is difficult; the data for comparison is limited and the behaviour of systems is highly path dependent so a small change in the conditions can cause a significant change in the outcome. Therefore, the validity of the outputs from this model depends upon the validity of the individual components. These components will be based upon the best available information and, wherever possible, this information will be triangulated with information from other sources. The structure of the model is carefully documented in the following chapter to ensure that the logic of the process can be followed and the potential influence of errors can be easily traced.

Chapter 4. Model 1: Development

This chapter describes the first model developed to address the requirement for realistic models of water networks' dependencies on other sectors. The first section provides a brief background to the catastrophe modelling and Performance Based Design (PBD) methods which have informed the method. Figure 4.3 illustrates these two processes and how they relate to the components of this model. A schematic providing an oversight of the model is included on a detachable A3 sheet in Appendix A.

The subsequent sections then describe in detail these model's components:

- *Section 4.2 outlines how two hazard models (one producing rainfall and temperature values, and the other wind speeds) are combined with a flood risk assessment to generate a time series of hazard values.*
- *Section 4.3 develops a library of fragility curves which capture the vulnerability of the assets in each of the four infrastructure sectors to the hazards.*
- *Section 4.4 produces a set of distributions which allow the duration of individual asset outages to be modelled.*
- *.Section 4.5 describes how the impact of individual asset outages on system performance is modelled, whether these outages are caused by the direct impact of hazards or are the result of failures in other sectors.*
- *Section 4.6 summarises how the customer impact is derived from the water network model.*

The application of the model to a real-world case study follows in Chapter 5.

To support the potential implementation of the model in their organisations the industrial sponsors recommended that a Sources-Inputs-Process-Outputs-Consequence (SIPOC) table was prepared for each section of the method describing:

i. The sources of the information on which the component is built.
ii. The inputs to that component of the model.
iii. The processes which the component follows.
iv. The outputs of the components.
v. The connection for the component (i.e. where the outputs are used).

For the convenience of the reader these tables have been placed at the start of the corresponding section to provide a brief and accessible overview. For consistency the main text then follows the same structure with a sub-section corresponding to each row or rows of the table.

4.1 Review of Catastrophe Modelling and Performance-Based Design

In light of the different components of resilience and Swiss Cheese model of resilience presented in Chapter 2 it is logical that a risk assessment method should be composed of a number of sequential layers. Chapter 3 notes that, in their work on the vulnerability of interdependent infrastructure networks to seismic events, Duenas-Osorio and co-workers use an approach analogous with catastrophe modelling and performance based earthquake engineering.

Earthquake engineers, most notably the Pacific Earthquake Engineering Research (PEER) Center, have developed the concept of Performance-Based Design (PBD). Though originally developed for seismic analysis the approach is now being applied more widely, especially with regards to hurricane engineering (Gurley et al. 2005, Herbin & Barbato 2012). The focus of these studies is the response of individual structures to events and they move away from design based on prescriptive codes to designing structures which have a suitably low probability of exceeding a set of performance criteria (Herbin & Barbato 2012). There are four components, shown diagrammatically in Figure 4.1 and described below:

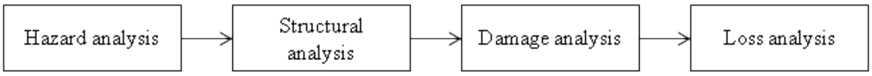


Figure 4.1 PEER Analysis Methodology (from Porter 2003)

i. **Hazard analysis:** define the hazard intensity at the specific location.

ii. **Structural analysis:** analyse how the components of the structure respond to the intensity of the hazard. This is described by probability density functions of engineering demand parameters such as internal member forces, ground deformation, etc.

iii. **Damage analysis:** input the results of the structural analysis into fragility functions which estimate the probability of reaching various levels of damage.

iv. **Loss analysis:** estimate how the level of damage which is reached affects the performance of the structure in variables related to its use (e.g. cost, down-time etc.)

Similarly, catastrophe modelling is used by the insurance industry to assess exposure to low probability, high consequence risks (Woo 2002). There are numerous examples of individual applications (flooding: Hall et al. 2005, Wood et al. 2005; tropical storms: Tabuchi & Sanders 1999; earthquakes: Jones 1999). In their simplest form catastrophe models combine a hazard intensity (e.g. wind speed at a particular location) with an inventory of the property at risk. They then use models characterising the vulnerability of the property to the hazard and the economic loss as a consequence (Figure 4.2).

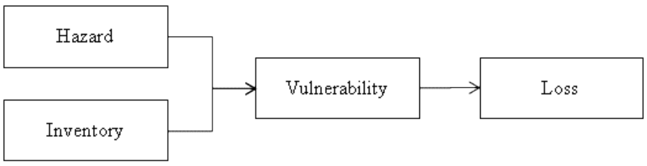


Figure 4.2 Structure of catastrophe models (Grossi et al.2005)

HAZUS-MH is a catastrophe modelling tool created by the United States Federal Emergency Management Agency (FEMA) to help public and private organisations assess their exposure to natural hazards (Kircher et al. 2006, Schneider & Schauer 2006, Vickery et al. 2006). Hansen & Bausch (2007) provide a methodology for global application but, to date, the international uptake has been slow (Robinson et al. 2012). Where the tool has been applied the experience has been positive (e.g. Levi et al. 2010, Ploeger et al. 2010) but both Hansen & Bausch (2007) and Ploeger et al. (2010) note the challenges of replacing the U.S. databases with their international (or UK) equivalents.

The existing PBD and catastrophe models, including HAZUS-MH, have not been used directly in this research because their focus is subtly different. These approaches concentrate on the physical damage to structures because they are either interested in protecting occupants from collapse or understanding the potential cost of repair or replacement. In contrast, the value of infrastructure systems lies in their ability to deliver service to customers. Therefore this research must address the functionality of components.

Notwithstanding - as both structures and infrastructure networks are systems - the two methods can be adapted with a small number of modifications. The similarity between Figure 4.1 and Figure 4.2 show that they are already very similar. Their differences lie in the level of the analysis; catastrophe models (such as HAZUS-MH) calculate the regional losses across a cohort of structures whereas PBD (such as the PEER method) computes losses specific to a particular building (Ramirez et al. 2012). PBD works to a greater level of precision so it splits the 'vulnerability' component of Figure 4.2 into two parts; Structural Analysis and Damage Analysis. Figure 4.3 shows a comparison of the structures of PBD, catastrophe modelling and this model's approach.

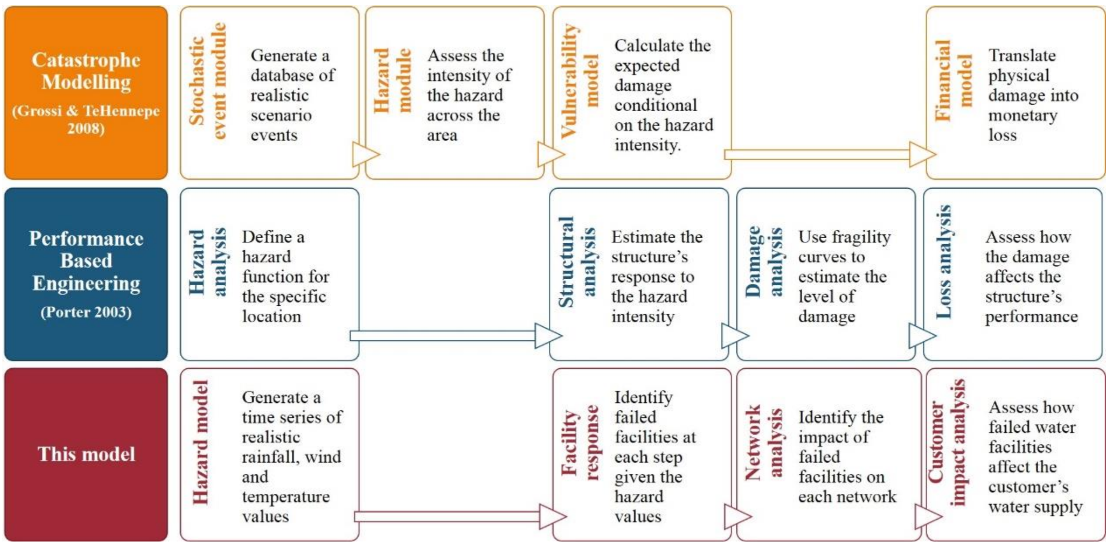


Figure 4.3 The process followed by this model compared to catastrophe modelling and performance based design

The scale of the systems analysed in this thesis mirrors that of catastrophe modelling because the infrastructure network is spread over a wide geographical area. However, it is useful to mirror PBD and divide vulnerability into two parts to model the different components of resilience (i.e. reliability, redundancy etc.).

In terms of nomenclature, the translation is very simple: individual infrastructure facilities correspond to the structural elements in PBD and the infrastructure network as a whole is interpreted as the structure. Thus, ‘Structural Analysis’ calculates the response of infrastructure facilities to the intensity measure and ‘Damage Analysis’ refers to the ability of the network to fulfil its function given the response of individual facilities to the hazard.

The other modification is in the order of the methods. Porter (2003) states that the ‘Structural Analysis’ first uses analytical structural models to capture system performance, while the ‘Damage Analysis’ uses fragility curves to calculate the level of damage. In this case the order is reversed. Empirical relationships are used first to assess the damage to the infrastructure facilities and sophisticated network model are used second to assess the impact of this damage on service provision.

This reflects:

i. The relative importance of the two steps. PBD is interested in how structural deformations cause damage to structures. This research is concerned with how damage to structures (i.e. infrastructure facilities) causes a deterioration in infrastructure system performance.

ii. The availability of models for each step. In PBD there are sophisticated physically-based models to calculate the response of a structure but no such models for the damage resulting from this response. Therefore empirical relationships are used for the latter. In this research sophisticated models of damage due to exposure to a hazard are limited, so empirical relationships are employed, but there are well-established network models.

4.2 Hazard Analysis

4.2.1 Hazard Identification

Chapter 3 identified the principal threats to UK infrastructure. This section addresses this further by identifying or developing models to represent these hazards.

It is worth noting that two of the hazards identified in Chapter 3 are omitted from this model:

i. Coastal flooding is not included because this model only considers the potable water infrastructure which is very rarely placed in coastal locations. The coast represents the boundary of any water distribution network and, because water distribution systems operate by gravity, facilities are placed on higher ground further inland.

ii. Prolonged hot, dry weather has been excluded because it principally affects demand (for example, water for gardens and electricity for cooling systems). Modelling demand alongside hazards creates a complex joint probability problem and therefore is outside the scope of this model (however, this is explored using Model 2 in Chapter 6).

The method therefore assesses the vulnerability of the systems to the three remaining hazards: excessive cold, inland flooding and windstorms. The following section describes how hazard intensities were obtained and processed for each.

4.2.2 Method of obtaining rainfall intensity and temperature

Table 4.1 SIPOC table for the method of obtaining rainfall intensity and temperature

Source	UKCP09 Weather Generator.
Input	Location of the case study.
Process	Combine thirty four 30-year records into one single record.
Output	1,020 years of synthetic hourly rainfall intensity and temperature.
Connection	Chapter 4.2.4 describes how the combined Weather Generator and wind speed model outputs were processed.

<u>Source</u>

Critical National Infrastructure is expected to be protected from flood events with a return period of less than 200 years (Cabinet Office 2011a). The Cabinet Office does not set standards for less critical infrastructure or other hazards but it is reasonable to expect the level to be similar. Therefore this method cannot rely upon observed weather records to test the resilience of infrastructure because the records are too short to be certain of containing a full range of events.

The UK Climate Projection 2009 Weather Generator is a useful source of large quantities of hazard values. It is designed to produce synthetic time series of weather in a changed future climate (Kilsby et al. 2007) but it also creates a control time series of weather variables in the current (2009) climate which is used in this model. Using the output of the climate change model would be a simple and effective way of conducting a climate change impact assessment but this is outside the scope of this research.

<u>Input</u>

The Weather Generator has an interface which takes the user through a number of steps to obtain the correct data, including a map to select the 25km^2 grid squares which corresponds to the area of interest (Figure 4.4). The Demand Monitoring Zones (DMZ) which the sponsors use for asset planning, and which define the scale of this project, typically cover 100-200km^2. Whilst there is a disparity in scale it is assumed that neighbouring grid squares will share similar weather.

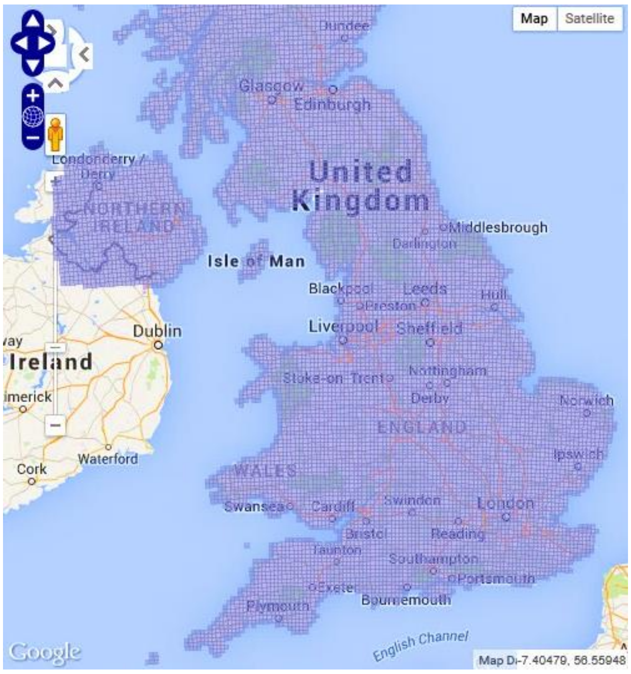


Figure 4.4 The UKCP09 Weather Generator interface showing the 5x5km grid cells (Defra. No date)

Process, Output & Connection

The Weather Generator outputs time series of up to 100 years, these can be combined to create records of sufficient length to assess extreme events.

4.2.3 Method of obtaining gust wind speeds

Table 4.2 SIPOC table for the method of obtaining gust wind speeds

Source	Met Office MIDAS data sets, accessed through the British Atmospheric Data Centre.
Input	Hourly three-second gust wind speeds from 1977-1993 and 2000-2012 for one weather station.
Process	i. Remove errors and interpolation of missing data. ii. Remove seasonal variation. iii. Transform to a normal distribution. iv. Identify and fit an appropriate ARMA model. v. Validate the model.
Output	A synthetic time series of hourly 3-second gust wind speeds.
Connection	The fragility curve components of Case Study 1.

Source

The Weather Generator does not output wind speeds so a standalone method is required to generate the synthetic time series. There is extensive literature exploring different stochastic methods for generating synthetic time series of wind speed; Aksoy et al. (2004) provide a useful review and comparison of the more popular approaches including:

i. Random samples from a transformed normal distribution.

ii. Random samples from a Weibull distribution.

iii. Autoregressive moving average (ARMA) models.

iv. Markov chain models (as used by the Weather Generator for rainfall).

The complexity of these approaches varies; the first two are relatively simple, requiring only the first and second moments of their respective distributions. Their weakness is that they assume that the wind speed in one time step is independent of the wind speed in the surrounding steps. This is clearly not realistic; the weather does not turn from a dead calm to a gale within the space of an hour. ARMA and Markov chain models address this issue by including the wind speed in previous time steps in the calculation of wind speed in the present step.

The ARMA model is the sum of two parts:

i) An autoregressive model which describes a linear association between the value in the current step (x_t) and its value in p previous steps (Papoulis & Pillai 2002). To this is added a constant (c) and a random error term (ε_t) (Eq. 4.1).

$$x_t = c + \phi_1 x_{t-1} + \cdots + \phi_p x_{t-p} + \varepsilon_t \qquad 4.1$$

Where:
x_t = value in time step t
c = constant
ϕ_i = the autoregressive parameter
p = the number of autoregressive parameters
ε_t = a random error term with a mean of zero

ii) A moving average model which expresses the value in the current step as a function of the random error in q previous time steps (Equation 4.2) (Papoulis & Pillai 2002).

$$x_t = c + \varepsilon_t + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \qquad 4.2$$

Where:
x_t = value in time step t
c = constant
ε_t = a random error term with a mean of zero
θ_i = the moving average parameter
q = the number of moving average parameters

A synthetic time series of wind speeds can be created by providing an appropriate number of initial values and then using the output as inputs for subsequent time steps.

Markov chain models divide the range of potential wind speeds into a range of bins and produce a 'transition probability matrix' where each element P_{ij} describes the probability of the wind speed transitioning from speed i to speed j (Sahin & Sen 2001). An initial state is assumed and Monte Carlo sampling used to determine the transitions between subsequent time steps.

The transition probabilities can be calculated simply from the frequency with which each transition occurs in an observed record. This, however, becomes more challenging when the principle interest is in extreme events where there are fewer observed transitions. The choice of bins also poses a challenge as there is no defined or consistent way of defining the width or number of bins (Aksoy et al. 2004). Different studies take different approaches (e.g. fixed width, defined number or a function of the average and standard deviation) and the selection can clearly influence the precision and accuracy of results.

An ARMA model is selected because it can be more readily applied to create a synthetic time series of wind speeds and has been widely used (e.g. Gomes & Castro 2012, Naimo 2014). This study follows the method described by Torres et al. (2005) and subsequently Philippopoulos & Deligiorgi (2009); for completeness this is outlined in the following paragraphs.

Input

Data to fit the ARMA model is extracted from the Met Office Integrated Data Archive System (MIDAS) record from surface weather stations. These are accessible for academic research through the British Atmospheric Data Centre (http://badc.nerc.ac.uk).

The nearest weather selection which satisfies the following criteria is selected:

i) It must have a suitably long record (more than 30 years).

ii) It must reflect the situation of the infrastructure networks (a weather station on a mountain peak will be a poor analogue for most of the surrounding area).

The UK Met Office's Semi-Automatic Meteorological Observing System (SAMOS) typically averages wind speeds over three seconds (BADC 2012). They then record the highest averaged speed within an hour as the 'maximum hourly three second gust'. These values are used in this research.

The downloaded data is checked for records which are duplicate or have not been processed by the Met Office's quality control process; these are removed. Likewise, months with more than 10% of records missing are removed because there is a high probability of instrument or recording error. In months where fewer than 10% of records are absent the missing values are infilled by simple linear interpolation.

The resulting data set is then divided into two parts: even years are used to fit the model and odd years are set aside for validating the model. This division ensures that the influences such as climate change, potential inter-annual cyclical patterns and extreme events such as the 1987 and 1990 storms are evenly divided between the two sets.

Process

1. The data set is split into months and a separate ARMA model created for each month. This means that the statistical model does not need to include seasonal patterns because they are already accounted for when the months are recombined at the end of the process. The following steps were therefore repeated for each of the twelve months.

2. Wind speed records typically follow a Weibull distribution. To allow this distribution to be fitted all zero values are replaced with a trivially small value of 0.001.

3. The ARMA model requires normally distributed data so the positive skew on the Weibull distributed wind speed is eliminated by raising each value by the power m which is calculated by minimising the value of S_m:

$$V'_{n,y} = {V_{n,y}}^{m} \tag{4.3}$$

$$S_m = \sum_{y=1}^{Y}\sum_{n=1}^{N}\frac{\left[\left(V'_{n,y} - \overline{V'}\right)/s\right]^3}{Y \cdot N} \tag{4.4}$$

Where:

m = the power by which values are raised to remove the distribution's asymmetry

S_m = asymmetry

Y = the number of years in the time series

N = the number of hours in the month of interest

$V'_{n,y}$ = the transformed wind speed

$\overline{V'}$ = the mean of $V_{n,y}$

s = the standard deviation of the series

4. Diurnal patterns within the time series were removed by normalising each value according to the mean and standard deviation of the wind speeds at that hour of the day (Torres et al. 2005).

$$V^*_{n,y} = \frac{V'_{n,y} - \mu(t)}{\sigma(t)} \tag{4.5}$$

$$\mu(t) = \frac{\sum_{i=0}^{d\cdot Y-1} V'_{24\cdot i+t}}{d \cdot Y}, 1 \leq t \leq 24 \tag{4.6}$$

$$\sigma(t) = \left[\frac{\sum_{i=0}^{d\cdot Y-1}\left(V'_{24\cdot i+t} - \mu(t)\right)^2}{d \cdot Y}\right]^{1/2}, 1 \leq t \leq 24 \tag{4.7}$$

Where:

$V^*_{n,y}$ = normalised wind speed

$V'_{n,y}$ = the transformed wind speed from Equation 4.4

μ(t) = mean wind speed at hour t of the day

d = the number of days in the month of interest

σ(t) = the standard deviation of wind speeds at hour t of the day

Y = the number of years in the time series

5. An ARMA model is composed of two component types – autoregressive and moving average – and can contain multiple components of each. Each parameter gives a better fit to the calibration data but an excess of parameters will produce an over-fitted model. This balance is achieved by fitting ARMA models with varying numbers of parameters by Maximum Likelihood Estimation within the software package Matlab and calculating the Bayesian Information Criterion (BIC) for each.

$$BIC = -2 \cdot \ln(\hat{L}) + k \cdot \ln(o) \tag{4.8}$$

$$k = p + q \tag{4.9}$$

Where:

BIC = Bayesian Information Criterion

L = The likelihood function of the fitted model

o = The number of observations, in this case the number of years multiplied by the number of hours in the month in question

k = The number of parameters in the model

p = the number of autoregressive components

q = the number of moving average components

6. The model structure with the lowest BIC score is retained with the relevant parameters. This model is used to generate a synthetic time series of normalised values ($V_{n,y}^{*syn}$) in Matlab, selecting the appropriate model based on the month of the time step being simulated.

7. The normalised values are returned to realistic values by reversing the steps above. As the normal distribution has no lower limit the model can produce negative wind speeds; these are replaced with 0.001 to represent a dead calm. This does not affect the model's usefulness because the focus is on high wind speeds.

$$V_{n,y}^{\prime syn} = V_{n,y}^{*syn} \cdot \sigma(t) + \mu(t) \tag{4.10}$$

Where:

$V^{*syn}_{n,y}$ = synthetic normalised wind speed

$V^{\prime syn}_{n,y}$ = synthetic wind speed with diurnal variation restored

μ(t) = mean wind speed at hour t of the day

σ(t) = the standard deviation of wind speeds at hour t of the day

$$V_{n,y}^{syn} = V_{n,y}^{\prime syn^{1/m}} \tag{4.11}$$

Where:

$V^{syn}_{n,y}$ = synthetic wind speed returned to Weibull distribution

m = the power by which values were raised to remove the distribution's asymmetry

Output

The ARMA model produces a synthetic time series of hourly maximum three-second gust wind speeds which matches both seasonal and diurnal variation. Figure 4.5 and Figure 4.6 show some illustrative results from the modelled fitted for the case study described in the following chapter.

However, Figure 4.6 indicates that the model overestimates the occurrence of very extreme events. Since these are the events which are likely to drive infrastructure failures this may have a bearing on the overall outputs. It is not feasible for this project to develop a more advanced wind model but further work may investigate replacing the Weibull distribution used in Step 2 above with an extreme value distribution or using a more complicated approach such as Wavelet methods.

Connection

Chapter 4.2.4 describes how the outputs from the wind model and data from the UKCP09 Weather Generator are combined into a single time series of hazard values.

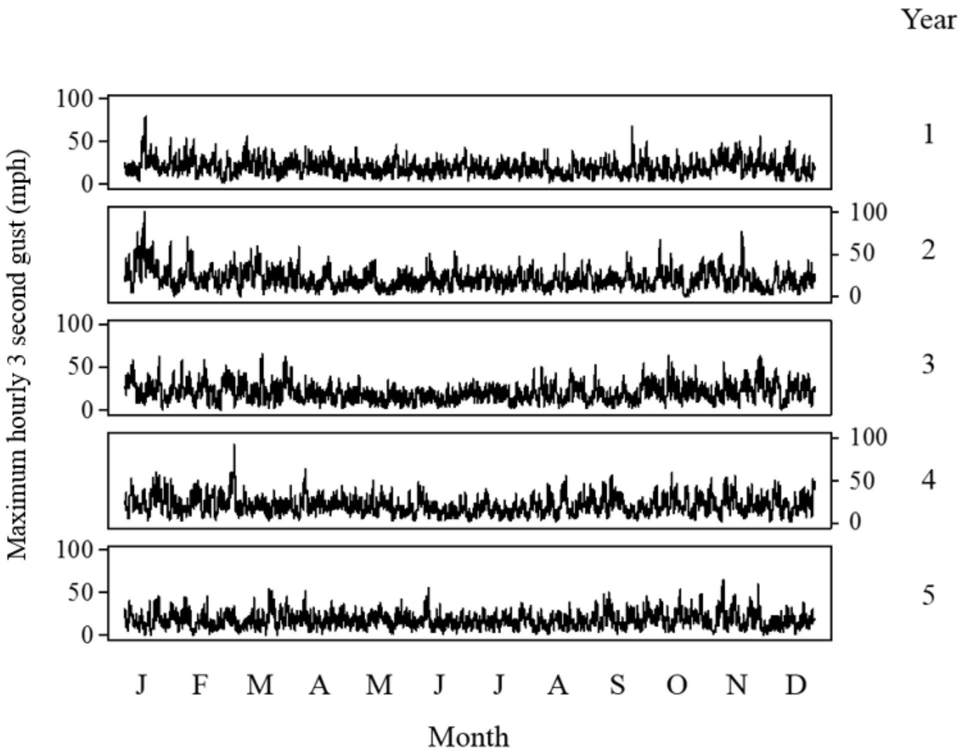


Figure 4.5 Five year-long times series of maximum three second gust wind speeds produced by the ARMA wind model created in the Chapter 5.

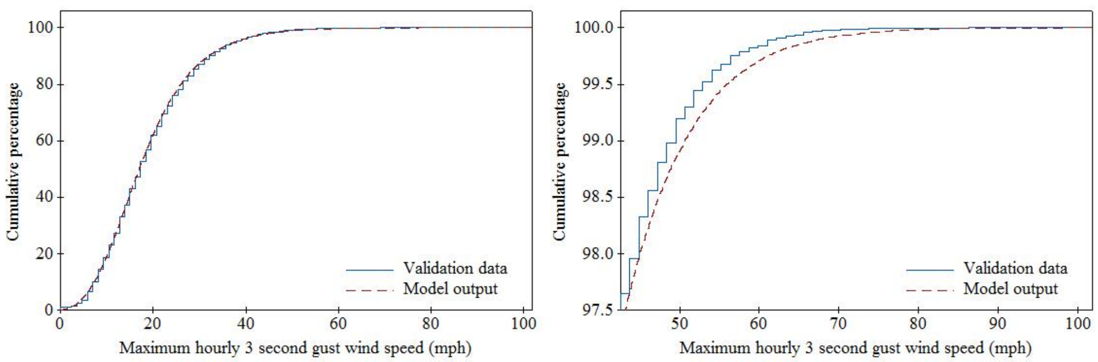


Figure 4.6 Comparison between a 30 year time series produced by the ARMA model (dashed red line) and a 15 year time series of observed data for the same location (solid black line). Note that over the full range (left panel) the model is a good fit but closer inspection of the severe wind speeds (right panel) shows the model results are higher; the 99th percentile is overestimated by 2% and similarly the 99.9th percentile by 9%

4.2.4 Method of processing the time series of hazard values

Table 4.3 SIPOC table for the method of processing the time series of hazard values

Source	• Rainfall and temperature hazard model. • Wind hazard model.
Input	Time series of hourly rainfall intensities, temperatures and wind speeds.
Process	i. Calculate the intensity of an event with a 1 year return period. ii. Identify events which exceed this threshold. iii. Extract the weather values covering the period from midnight on the day of the event to 11 o'clock in the evening of the day a fortnight later.
Output	A time series of severe weather events.
Connection	The fragility curves in Chapter 4.3 use the weather values to assess the probability of failure.

The focus of the model is extreme events, not normal day-to-day weather. Therefore its efficiency can be improved by removing unremarkable weather from the hazard data and only assessing events over a certain threshold.

<u>Source & Input</u>

The synthetic time series of wind speeds are combined with the temperature and rainfall data from the UKCP09 Weather Generator. Wind speed is assumed to be independent of the other variables and therefore the relevant months and time of day are simply matched in the two series. The assumption of independence is the conventional approach in weather generators (Ivanov et al. 2007, Supit et al. 2012), supported by evidence that the correlation between wind and other variables is small (Bürger 1996, Parlange & Katz 2000).

<u>Process</u>

Severe events are defined as having a return period greater than one year. This balances the desire to reduce the running time of the model and the need to minimise the number of events which may be missed as a consequence. The redundancy within infrastructure networks mean that multiple failures are normally required to affect customers, therefore the likelihood of an event with a lower return period having a significant impact is small.

The impact of an event cannot be assessed solely on its peak intensity. It is also important to consider what occurs in the hours leading up to the event and how attempts to recover from any disruption are affected by continuing bad weather. Therefore a two week period of hourly weather values is extracted, starting at midnight on the day of the event.

Extracting the peak events in this way causes two issues. Firstly, events are moved closer together so there is a risk that a facility failure may overrun into the next event. This is resolved by the model recognising a gap between time steps and resetting all the facilities to their original state before progressing to the next event.

Secondly, the fragility curves which are developed in the following section indicate that the risk posed by low temperatures does not increase in parallel with decreasing temperatures. The risk of road closures peaks at -2.2°C, and ice can form on electricity and telecommunications lines below 2.5°C. Setting a threshold of a one year return period event means that the new dataset only includes events where the temperature drops below -7.7°C. Neither issue, however, is critical to the model because these failure modes only have an impact when combined with other hazards. Roads only affect the speed with which other failed facilities are recovered and ice forming on transmission lines increases their exposure to strong winds. The other hazards crossing the threshold will trigger the event to be recorded regardless.

Output & Connection

The output of the process is a condensed time series of three hazard values: temperature; rainfall intensity; and maximum gust wind speeds. The temperature and wind speeds are used directly with fragility curves developed in Chapter 4.3 to determine the probability of failure. A further step is necessary to convert the rainfall intensity into local flood depths; this is described in the following section.

4.2.5 Method of assessing flood risk at individual facilities

Table 4.4 SIPOC table for the method of assessing flood risk at individual facilities

Source	• Rainfall hazard model. • Environment Agency 2010 short duration pluvial flood maps.
Input	• Time series of hourly rainfall intensities which match the statistical properties of the local climate. • GIS layers displaying the predicted flood depths in events with one, 20 and 100 year return periods.
Process	i. Calculate hourly rainfall intensity return periods. ii. Create of buffers around the centre point of infrastructure facilities. iii. Assess the maximum flood depth within these buffers at each return period. iv. Estimate inundation depths at intermediate return periods using linear interpolation.
Output	Functions allowing the prediction of flood depth at facilities given the return period of the rainfall event.
Connection	The fragility curve components of Case Study 1

Heavy rainfall is different to temperature and high winds because it rarely affects infrastructure facilities directly; damage occurs when the combination of heavy rainfall and local geography causes flooding. A full hydrological and hydraulic model is outside the scope of this research and would significantly increase the complexity and the computational cost of model. Therefore a simplified method is needed to assess the vulnerability of different facilities to flooding. The method described below matches the return period of the flooding to the return period of the rainfall event. In doing so it ensures that events of each magnitude occur with the correct frequency in the time series of hazard values.

Source & Inputs

The Environment Agency produce detailed flood maps of the extent and depth of flooding in a wide range of scenarios. These are available through the industrial sponsors who use them for planning drainage systems and understanding the impact of major pipe bursts. To limit the complexity of the model it is necessary to only consider one type of flooding. Short duration pluvial flooding events are the most appropriate for a number of reasons:

i. The case study area outlined in the following chapter is urbanised and within a steep sided valley. The risk from short duration, intense rainfall is high but flooding from accumulated rainfall over a number of weeks (such as in the Thames Valley in 2014) is less likely.

ii. Short duration events relate more directly to the rainfall intensities produced by the Weather Generator. In contrast fluvial flooding is strongly influenced by prior rainfall and catchment characteristics. Linking the return periods of rainfall and pluvial flooding is reasonable in this urban setting.

iii. Infrastructure facilities vulnerable to fluvial and groundwater flooding are more easily identified. By contrast, pluvial flooding can occur in unexpected locations and therefore may not have been identified in previous risk assessments.

Environment Agency flood maps are available for events of three different return periods (one year, 20 years and 100 years) and are supplied as GIS layers. These take the form of triangulated irregular networks where each triangle has a number of attributes including the maximum flood depth within it.

The location of each infrastructure asset is required to use the flood maps. Water assets and the road network are loaded directly into the GIS software from the sponsor's database and the Digimap service (http://digimap.edina.ac.uk/digimap/home). Electricity substations and telephone exchanges are identified using a combination of Google Earth and Ordnance Survey maps. The grid reference at the centre of each is recorded and loaded into the database.

Finally, it is necessary to understand the distribution of hourly rainfall intensities in the area in order to relate the return period of the rainfall event to the return period of the flood event. A large set of 9.5 million hourly rainfall intensities is created by using thirty six 30 year time series generated by the UKCP09 Weather Generator.

Process

1. A buffer is drawn around each infrastructure facility with the radius determined by the typical footprint of that type of facility (Table 4.5).

Table 4.5 Buffer radii for facilities

Facility type	Buffer radius (m)		Facility type	Buffer radius (m)
Water pumping station	10		132kV or 400kV substation	50
Service reservoir	25		400kV substation	50
Water treatment works	50		Road	10
6.6 kV / 11kV substation	10		Telephone exchange	25
33kV substation	25			

2. These buffers are overlain over the Environment Agency flood maps and the greatest depth of flooding within this buffer at each return period is extracted and taken as the inundation depth at that facility for an event of this magnitude (e.g. Figure 4.7).

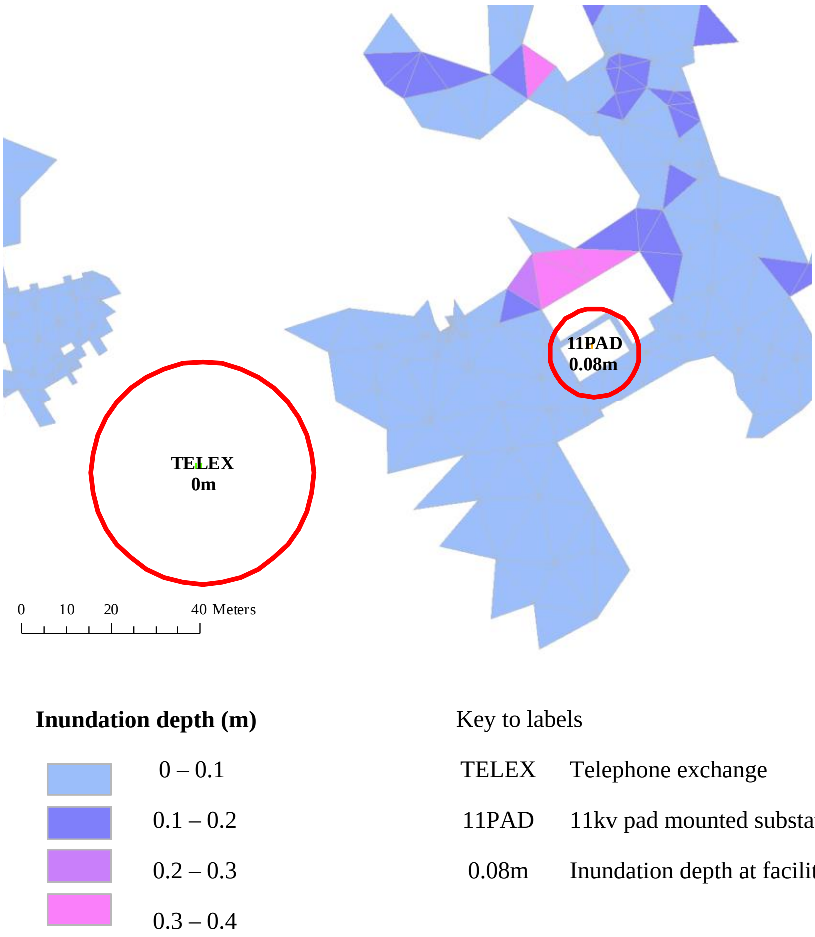


Figure 4.7 Environment Agency flood map, facility buffers and estimated inundation depth in a 100 year return period event

3. Flood depth for other return periods are estimated by linear interpolation between the flood depths extracted from the maps (Figure 4.8). The gradient between 20 year and 100 year return period events is also extrapolated beyond a return period of 100 years to predict flood depths during more extreme events. In reality the curve is likely to be stepped because of thresholds such as walls and kerb stones. However, without more detailed information, linear interpolation is the most valid technique because it assigns equal probability to these thresholds being at every depth between the known values.

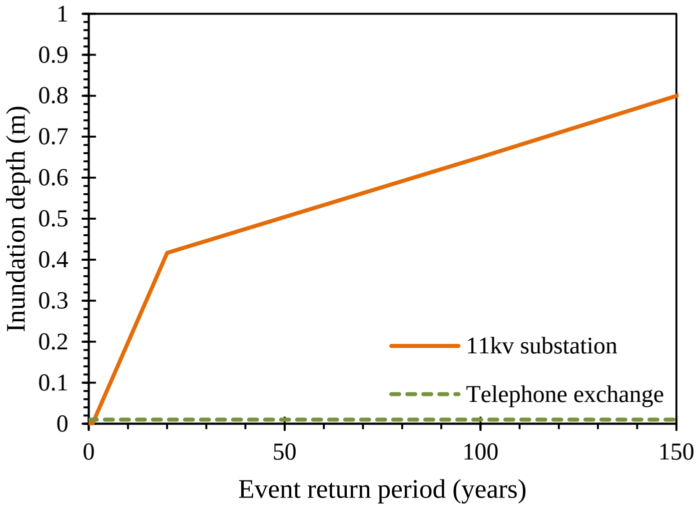


Figure 4.8 Example flood depth return period curves. The telephone exchange is not exposed to flooding so the depth remains at zero. In contrast the flood depth at the substation rises rapidly before levelling off. This indicates that a threshold has been reached where the water begins to overspill into a wider area.

4. The two previous steps give the flood depth for an event of any given return period. The final step is to calculate the return period of an event from the rainfall intensity to allow the calculation of the flood depth at each individual site. The return periods of rainfall events in the Weather Generator output are plotted and least squares regression is used to fit a line of best fit (e.g. Figure 4.9). The resulting equation allows the return period of an event to be predicted from its intensity.

$$R = 0.0000288p^{4.69} \tag{4.12}$$

Where:

R = Return period in years

p = Hourly rainfall amount in millimetres

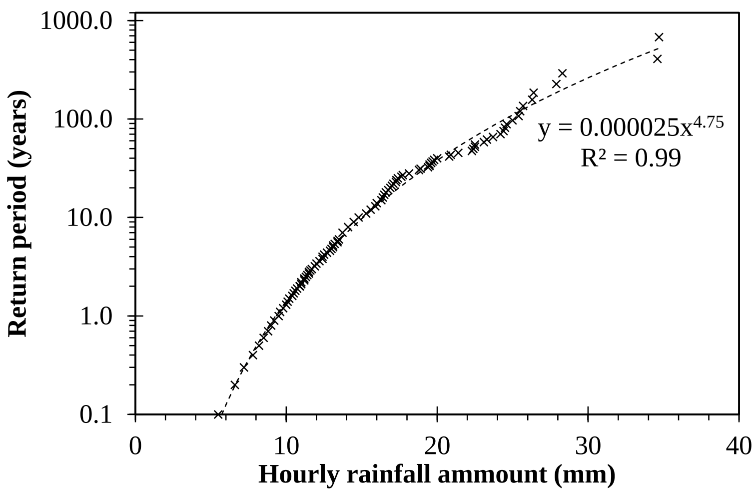


Figure 4.9 Return period of rainfall events and line fitted by least squares regression

Figure 4.10 compares the outputs from this process with those produced by the Depth-Duration-Frequency Model included in the proprietary Flood Estimation Handbook software (Reed et al. 2008). It shows that the regression fit is a good approximation but, relative to the FEH data, produces a lower return period for more frequent events (<10 years) and a higher return period for more extreme events (>10 years).

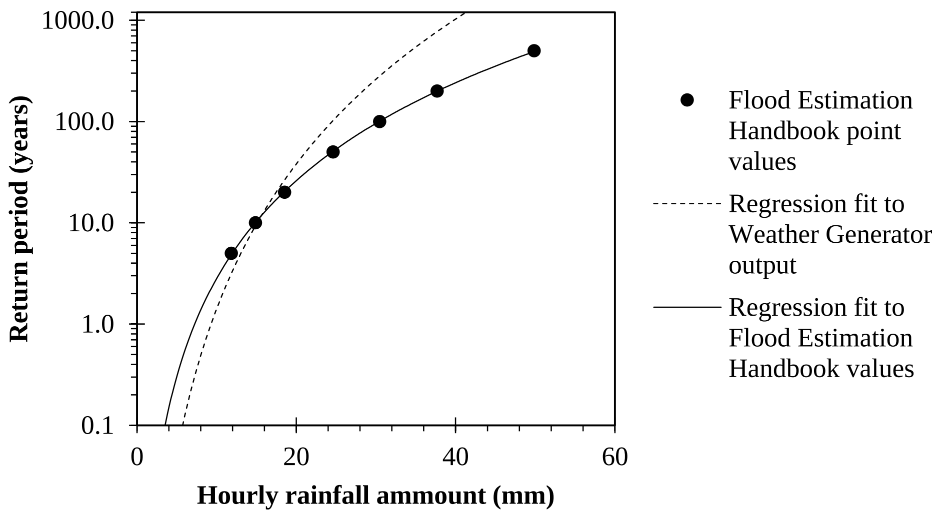


Figure 4.10 Comparison between the rainfall intensity - return period relationship produced by fitting a regression relationship to Weather Generator outputs and the outputs of the Flood Estimation Handbook Depth-Duration-Frequency model. The point values were calculated by selecting the catchment covering the majority of the case study network and requesting the rainfall depths within a one hour period. A sliding period is used as default in the model but a fixed one hour period was chosen to reflect the discrete hourly time steps used in this model.

The regression fit to Weather Generator values is used in this model because it maintains the direct link between the frequency with which events occur in the Weather Generator time series and the return periods of the flood events identified in the flood maps used in the previous section. However, if the model identifies key sites which are vulnerable to flooding then the Flood Estimation Handbook should be used to conduct a more detailed and robust assessment.

Output & Connection

At each time step the model reads the precipitation intensity and uses these curves to convert it to a flood depth for each facility. This depth is then combined with the fragility curves to determine the probability of failure.

4.3 Facility Response – Fragility Curves

The second step of the modelling process is an analysis of the infrastructure component's performance in response to the intensity of the hazards experienced. The uncertainty around the response of infrastructure facilities to hazards makes it logical to use probabilistic fragility curves.

This section creates a suite of fragility curves describing the vulnerability of UK infrastructure facilities across four sectors (water, electricity, highways and telecommunications) to the three hazards (floods, excessive cold and windstorms).

The literature outlines a number of possible approaches to creating fragility curves:

i. Laboratory testing (e.g. Fajfar 2000)
ii. Analytical modelling (e.g. McKenna 2011)
iii. Analysis of empirical data from past events (e.g. Sill & Kozlowski 1997, Hall et al. 2005)
iv. Engineering judgement (e.g. Van Der Lindt & Taggart 2009)

The scale of the systems in this research means that empirical data from past events is the main source of information. Laboratory testing is not feasible at an infrastructure facility scale and detailed analytical modelling is beyond the scope of this project. Engineering judgement is viewed as a 'last resort' due to the subjective results it produces (FEMA 2012a). Therefore it will only be employed where there is no empirical data and the relationship between the hazard and impact can be easily envisaged (e.g. the depth of water required to close a road).

Under the heading of empirical data there is a hierarchy of different information sources. Firstly, published and peer-reviewed fragility curves based on empirical data are an source of high-quality, defensible data (e.g. McColl & Palin 2010, McColl et al. 2012). However, care must be taken to ensure they are not applied out of context (e.g. curves developed for US buildings may not be representative of UK building stock).

Secondly, records of failures held by infrastructure operators can be mapped against observed weather patterns to produce new fragility curves. The quantity and quality of failure data varies; challenges include the size of data sets, the consistency of record keeping and the scale at which data is recorded. However they offer an opportunity to produce bespoke curves for this application.

Finally, anecdotal evidence can provide quantitative values to support and validate fragility curves (e.g. Flikweert & Simm 2008). For example, Channel 4 News reported that water came within two inches of shutting down Walham Substation in 2007 (McMaster & Baber 2006). This gives two pieces of information: firstly the substation was operating at a depth of 0.2m; and secondly it would have failed by 0.25m.

Table 4.6 shows which data types were used for each fragility curve in the model. The following sections describes each in detail. The model uses all of these curves in the same way so to avoid repetition the connection row of each SIPOC table is omitted and this is described at the end of the section.

Table 4.6 Data sources used to develop case study fragility curves

	Highways			**Electricity**			**Telecommunications**		
	Wind storms	Excessive cold	Flooding	Wind storms	Excessive cold	Flooding	Wind storms	Excessive cold	Flooding
Published fragility curves				✓	✓		✓	✓	
Information from failure databases	✓	✓							
Vulnerability studies						✓			
Anecdotal reports			✓			✓			✓

4.3.1 *Method of producing highways infrastructure fragility curves*

Table 4.7 SIPOC table for the method of producing highways infrastructure fragility curves

Source	• Highways Agency Command and Control incident management system. • Met Office MIDAS data sets, accessed through the British Atmospheric Data Centre.
Input	• Lane impact incidents resulting in a lane closure between 01/01/2009 and 31/12/2013. • Hourly air temperature, rainfall intensity and 3 second-gust wind speeds for locations across Great Britain.
Process	• Match incidents to hour long time steps and 100km x 100km grid cells and calculation of the length of the strategic road network within each cell. • Calculate the estimated hazard intensities within each cell at hourly time steps. • Correlate hazard intensity and the occurrence of incidents, then fitting of distributions to produce fragility curves.
Output	A curve which plots the rate of road closures per kilometre against the gust wind speed.

<u>Initial vulnerability assessment</u>

The first step towards understanding an infrastructure network's vulnerability is an initial assessment of which hazards affect which network elements. This is simple for highways infrastructure because it only consists of one type of asset which is known to be vulnerable to all three hazards (Figure 4.11).

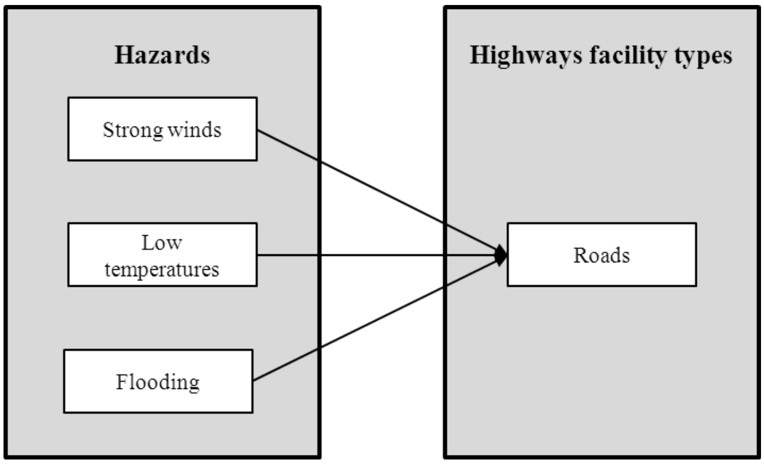


Figure 4.11 Initial assessment of highways infrastructure vulnerabilities

Source

The Highways Agency (HA), who are responsible for the strategic roads which form the backbone of the UK network, provided data on partial and full road closures due to severe weather between 2006 and 2013. They did not collect this data before 2006.

The local roads connecting individual assets to the strategic network are equally relevant to the case study. Therefore information was also requested from three authorities with responsibilities for local highway network resilience in the north-west of England (Cumbria County Council, Lancashire County Council and Transport for Greater Manchester). However, none of these organisations collected this information so it has been necessary to take the Strategic Road Network as representative of all roads.

The information on weather conditions was taken from the Met Office MIDAS archive of land surface weather observations available from the British Atmospheric Data Centre.

Inputs

The incident data provided by the Highways Agency (Appendix 1) included the time and date of any full or partial closures alongside a grid reference, description of location, reason for closure and the closure type (e.g. whole carriageway, one lane, slip road etc.).

The weather data is downloaded for the area bounded by -8°W, 56.5°N, 3.4°E and 49.3°S and separated into six month data sets. From each set a weather station's record is discarded if more than 1% of the hourly values were missing. Repeating this selection for each hazard and every six months accounts for any changes in which weather stations were active. (The figures illustrating this section use the dataset for wind speed in between July and December 2013.)

Three variables are selected to reflect the four closure reasons given in the incident data (Table 4.8).

Table 4.8 Closure reason mapped against weather variable

Closure Reason	Weather Variable	Unit
Flooding Heavy Rain	} Precipitation amount	mm
Snow / Ice / Freezing Rain	Air temperature	°C
Strong Winds	Maximum 3-second gust wind speed	knots

Process

1. Closures are separated into three groups according to the hazards outline in Table 4.8: snow / ice / freezing rain; strong winds; and flooding and heavy rain combined.

2. Closures for each group are assigned to the relevant hourly time periods and mapped against the 100km x 100km squares which form the highest level of the Ordnance Survey National Grid system (Figure 4.12).

3. The length of the network in each cell is calculated (Table 4.9).

Table 4.9 Strategic Road Length by Grid Square

Grid Square	Total Road Length (km)	Grid Square	Total Road Length (km)	Grid Square	Total Road Length (km)
SP	765	NZ	318	TR	72
SU	701	NY	313	SW	67
TQ	638	NS	278	SS	64
TL	609	SX	255	NU	59
SK	599	NT	181	SH	59
SE	516	SN	127	TA	57
SJ	494	TF	118	NO	34
ST	464	SY	111	SM	30
SO	395	TM	109	SZ	5
SD	363	TG	82		

4. The incident rate for a given hazard in each cell at each time step is calculated as the number of incidents within it divided by the length of the strategic network in that cell:

$$r_{c,t,h} = \frac{i_{c,t,h}}{l_c} \qquad 4.13$$

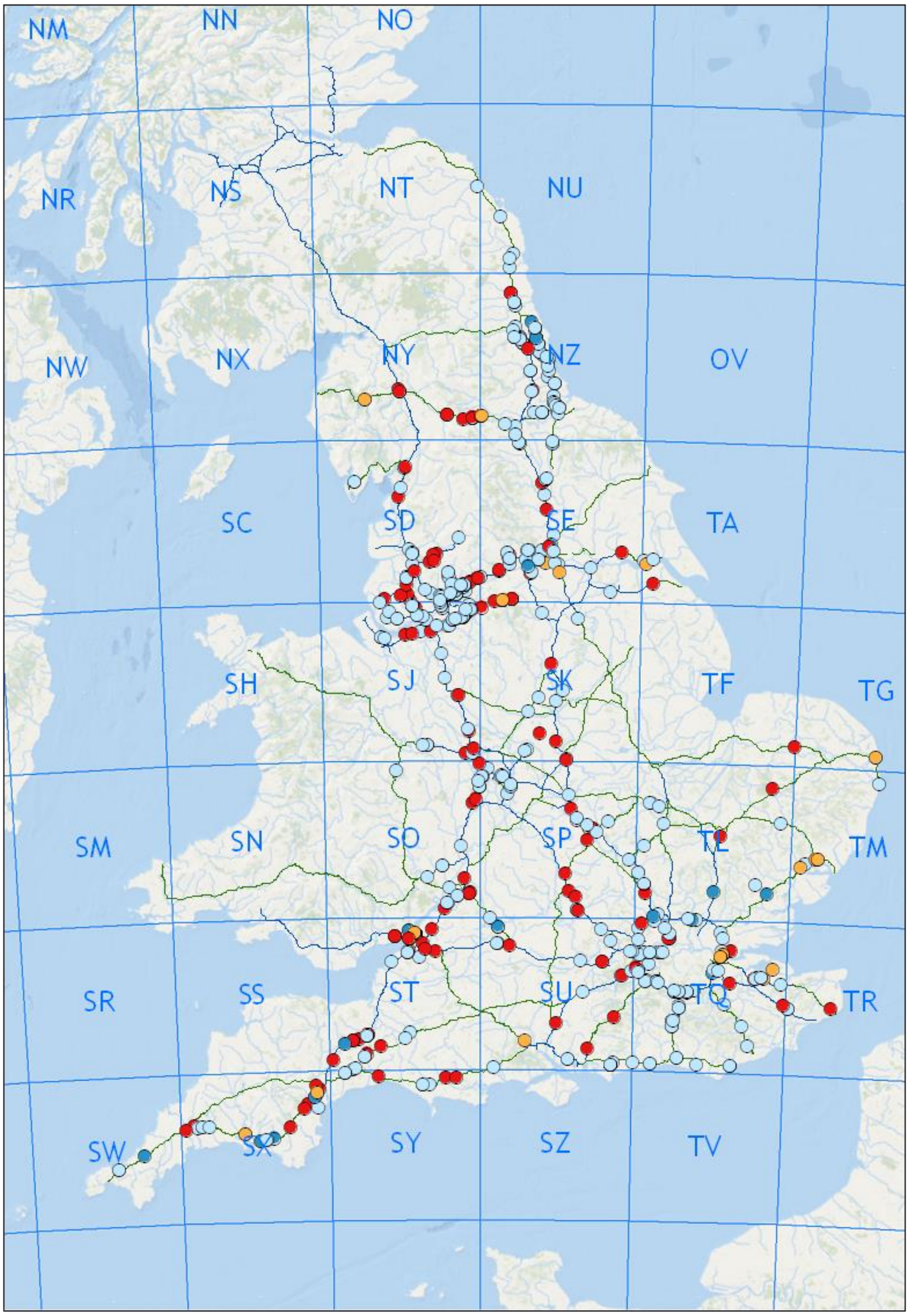
Where:

$r_{c,t}$ = incident rate for cell c at time t for hazard h

$i_{c,\,t,\,h}$ = the number of incidents in cell c at time t caused by hazard h

l_c = the length of strategic network in cell c (km)

5. The locations of the active weather stations are plotted and Thiessen polygons used to calculate their areas of influence (Figure 4.13).



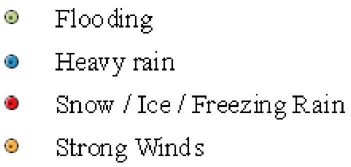


Figure 4.12 UK Strategic Road Network and closures due to severe weather between 2006 and 2013.(Base map: ©2014 Esri, DeLorme, HERE. Road network: Digimap).

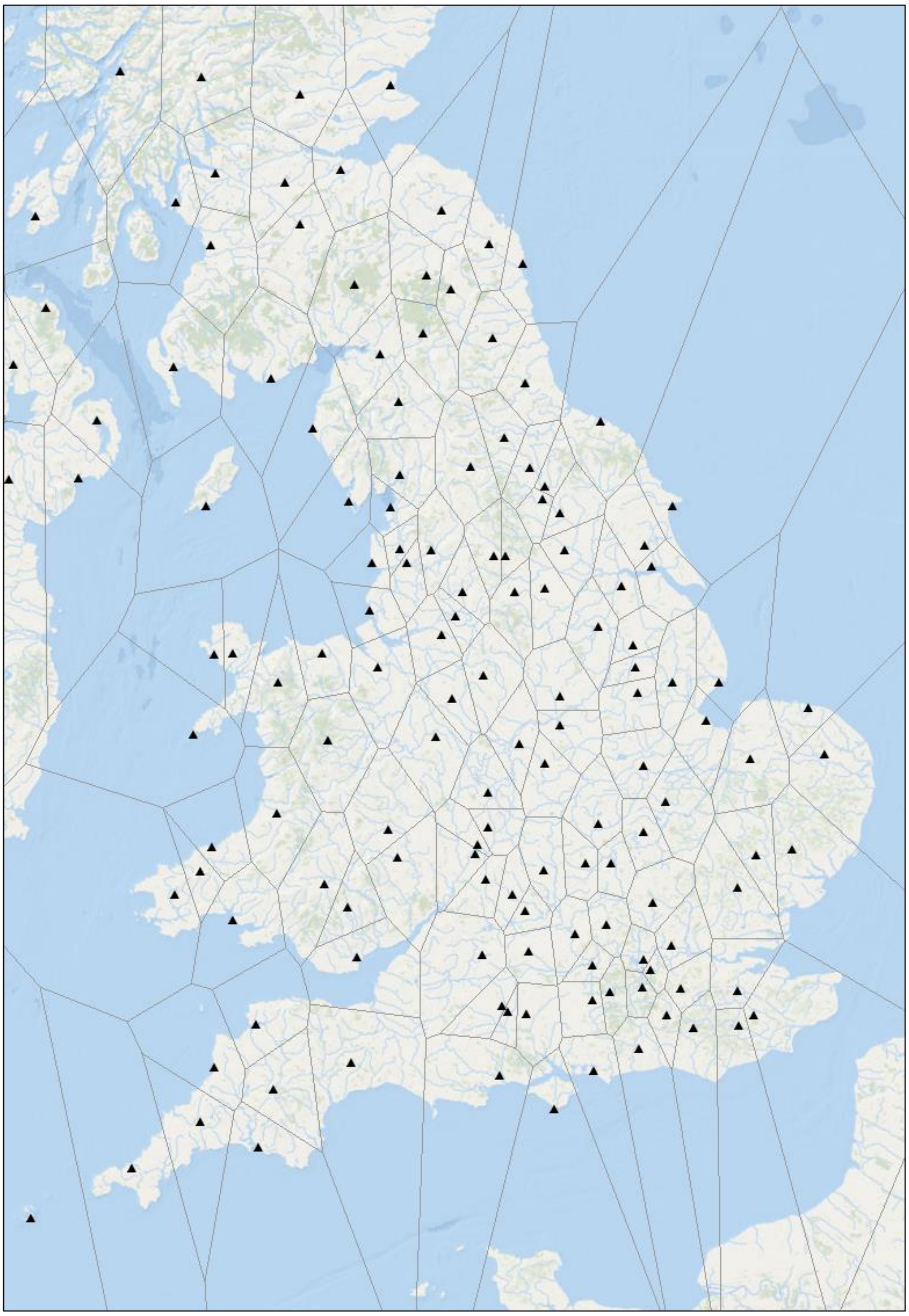


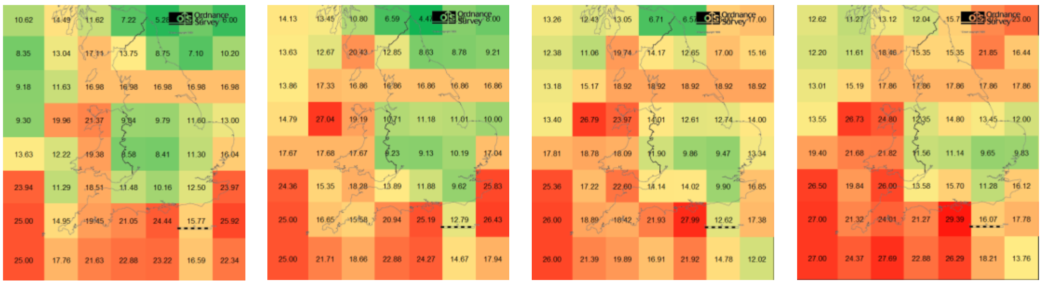
Figure 4.13 Weather stations measuring hourly precipitation between July and December 2013, and associated Thiessen polygons (Base map: ©2014 Esri, DeLorme, HERE.)

6. The grid squares and Thiessen polygons were cross tabulated to calculate the proportion of a grid square which could be attributed to each weather station (Figure 4.14) and hence calculate a weighted average weather value for each cell at every time step (Figure 4.15).

More advanced spatial averaging methods to create a smoother surface between data points were considered (e.g. splines or kriging). However, these layers would need to be re-calculated at every time step in response to different wind speeds with a considerable computational cost. The relative simplicity of the Thiessen polygons gives them an advantage.

Station ID	Name	Weight (%)
1144	Hawarden Airport	22.4
651	Newport (Salop)	17.1
1190	Lake Vyrnwy No 2	12.3
57199	Rostherne No 2	10.9
622	Keele	10.7
1137	Rhyl No 2	8.0
17309	Crosby	6.0
30690	Leek: Thorncliffe	4.5
18904	Manchester: Hulme Library	3.9
669	Shobdon Airfield	1.9
56424	Winterbourne No2	1.7
1111	Preston: Moor Park	0.4
1125	Rochdale	0.3

Figure 4.14 Weather stations contributing to the SJ grid square



27/10/2013 02:00 27/10/2013 03:00 27/10/2013 04:00 27/10/2013 05:00

Figure 4.15 Example estimated hourly grid square wind speeds. Note the pattern of increasing wind speeds developing off the south west coast and spreading across the country. This is indicative of a typical UK weather system 'moving in' from the Atlantic.

7. The incident rates for each grid cell at each time step (Step 4) are gathered into bins according to the hazard intensity in that cell at that time.
8. The mean incident rate is calculated for each bin.

Output

Vulnerability of road links to windstorms

Figure 4.16 shows that the distribution of grid cell average wind speeds is positively skewed but, in contrast, the number of highways incidents within each range of wind speeds follow an almost symmetrical distribution. Therefore, whilst the majority of failures occurs at lower wind speeds, the probability of failure is greater at higher wind speeds. This is confirmed by Figure 4.18 which shows the conditional probability of failure, calculated by dividing the number of incidents within each range of wind speeds by the frequency with which these wind speeds have occurred (Equation 4.14).

$$P(i|w) = \frac{P(i \cap w)}{P(w)} \qquad 4.14$$

Where:

P(i | w) = probability of an incident within a cell given gust wind speed w

P(i ∩ w) = probability of an incident within a cell and the gust wind speed w occuring

P(w) = probability of the gust wind speed w occuring

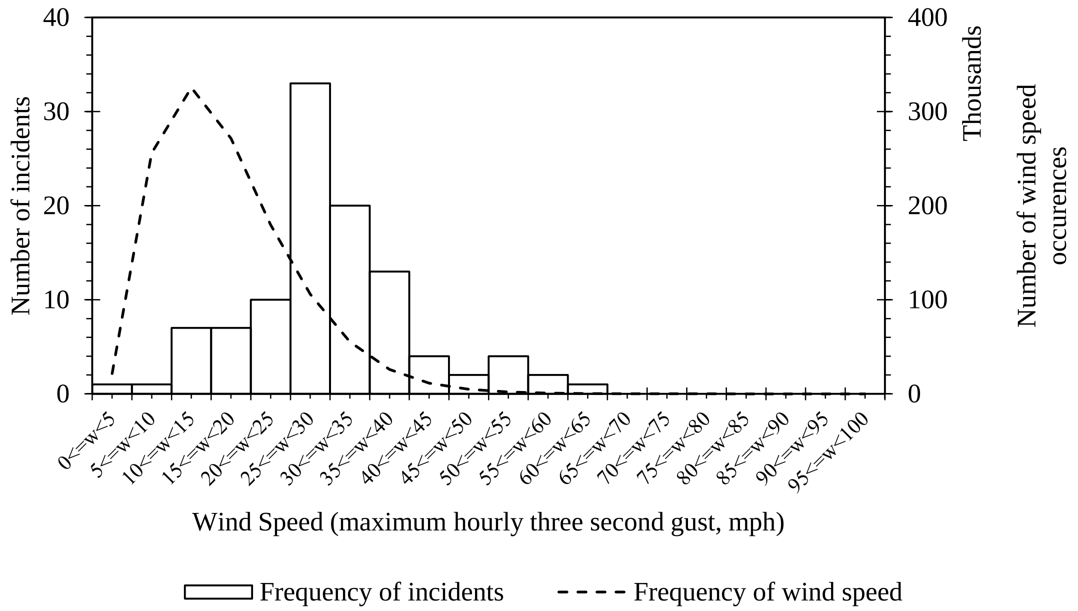


Figure 4.16 Frequency of wind speeds and the number of highways incidents conditional upon that wind speed. The distribution of grid cell average wind speeds is positively skewed and approximates the Weibull distribution expected for wind speeds. Highways incidents begin to occur at surprisingly low wind speeds and the mode is between 25 and 30 miles per hour. Thereafter the number of incidents declines. Note that the raw number of incidents is an intermediate output produced in step 2 of the previous section, not the ultimate output of the rate per kilometres of highways produced in step 4.

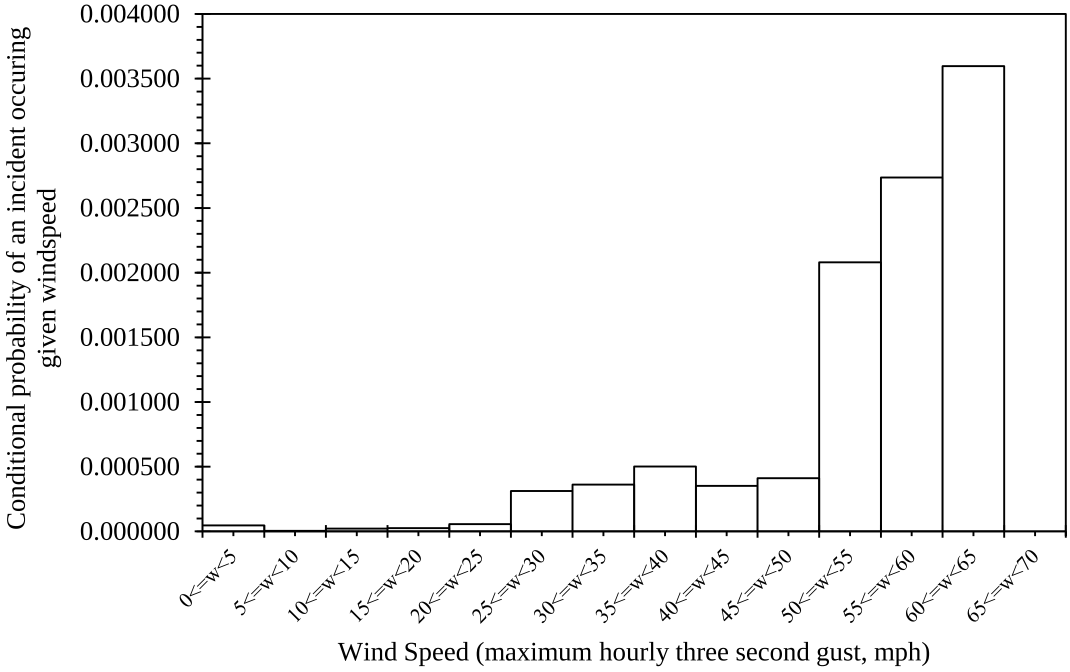


Figure 4.17 The conditional probability of highways incidents due to strong winds. The probability is negligible at gust wind speeds below 20 miles per hour. Thereafter it rises slowly before a significant increase in the incident probability when wind speeds exceed 45 miles per hour.

The shortcoming of Figure 4.17 is that it only provides the abstract probability of a highways incident within a 100km x 100km grid cell. It overlooks that incidents were more likely in grid cells containing high lengths of major road and does not provide a failure rate for a given length of road.

Therefore the rate of incidents in each cell at each time step per kilometre of road in that cell was calculated (Step 4 above). The mean rate of incidents per kilometre of road within each band of wind speeds was then calculated (Steps 7 and 8 above) and is shown plotted in Figure 4.18. An exponential relationship was fitted by least squares regression through the mid-point of each range of wind speeds to produce the following fragility curve:

$$IR = 1.47 \cdot 10^{-8} \cdot e^{0.115w} \tag{4.15}$$

Where:

w = three second gust wind speed (mph)

IR = the incident rate per kilometre of road given gust wind speed w

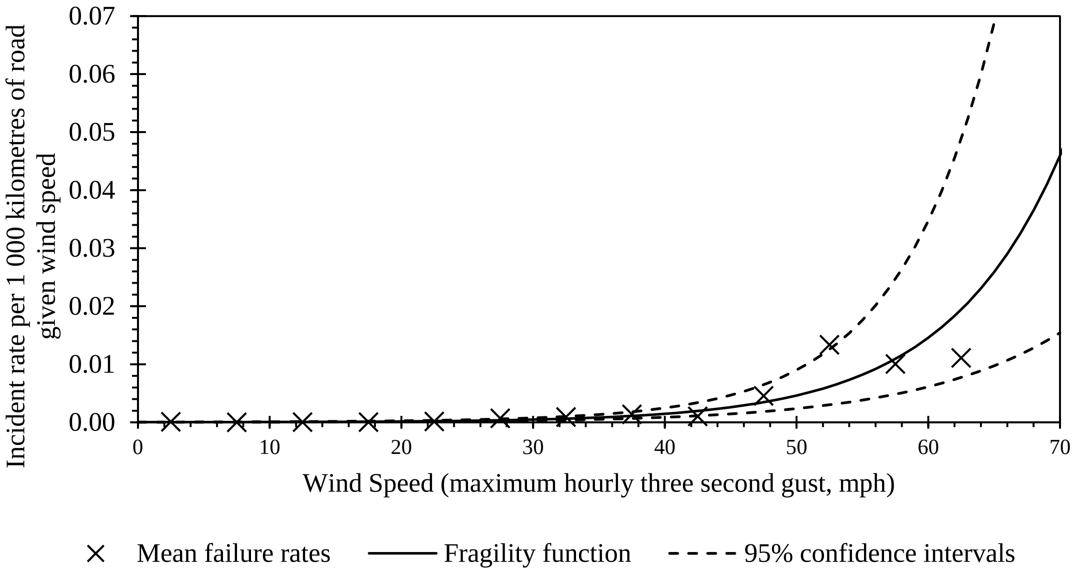


Figure 4.18 Average failure rates for highways exposed to strong winds and fitted fragility curve. The rate of failure remains very low below gust wind speeds of 25 miles per hour, above these

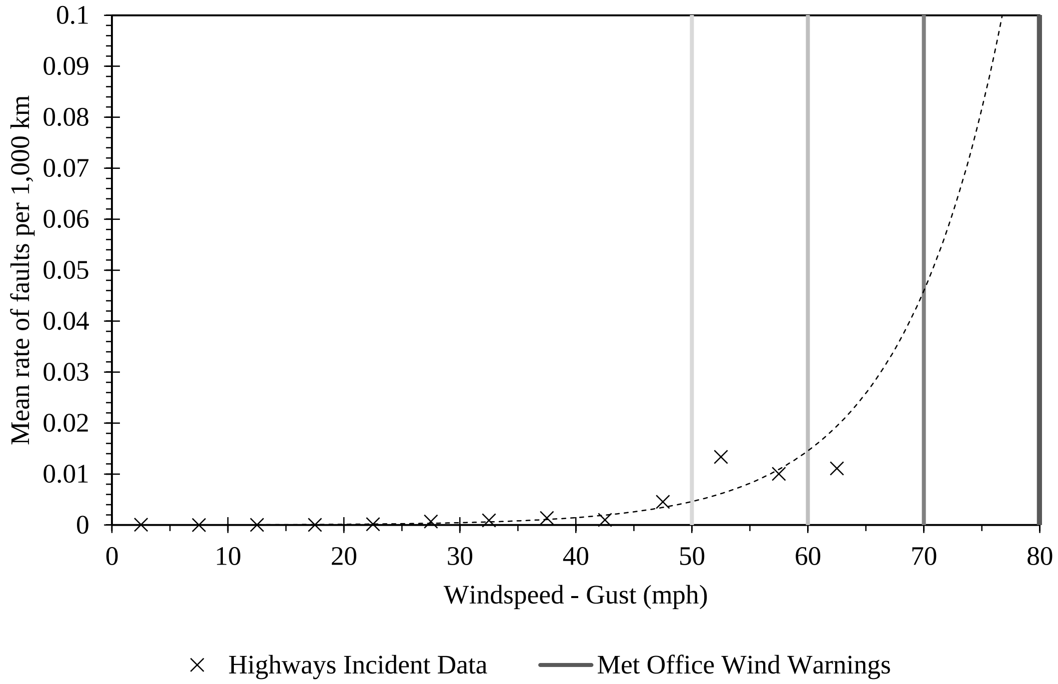
The fragility curve can be benchmarked against other work. Liang et al. (1998) used multiple regression to explore the effects of different hazards on free flow traffic speed. They found that traffic began to slow when wind speeds exceeded 25 miles per hour; a threshold which is consistent the first significant increase in failure rate in Figure 4.18.

Notably the failure rate appears to plateau, or even decline, when wind speeds exceed 50 miles per hour. Two potential explanations are identified:

i. This plateau may reflect human behaviour. Fragility curves are normally produced for fixed, civil engineering assets and there is little engineers can do in response to a forecast storm. By contrast drivers may choose to postpone journey or adapt their driving style so the risk of accidents and consequential road closures is reduced.

ii. Alternatively, the sample size means there are only a small number of events at these hazard intensities. Therefore there is a greater chance that the empirical data does not reflect the true failure probability. The averages of the 55-60mph and 60-65mph bins, and therefore the fitted line, may under-estimate the risk or, equally, the average for the 50-55mph bin may be a high outlier and therefore the risk is over-estimated. This is reflected in the confidence intervals for the fitted line which diverge considerably when gust wind speeds exceed 50 miles per hour.

The limited sample size also means there is no support for the fragility curve above wind speeds of 65 miles per hour. However the fragility curve reflects the wind warnings which the Met Office began to issue in 1992 (Figure 4.19). These suggest that disruption begins to occur when wind speeds reach around 50 mph and there is an increasing risk of over-turned vehicles and wind-blown debris through to 80 mph winds. Above this speed driving becomes inadvisable.



Gust wind speed	Legend	Conditions (Met Office 1992, referenced by Perry & Symons 1994)
50 mph	—	Difficult driving conditions for high-sided vehicles, especially on exposed roads or bridges.
60 mph	—	Difficult driving conditions, un-laden high-sided vehicles at risk of being over-turned. Some damage to trees. e.g. falling branches.
70 mph	—	Hazardous driving conditions, motorists advised to drive with particular care. Damage to trees, with some being uprooted.
80 mph	—	Dangerous driving conditions, motorists advised to avoid driving if possible. Considerable damage to trees.
90 mph	—	Driving extremely dangerous. Widespread uprooting of trees, public advised not to venture out of doors.

Figure 4.19 Benchmarking of the fragility curve against Met Office wind warnings.

The benchmarking gives confidence that the method is effective and the fragility curve represents the vulnerability of the infrastructure. There is, however, a clear opportunity for further work to improve the data brought into the process, both in terms of the sample size and relevance to the roads in the case study.

Vulnerability of road links to excessive cold

The pattern of failure rates for roads exposed to low temperatures is very different to the previous curve. Surprisingly, the number of incidents peaks around -2ºC before dropping away at lower temperatures (Figure 4.20).

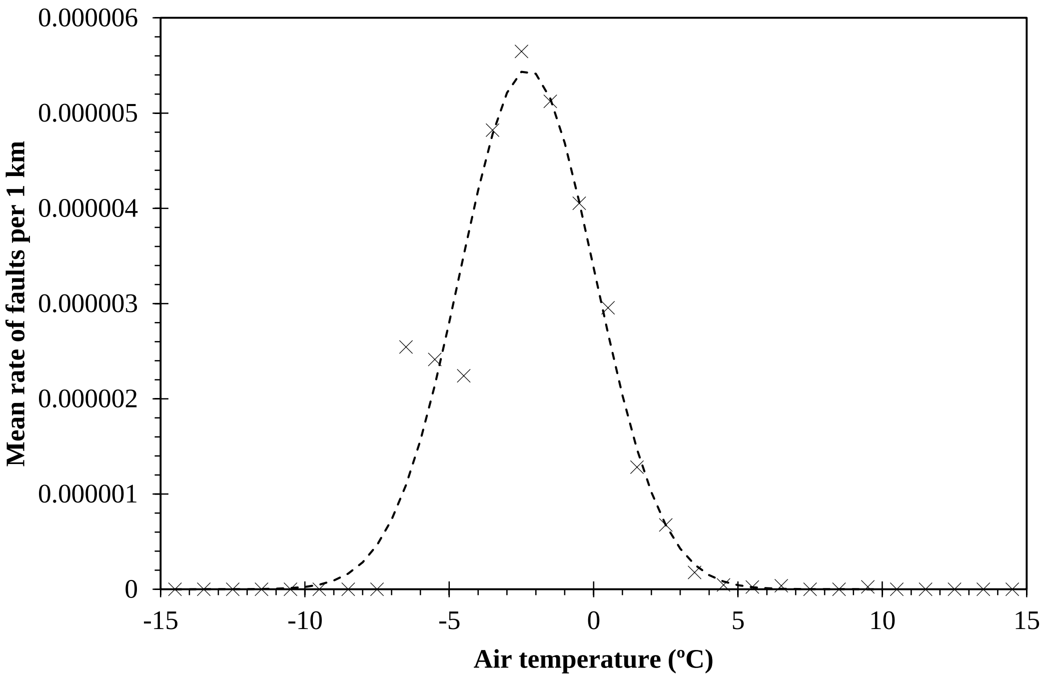


Figure 4.20 Average failure rates for highways exposed to low temperatures.

There are many possible explanations. In addition to reasons i & ii given in relation to windstorms above, there are factors particular to low temperatures:

i. The ability of the air to hold moisture is reduced by cold temperatures so there is a reduced likelihood of snow or damp conditions creating icy road surfaces.

ii. Temperature and road use both have pronounced diurnal patterns. Because these patterns are out of phase – the lowest temperatures occur in the middle of the night when traffic is lightest – many of the most extreme hazard values occur when the exposure is low.

It is also noted that the data contains two incidents at high temperatures. One is assumed to be an error and removed (an internet search found no reports of freak snowfall in Yorkshire in July 2011). The other occurs at 9 o'clock on a February morning when ice could have remained on the ground whilst the air temperature rose rapidly.

The incident rates between -4ºC and -7ºC appear to rise again. It could be argued that there are two different failure modes in operation: a flurry of failures at cool temperatures due to snow and the onset of a cold spell; and a further concentration of issues when the temperatures become truly low. This, however, is purely hypothetical and countered by the immediate drop in the failure rate below -7ºC. It is therefore proposed that the true rate drops smoothly and this variation is an artefact of a relatively small sample.

The data points in Figure 4.20 appear to follow the characteristic shape of a normal distribution so this shape was used as the foundations of the fragility curve. The fitted curve has a mean of -2.29 and a standard deviation of 2.35. Because the points shown in Figure 4.20 are not a true probability distribution the integral does not equal one and therefore the curve is scaled by multiplying it by the sum of the incident rates. The resulting fragility curve described by:

$$P(fault|t) = 3.21 \cdot 10^{-5} \cdot \frac{1}{2.35 \cdot \sqrt{2\pi}} e^{-\frac{(t+2.29)^2}{2 \cdot 2.35^2}} = 5.45 \cdot 10^{-6} \cdot e^{\frac{(t+2.29)^2}{11.0}} \tag{4.16}$$

Where:

t = air temperature (ºC)

P(fault|t) = the fault rate given temperature t

The dashed line in Figure 4.20 shows the curve is a good fit. The uncertainty over the underlying pattern below -4ºC makes it difficult to assess the accuracy of the curve but it is noted that these temperatures make up less than 0.5% of those observed. In contrast, the curve is a strong fit for temperatures greater than -2ºC which occur much more frequently.

<u>*Vulnerability of road links to flooding*</u>

There are two sources of information on the vulnerability of roads to flooding; the results from the analysis of the Highways Agency data and the outputs of the Flood Risk Assessment in Chapter 4.2.5. The former provide a direct estimate of the rate of road closures given the rainfall intensity, the latter requires the further processing described in the following paragraph.

The output of the flood risk assessment is an inundation depth for each highways link given the rainfall intensity. Therefore we need to capture the probability of a road being impassable given the depth of water. During the 2013 Winter floods the Environment Agency and Automobile Association issued a press release stating that:

> *"The Environment Agency and the AA strongly advise not entering flood water that is moving or more than 10cm deep."* (Environment Agency 2013)

The sponsors would not expect their employees to disregard this advice without specialist equipment. In this regard the sponsors have a number of off-road Toyota Hilux vehicles and a specialist 'Unimog' vehicle which have wading depths of 0.7m and 0.8m respectively. Considering the likely demand for these vehicles and trained drivers during a flood event it is estimated there is a 10% chance of them being available. A fragility curve can be based on these rules:

$$P(fault|d) = \begin{array}{ccr} 0 & ; & d < 0.1 \\ 0.9 & ; & 0.1 \leq d < 0.7 \\ 1 & ; & d \geq 0.7 \end{array} \qquad 4.17$$

Where:

d = inundation depth (m)

P(fault|d) = the fault rate given inundation depth d

Figure 4.21 compares the outputs from the analysis of the Highways Agency data and the flood risk assessment. The Flood Risk Assessment method predicts a higher rate of failure at lower and medium rainfall intensities before being overtaken by the exponential growth of the curve fitted to the Highways Agency data.

The rapid rise in the failure rate predicted by the Highways Agency data is influenced by the large gap between the highest and second highest value (note that the high value is not erroneous but results from the 2012 Newcastle floods – a perfect example of extreme, high intensity rainfall causing traffic disruption).

Another explanation is the influence of local geography and the exposure of the networks. The Highways Agency data is an average across a national network which, by virtue of its importance, is generally well-defended from flooding. By contrast the Flood Risk Assessment data contains specific information about local roads which are more exposed to flooding. Given this fact, the flood risk assessment data and Equation 4.17 are the better option for this research.

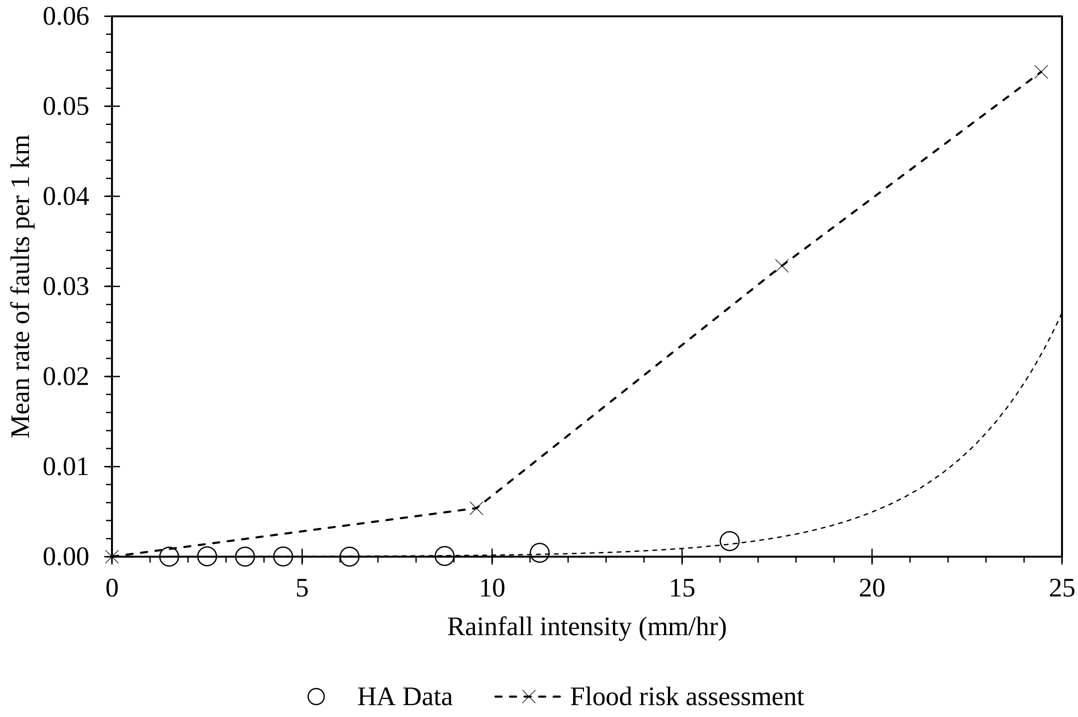


Figure 4.21 Comparison of average incident rates for highways exposed to rainfall derived from the Highways Agency's incident log, and those obtained through the flood risk assessment for the case study described in the following chapter. The failure rate for the latter was calculated by dividing the number of links which were impassable at a given rainfall intensity by the total length of roads included in the flood risk assessment.

4.3.2 Method of producing electricity infrastructure fragility curves

Table 4.10 SIPOC table for the method of producing electricity infrastructure fragility curves

	Windstorms and Excessive Cold	Flooding
Source	Met Office study commissioned by the Electricity Networks Association.	Anecdotal reports and personal communication from National Grid staff.
Input	Curves describing the number of faults given wind speed.	Information on substation failures during floods.
Process	i. Divide the number of faults in warm conditions by the average length of transmission operated by a Distribution Network Operator. ii. Fit a curve to the relationship. iii. Identify how cold weather affects the vulnerability of National Grid components to strong winds. Apply the same change in vulnerability to distribution networks components.	i. Search the literature for historical substation failures and flood depths. ii. Review of other literature on substation flood vulnerability. iii. Discuss substation vulnerability with National Grid employees to benefit from their expert knowledge.
Output	A curve which plots the rate of faults per kilometre against the gust wind speed in warm and cold conditions.	A curve which plots the probability of failure against flood depth.
Connection	Failed assets are identified at each time step by reading the probability of failure from the fragility curve and comparing this with a random number.	

Initial vulnerability assessment

The main cause of faults in the English and Welsh electricity networks is strong winds affecting overhead lines (McColl et al. 2012). The second key relationship is the vulnerability of ground-mounted substations to flooding; examples include Neepsend substation in 2007 and Gatwick Airport's substations in December 2013.

The opposite relationships can be discounted. It is highly unlikely that flood depths will be sufficient to damage transmission lines and the structure of substations makes them robust against strong winds. There are no known incidences of wind damage to UK substations and the risk is far outweighed by the vulnerability of the transmission lines supplying them; whilst eight substations in Florida required repairs following Hurricane Wilma (KEMA Inc. 2006), 227 were incapacitated by the loss of supply.

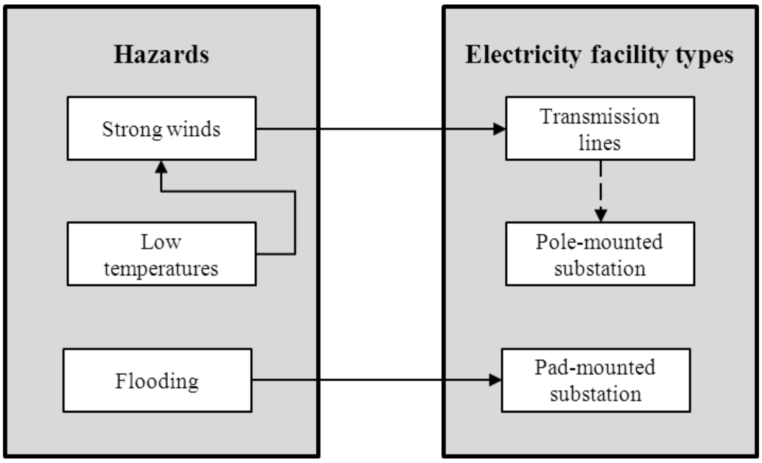


Figure 4.22 Initial assessment of electricity infrastructure vulnerabilities

The accumulation of ice on transmission lines can contribute significantly to network faults (Wang & Jiang 2012, Bonelli et al. 2011, Brostrom 2007). The effect is intertwined with wind speed; wind blows moisture onto the lines and the accumulated ice increases the cross-sectional area exposed to winds. The impact of cold weather is therefore incorporated into the impact of strong winds.

Finally, the direct impact of hazards on pole mounted substations is not considered because it is inherent in the transmission line infrastructure on which they are mounted.

<u>Source & Input – Windstorms and excessive cold</u>

The Electricity Networks Association (ENA) commissioned the Met Office to undertake a climate change risk assessment for the UK electricity networks including an analysis on the relationship between faults and severe weather. The majority of this information is not publicly available but the published work (McColl et al. 2012) includes an example for an anonymous operator (Figure 4.23).

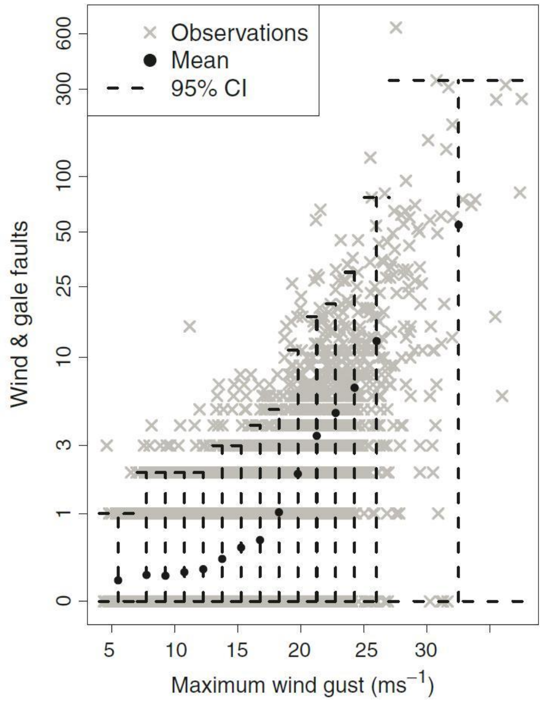


Figure 4.23 Observed daily record of wind and gale faults plotted against maximum wind gust for one licence area on the distribution network (McColl et al. 2012). The mean estimate of the observed gale fault distribution in each maximum wind gust bin is shown by the black circles and the dashed lines indicate the associated 95% confidence interval (CI). N.B. McColl et al. use metres per second whereas miles per hour is used elsewhere in this thesis.

<u>Process – Windstorms and excessive cold</u>

McColl et al.'s results provide an absolute number of faults within this anonymous DNO's licence area. This is converted to a fault rate per kilometre by dividing the mean number of faults by the mean length of wires owned by a DNO (56,590km, Ofgem 2012).

Figure 4.24 shows that the very low failure rates at unexceptional wind speeds exert a strong influence over trend lines fitted to the whole data. This is to the detriment of the fit at the higher wind speeds which are most critical to the study so the option of fitting a relationship to a subset of the data was explored. The best fit was found by establishing a threshold at a wind speed of 28 miles per hour and using least squares regression to fit a power relationship to the points above this threshold.

$$P(fault\ in\ 1\ km\ of\ line|w) = 2.77 \cdot 10^{-17} \cdot w^{7.30} \tag{4.18}$$

Where:

w = windspeed – gust [mph]

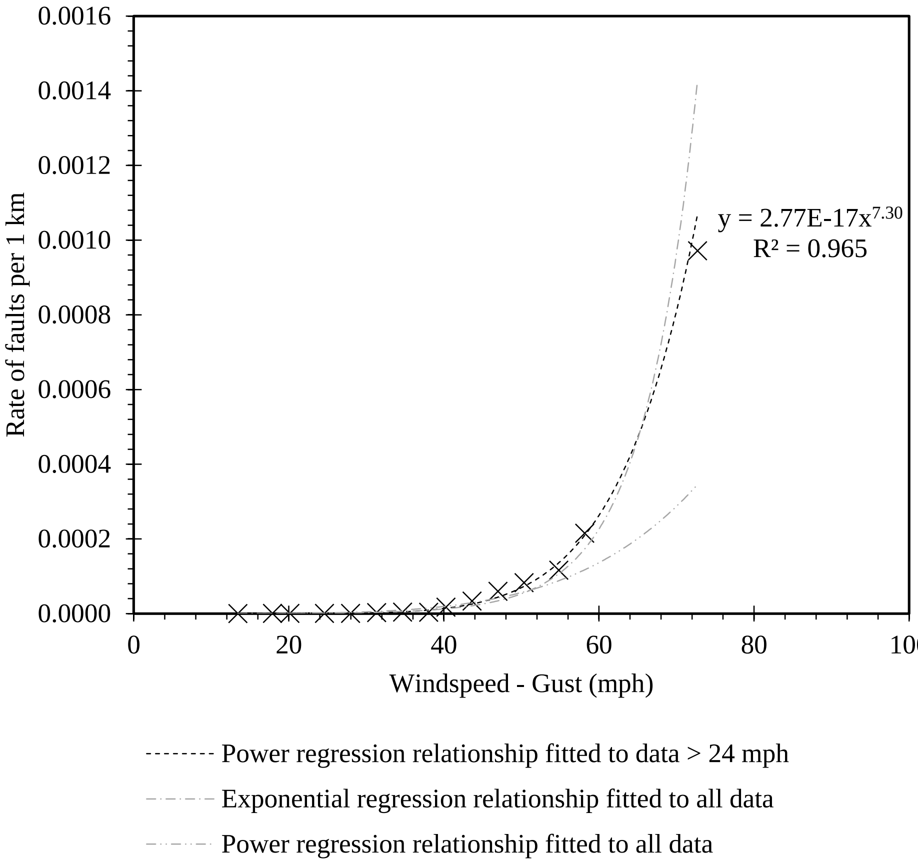


Figure 4.24 A power relationship fitted by least squares regression is a good fit to the wind and gales DNO fault data from McColl et al. 2012

Ice accretion on transmission lines has been addressed by a number of models (e.g. McComber et al. 1995, Wang & Jiang 2012) but none have replicated all the processes fully (Bonelli et al. 2011). These studies also create the subsequent challenge of determining the thickness of ice required to cause a particular line to fail.

An alternative is to use empirical data to understand historical vulnerability. This is the approach used by the Met Office in their work for the ENA as they replicate the same approach used for high winds on temperate days and apply it to only days where snow is recorded. The paper published by McColl et al. (2012) does not include any of the results of their analysis of cold weather impacts but the report specific to the National Grid, to which the researcher had access, includes the information for their network (Figure 4.25a) (McColl & Palin 2010).

This information cannot be applied directly since the high voltage transmission network operated by National Grid is typically more robust than the local distribution networks relevant to this study.

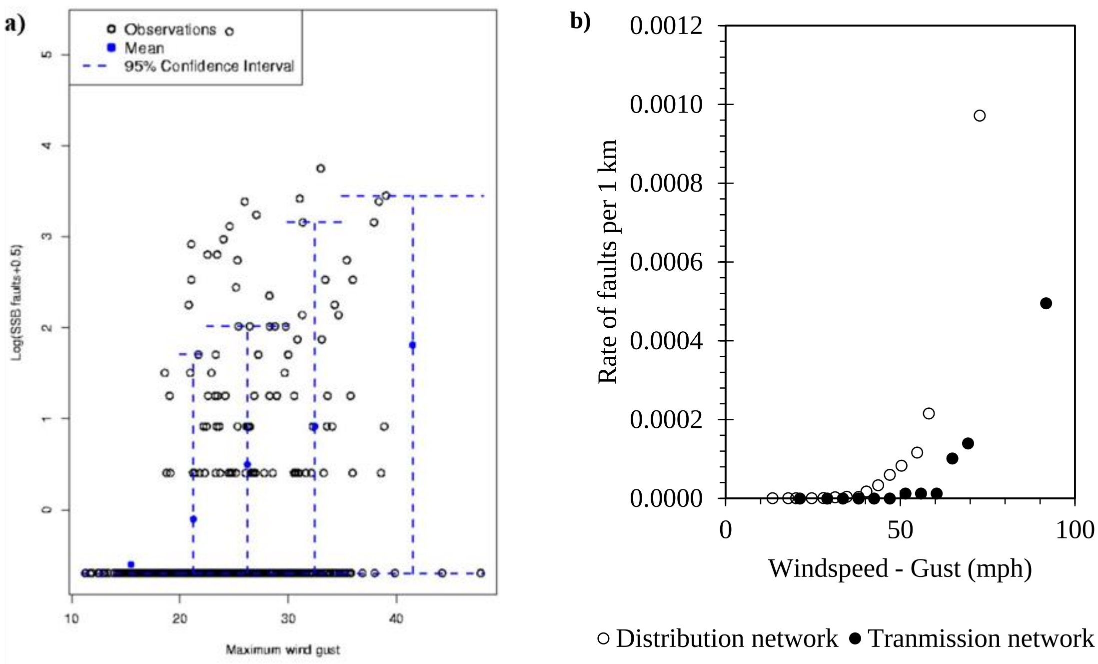


Figure 4.25 a) Observed daily record of wind and gale faults plotted against maximum wind gust given low temperatures for the UK transmission network (from McColl & Palin 2010). b) A comparison of the vulnerability of transmission and distribution networks to high winds in temperate conditions shows that distribution networks have a higher failure rate than the National Grid (Data from McColl & Palin 2010 and McColl et al. 2012)

The gap in information is resolved by assuming the increase in vulnerability due to cold weather is constant between both types of network. Equation 4.19 can be derived by comparing trends fitted to the failure data for the National Grid in normal and cold weather conditions (Figure 4.25b).

$$P(fault|w,s) = P(fault|w) \cdot 1{,}690{,}000w^{-3.15} \qquad 4.19$$

Where:

w = three second gust wind speed (mph)

P(fault|w,s) = the fault rate given windspeed w and the occurrence of snow and ice.

P(fault|w) = the fault rate given windspeed w in normal conditions.

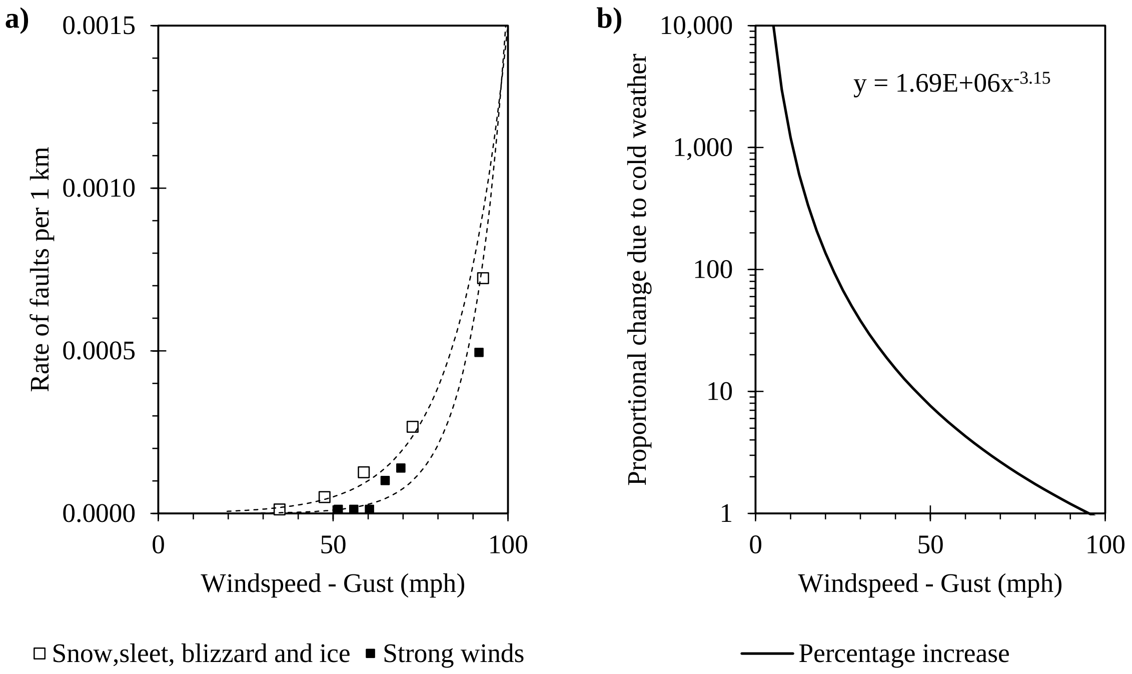


Figure 4.26 a) Fault data for the UK transmission network from McColl and Palin (2010) under normal and snow, sleet, blizzard and ice conditions. b) Increase in failure rate due to snow, sleet, blizzard and ice conditions, based upon McCall & Palin's analysis of failures in the National Grid transmission network. Above 95 mph ice accretion is assumed to have no impact.

Equation 4.19 can then be applied to McColl et al. (2012)'s data for distribution networks exposed to high winds in temperate condition to produce a curve for distribution networks exposed to high winds in cold weather (Figure 4.27). The disadvantage of this approach is that the high value of Equation 4.19 at low wind speeds creates elevated failure rates at low wind speeds. However this is insignificant because, to be consistent with Equation 4.18, a regression relationship is only fitted to wind speeds where the wind speed exceeds 28 miles per hour (Equation 4.20).

$$P(fault|w,s) = 4.68 \cdot 10^{-11} w^{4.15} \qquad 4.20$$

Where:

w= three second gust wind speed (mph)

P(fault|w,s) = the fault rate given windspeed w and the occurrence of snow and ice.

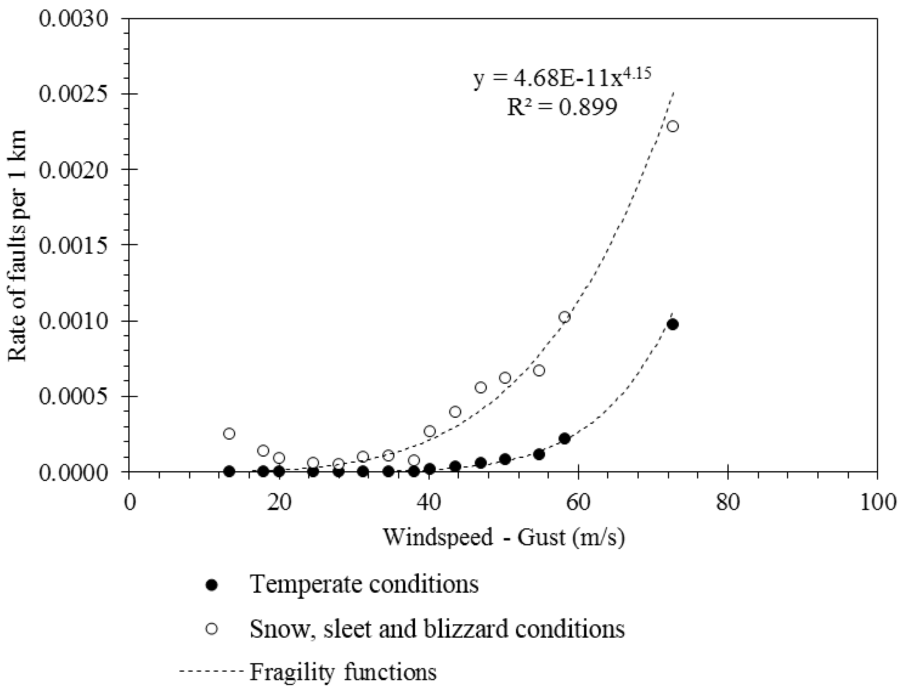


Figure 4.27 McColl et al. (2012)'s data converted to account for cold temperatures. Least squares regression is used to fit a fragility curve.

The final step is to identify the threshold between temperate and cold conditions. The Weather Generator output does not identify when precipitation falls as rain or snow so another method is required. Lopez-Moreno et al. (2009) set the temperature threshold at 0.01°C, the triple point of water, but Wen et al. (2013)'s comprehensive review of different rain-snow thresholds finds that a threshold of 2.5°C performs better than a 0°C threshold and is comparable or better than more complex models. Consequently in this model where precipitation occurs at temperatures lower than 2.5°C it is assumed to fall as snow.

Output – Windstorms and excessive cold

In summary, there are two fragility curves describing the performance of the electricity network in response to have strong winds:

$$P(fault|w) = \begin{matrix} 4.68 \cdot 10^{-11} w^{4.15} \;\; ; \;\; t < 2.5 \; and \; r > 0 \\ 2.77 \cdot 10^{-17} \cdot w^{7.30} \;\; ; \;\; t > 2.5 \;\; or \; r = 0 \end{matrix} \qquad 4.21$$

Where:

P(fault|w) = the fault rate given wind speed w in normal conditions.

w = three second gust wind speed (mph)

t = air temperature (°C)

r = precipitation intensity (mm/hr)

Source & Input – Flooding

The impact of flooding on substations is very easy to picture; one can imagine a typical substation and the height of critical equipment. However, the information on failures is scarce and mainly in the form of anecdotes and news reports.

A literature review located reports of flooding at seven different substations sites in the past decade. Of these seven incidents:

- Five resulted in a loss of supply.
- In two cases the substation resisted the hazard.
- In one of these resistant cases it was also reported that a further two inches of flooding would have resulted in failure.

This information is shown in Figure 4.28 and summarised in Table 4.11.

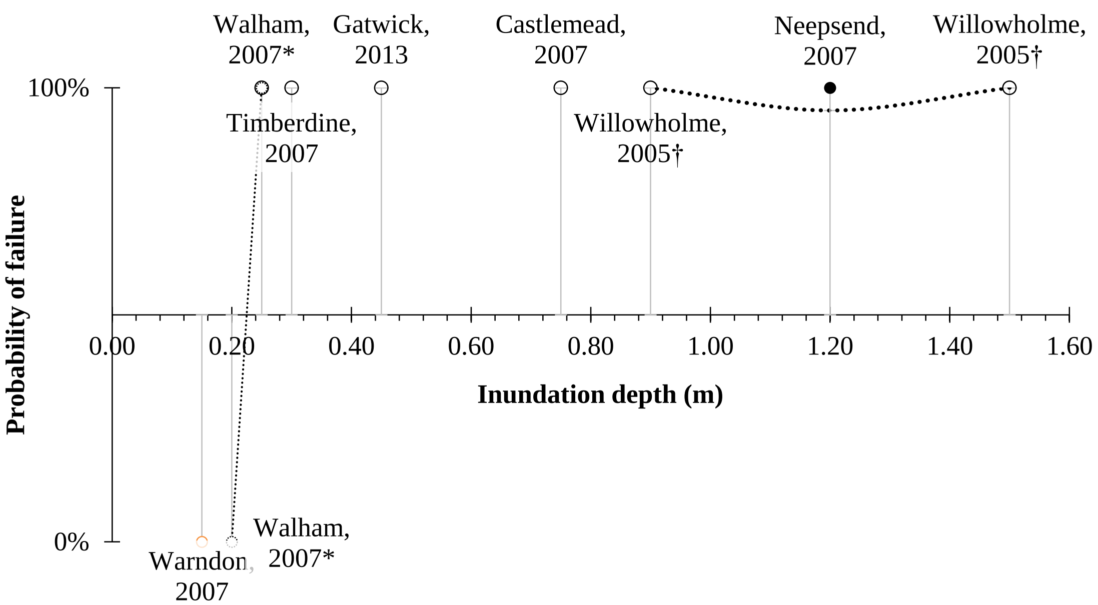


Figure 4.28 Summary of information gained from historical substation flood events and near misses

* Walham 2007 – Walham substation did not fail but media reports indicate that a further 2 inches of flooding would have been critical.

† Willowholme, 2005 – reported water depths at Willowholme vary widely. United Utilities (who operated the substation) quote a depth of 0.9m in their post-incident review whereas the Environment Agency state 1.5m. The difference is not important since both are deep enough to almost certainly incapacitate a site.

Table 4.11 Historical substation flood events and near-misses

Event	Known Depth	Failure?	Description	Source
Warndon, Worcestershire. 2007	~0.15m	No	Photograph from presentation by E-on staff: 	Simpson & Nutter (2008)
Walham, Gloucestershire. 2007	~0.2m	No	Still from BBC News report: 	BBC (2008)
Walham, Gloucestershire. 2007	~0.25m	Likely	Paraphrased Channel 4 News report: “The flood water in the main switching room reportedly came to within 2 inches of the height at which the substation would have to be shut down (Snow and Manning, 2007)”	McMaster & Baber (2008)
Timberdine, Worcestershire. 2007	~0.3m	Yes	Photograph from presentation by E-on staff: 	Simpson & Nutter (2008)

Event	Known Depth	Failure?	Description	Source
Gatwick Airport, Surrey. 2013	0.45m	Yes	Entry into events log: "EDM made entry into NT [North Terminal] basement. Found approximately 2ft of water at road level. South switch room flooded to 18"."	McMillan (2014)
Castlemead, Gloucestershire. 2007	0.75m	Yes	Quote from J. Crackett, Managing Director of Central Networks: "They worked around the clock to put in place the flood barrier and were then able to pump water out of the site that had reached a level of 2.5 feet and switch the power back on."	Walliman (No date)
Neepsend, South Yorkshire. 2007	1.2 – 1.5m	Yes	Quote from Memorandum submitted by National Grid: "Further reports from National Grid's site staff indicated that the floodwaters inside Neepsend substation had reached a depth of 1.2-1.5 m. The 275kV circuits connecting Neepsend substation to the rest of the transmission system were opened in order to de-energise the substation for safety reasons."	Select Committee on Environment, Food and Rural Affairs (2008)
Willowholme, Carlisle 2005	1.5 or 0.9m	Yes	The Environment Agency report and United Utilities' incident report differ widely on the inundation depth. However, both depths are severe enough to make the difference inconsequential. Environment Agency: "The electricity sub-station at Willowholme was under 1.5m of water on 8 January, which cut off power to 60,000 properties."	Environment Agency (2006) Cox (2005)

This information is supplemented with expert knowledge from other sources. In their HAZUS-MH model, FEMA suggest that the 'Functionality Threshold Depth' for an electricity substation is four feet (1.2 metres) (FEMA, 2012b) whilst, in a case study into the National Grid climate change adaptation practices, Peace et al. (2013) note that:

"Most sites have a resilience to flooding to an approximate depth of 300mm." (p79)

Further informal conversations with a National Grid expert on infrastructure resilience indicated that very few substations would continue operating if flooded to a depth greater than 0.5 metres.

Process - Flooding

There is a considerable disparity between the HAZUS-MH estimate and both the empirical data (four UK substations have failed, or were predicted to fail, at lower depths) and the other experts' opinions. The lack of any background information on how the value was obtained and potential difference between UK and US substations means there is no justification to give it precedence over the other information. Therefore it is not used to fit the fragility curve.

By contrast, the opinion of the other experts adds richness to the binary reports of failures in Figure 4.28. Therefore the fragility curve is formed by fitting a linear relationship between the two points provided by the expert opinion and forcing the probability of failure to equal zero when there is no flooding. The resulting line summarised by Equation 4.22 and shown in Figure 4.29.

$$P(fault|d) = \begin{matrix} 1.91d & ; & d < 0.52 \\ 1 & ; & d > 0.52 \end{matrix} \qquad 4.22$$

Where:

P(fault|d) = the fault rate given inundation depth d

d = inundation depth (m)

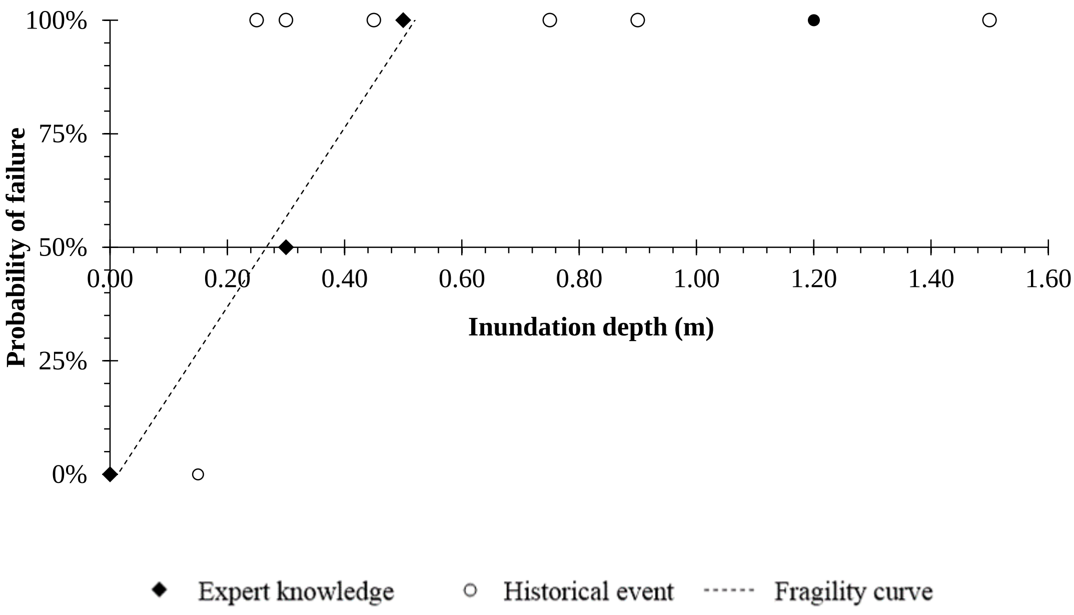


Figure 4.29 Fragility curve for substations exposed to flooding fitted using expert knowledge and data from historical events

Output – Flooding

Figure 4.29 shows that this line is supported by the record of past failures. Two substations did not fail when flooded to depths at which the estimated probability of failure is between 25 and 40%. On the other hand, two failures and one predicted failure did occur at depths where the probability of failure is estimated to be greater than 50%. It is a reasonable assumption that the failures at Castlemead and Neepsend would have occurred at a lower depth than the peak reported in the source information. This gives reassurance that the fragility curve is a good estimate of substation vulnerability.

4.3.3 Method of producing telecommunications infrastructure fragility curves

Table 4.12 SIPOC table for the method of producing telecommunications infrastructure fragility curves

	Windstorms and excessive cold	**Flooding**
Source	A study into the effect of the 1987 and 1990 hurricanes on British Telecommunication's networks.	Anecdotal reports.
Input	Two data points which are used in combination with the electricity network data used above.	Estimated flood depths for two flooded exchanges.
Process	Calculate failure rates for the 1987 and 1990 storms. Combine these points with those used for overhead electricity lines above. Apply the same transformation to understand the effect of cold weather.	Search the literature information on past flooding of telephone exchanges.
Output	A curve which plots the rate of faults per kilometre against the gust wind speed in warm and cold conditions.	A curve which plots the probability of failure against flood depth.
Connection	Failed assets are identified at each time step by reading the probability of failure from the fragility curve and comparing this with a random number.	

Initial vulnerability assessment

The public switched telephone networks (PSTN) is similar to the power network; it consists of a number of point assets, in this case telephone exchanges, connected by a mixture of overhead and buried lines. Therefore the vulnerabilities of the system are also similar (Figure 4.30).

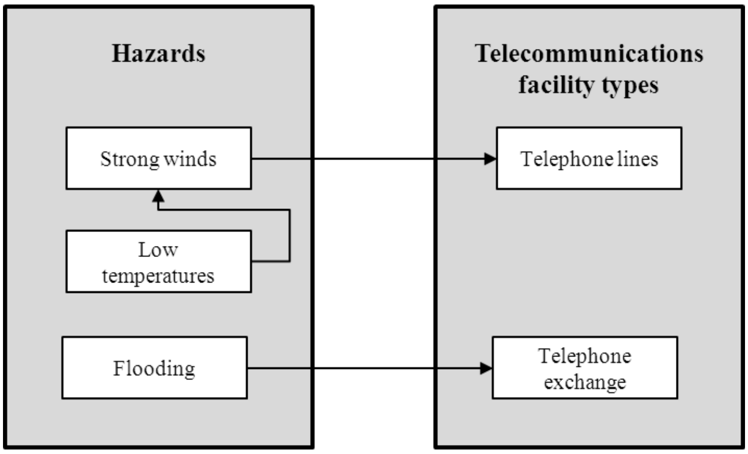


Figure 4.30 Initial assessment of electricity infrastructure vulnerabilities

There is a surprising shortage of published information on the physical vulnerabilities of the PSTN as research efforts have concentrated on cyber threats (Kwawinski et al. 2009, Horrocks et al. 2010). A number of studies describe physical hazards and past events in general, qualitative, terms but rarely provide the depth of information required to form fragility curves (e.g. Marchetti 2010, ITU-T 2013). The following section describes how fragility curves were formed based on the available information.

Source & Input– Windstorms and excessive cold

The main source of information on the impacts of strong winds are hurricanes in the southern United States: Hurricane Hugo led to the loss of 1,500 utility poles (Griswold 1990); Hurricane Andrew led to a loss of service to around 75% of one company's customers (Jacob et al. 2011); and Hurricane Katrina caused a loss of service to 3 million customers (Victory et al. 2006). A literature search only found one UK study: a survey of the effects of the 1987 and 1990 storms by Coppinger (1990).

Coppinger provides details on both the number of faults reported (Table 4.13) and the regions affected by the storms (Figure 4.31). This information is combined with weather observations downloaded from the MIDAS data set to produce a failure rate related to the hazard intensity.

Table 4.13 Impact of the 1987 and 1990 storms on the UK PSTN network (Coppinger 1990)

Event	1987	1990
Number of line faults reported on the first day	50 000	100 000
Number of telephone poles replaced or reset	2 500	3 350
Overhead cable replaced (miles)	300	276

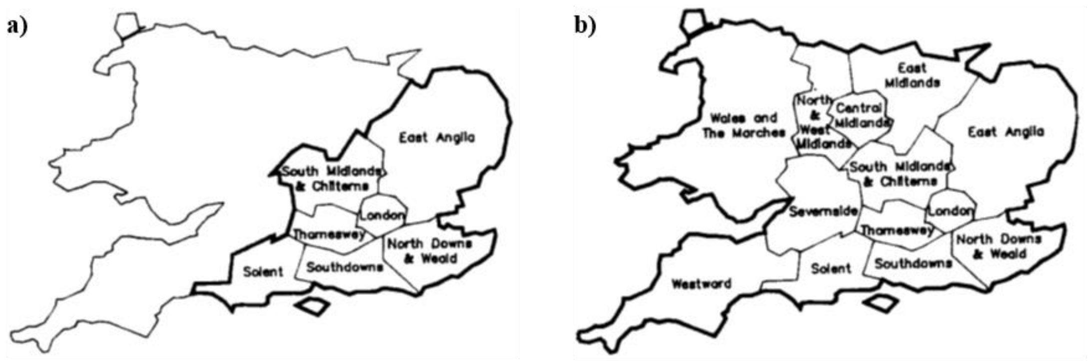


Figure 4.31 Areas affected by the a) 1987 and b) 1990 storms in the UK (Coppinger 1990)

Process – Windstorms and excessive cold

The failure rates and associated wind speeds for the two events were calculated by the following procedure.

1. The first step is to calculate the fault rate per kilometre of telephone line in each event (Table 4.14).

Table 4.14 Fault rates per telephone connection for the 1987 and 1990 UK windstorms

Event	Estimated no. of customers affected (million)	Number of faults (million)	Fault rate per connection	Fault rate per km
1987	11.1	0.05	0.00449	0.00135
1990	12.0	0.10	0.00535	0.00160

   a. It is assumed that the density of population and telephone connections are proportional. GIS software is used to overlay the footprints shown in Figure 4.31 with Census data (ONS 2011). This indicates that 37% and 62% of the UK population were affected by the 1987 and 1990 storms respectively. These percentages are applied to the total number of BT customers (approximately 30 million (MacFadyen 2007)) to calculate the number of connections within the footprint of each storm.

   b. The fault rate per connection is calculated by dividing the number of faults in each event (Table 4.13) by the number of customers within the footprint.

   c. The average length of a customer connection in the UK is 3.34km (Williamson et al. 2008). The fault rate per kilometre can be calculated by dividing the fault rate per connection by this value.

2. The second step is to calculate the maximum gust wind speeds in each storm.
   a. The maximum hourly 3 second gust wind speed during the period of interest is extracted the MIDAS data held by the BADC.
   b. Thiessen polygons are used to assign the areas shown in Figure 4.31 and to their nearest weather station, and therefore calculate a weighted average wind speed.
3. The fault rate and wind speed are combined to provide points on a fragility curve.

Two data points are insufficient to create a fragility curve but similarities between telephone and electricity distribution networks allow the information to be pooled. In both cases the vulnerable elements are wires hung between wooden poles and they are equally exposed to the windblown debris which is a significant cause of failure (Coppinger 1990, Cox 2005, Winkler et al. 2010).

Figure 4.32 supports this connection by plotting the failure data from McColl et al.'s 2012 study of an electricity distribution network operator together with the two points derived from Coppinger's work. The two data sets do not overlap but the gradient and relative position are similar. This gives confidence that the process has produced a coherent result; the second model described in Chapter 6 can be used to assess the sensitivity of impacts to changes in fragility curves.

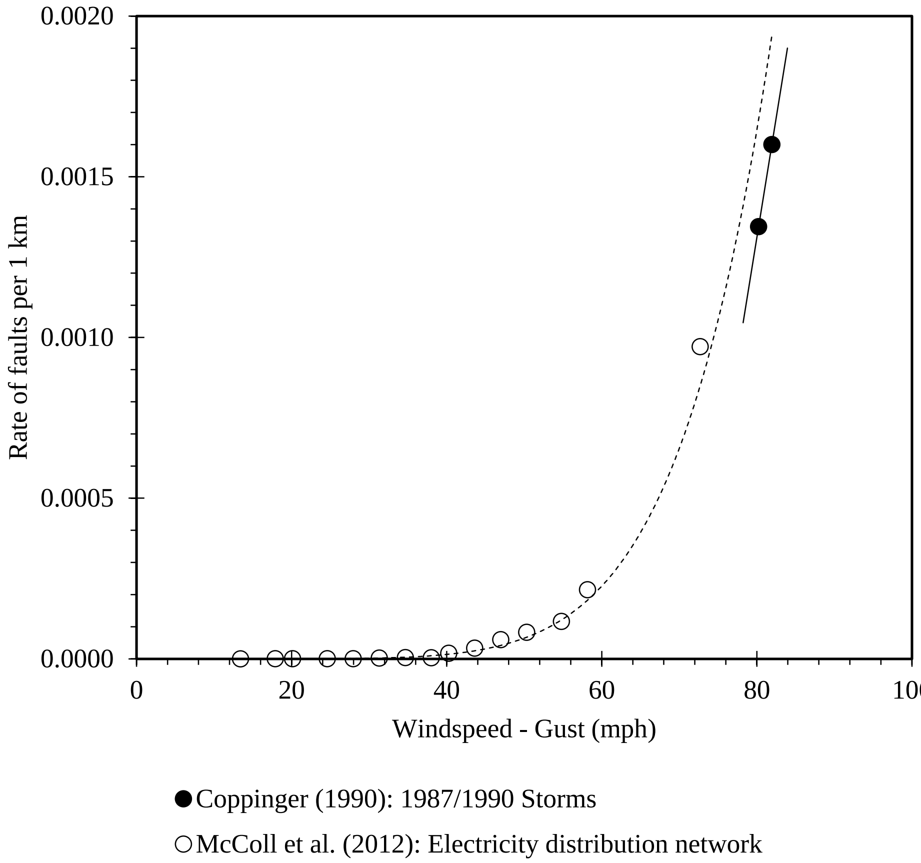


Figure 4.32 Failure rates for the British Telecommunications' network in the 1987 and 1990 storms are slightly lower (the same failure rates occur at wind speeds approximately 2.5 miles per hour greater) but otherwise they are consistent with the relationship for the electricity distribution network found by McColl et al. (2012)

Fragility curves are developed in the same way as for the electricity network data above: least squares regression is used to fit a relationship to the combined data set for those points which had a failure rate greater than 10^{-6} and Equation 4.19 used to calculate the increased vulnerability due to snow and ice in cold conditions.

Output – Windstorms and excessive cold

The resulting fragility functions are described by Equation 4.23 and shown in Figure 4.33.

$$P(fault|w) = \begin{matrix} 2.09 \cdot 10^{-10} \cdot w^{3.75} & ; & t < 2.5 \; and \; r > 0 \\ 1.24 \cdot 10^{-16} \cdot w^{6.90} & ; & t > 2.5 \; \; or \; r = 0 \end{matrix} \qquad 4.23$$

Where:

P(fault|w) = the fault rate given wind speed w in normal conditions.

w = three second gust wind speed (mph)

t = air temperature (°C)

r = precipitation intensity (mm/hr)

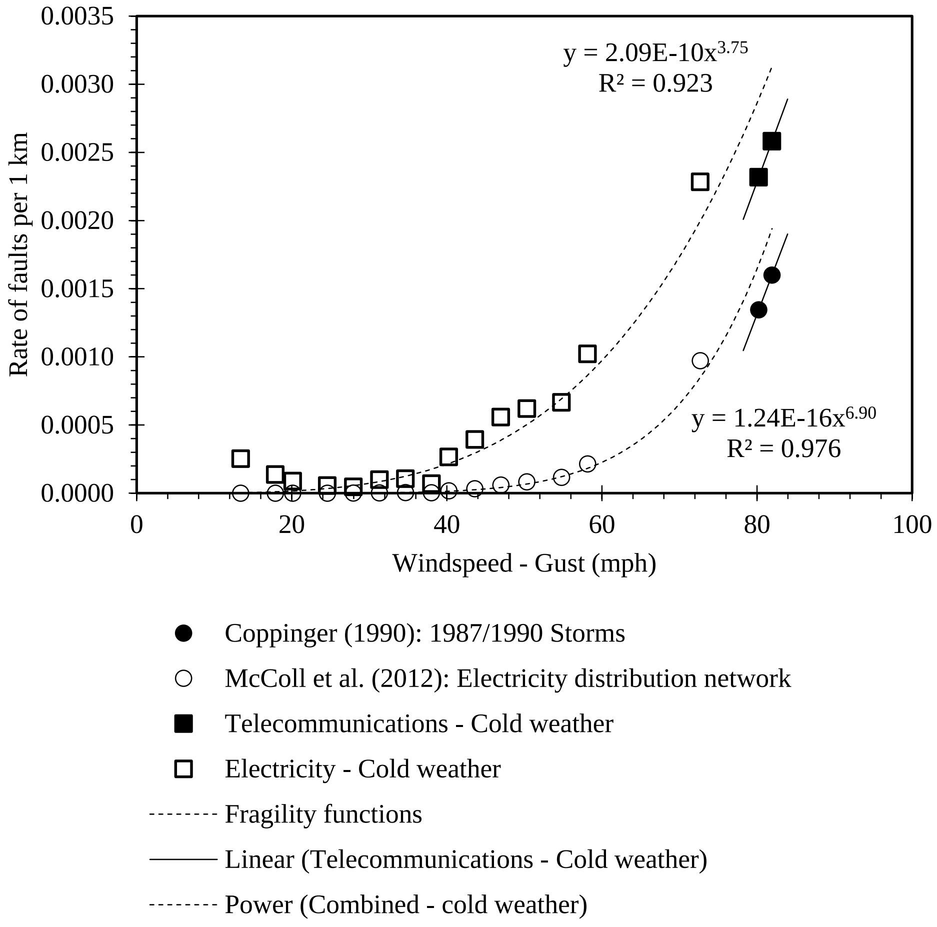


Figure 4.33 Failure rates for the British Telecommunications' network in the 1987 and 1990 storms, and those for the electricity distribution network calculated by McColl et al. (2012)

<u>Source & Input – Flooding</u>

A literature search found a small number of news reports on flooding at UK telephone exchanges. More comprehensive reviews of damage caused by Hurricanes Katrina and Sandy were also obtained.

The depth of flooding is only recorded in one UK event and the value of this information is limited because only a basement containing cabling was flooded. In two other cases the depth can be inferred from photographs (Figure 4.34). The data on Hurricane Katrina and Sandy is more wide-ranging but depth information is still scarce – it is only reported for two exchanges where waters reached 2 and 2.5m. Predictably, both exchanges failed. Failures could be mapped against the flood depth data available for some events (e.g. Fritz et al. 2008) but the resolution of this data makes it difficult to assess depths at individual sites with confidence.

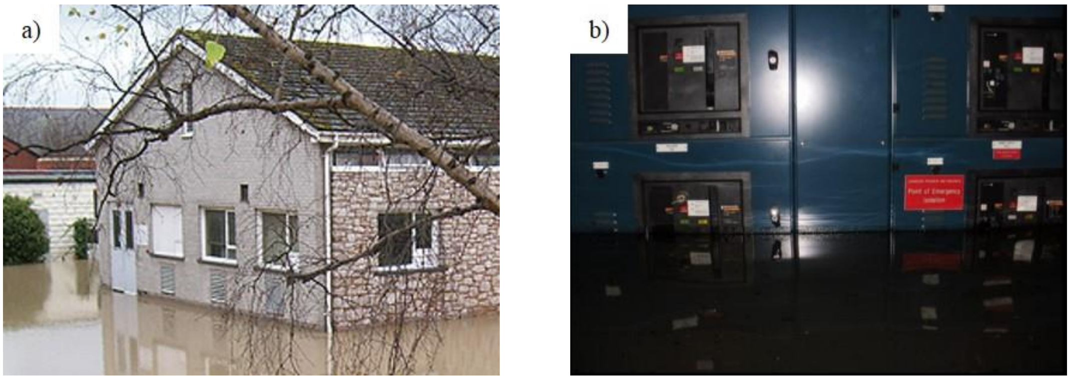


Figure 4.34 a) St Asaph telephone exchange November 2012 (BT 2012). Customer service was unaffected. b) Paddington telephone exchange March 2010. The water reached 0.5m cutting off customers across North and West London.

<u>Process & Output – Flooding</u>

The shortage of telecommunications specific information makes it impossible to draw a bespoke curve. Therefore the vulnerability of telephone exchanges is assumed to be equal to electricity substations. This is supported by the two pieces of failure information which are available: one exchange did not fail when the probability of failure is estimated at around 60%; the other did fail when the probability is about 95%.

There are structural differences between exchanges and substations; substations are normally on one level but an exchange may be spread over a number of floors. However, as the Paddington example (Figure 4.34b) shows, the lowest piece of vulnerable equipment determines the fragility of a whole exchange.

4.3.4 Method of producing potable water infrastructure fragility curves

Table 4.15 SIPOC table for the method of producing water infrastructure fragility curves

	Flooding of Water Treatment Works	**Flooding of Pumping Stations**
Source	Expert opinion	Expert opinion and site surveys.
Input	-	Understanding of pumping station layouts.
Process	-	i. Establish what proportions of pumping stations are above and below ground. ii. Create a distribution showing the lowest points of ingress into pumping station buildings. iii. Assess the height of equipment within pumping stations. iv. Gather this information into a single fragility curve.
Output	Any flooded water treatment works is likely to be shut down.	A curve which plots the probability of failure against flood depth.
Connection	Failed assets are identified at each time step by reading the probability of failure from the fragility curve and comparing this with a random number.	

<u>Initial vulnerability assessment</u>

To understand the impact of dependence on other networks it is necessary to also explore the vulnerability of the water assets themselves. For regulatory purposes water infrastructure is often divided into two groups, infrastructure and non-infrastructure, which (in general terms) describe below and above ground assets respectively.

Infrastructure assets, by virtue of being buried, are invulnerable to most hazards. There is a link between cold temperatures and burst pipes, as demonstrated in Northern Ireland in 2010-2011 (McDonald 2010), but this is omitted from this case study. The relationship between temperature and bursts is poorly understood and cannot be represented with precision. Figure 4.35 shows there is no clear relationship between temperature and the number of burst repairs and, furthermore, it is unclear why cold weather causes bursts because pipes are buried below the depth to which a UK frost will penetrate (Clucas 2011, *pers. comm*.).

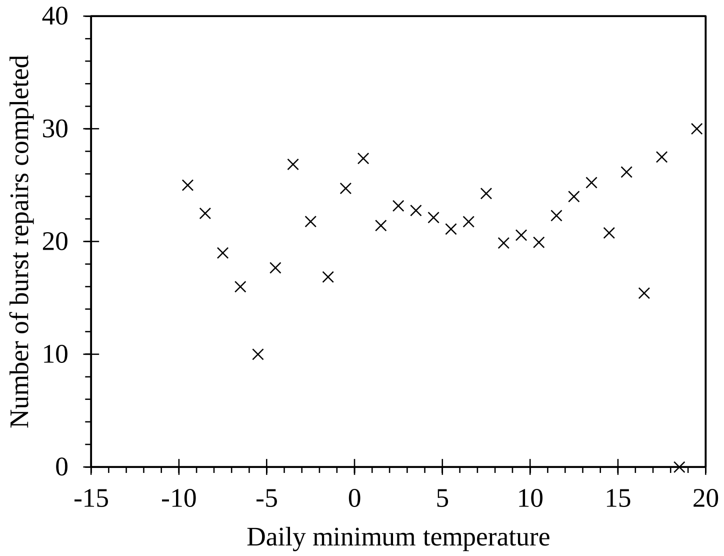


Figure 4.35 The correlation between daily minimum temperature and the number of completed burst repairs is noisy due to complicating factors such as the increasing focus on leak reduction during hot summers and difficulties of repairing bursts in adverse conditions.

Non-infrastructure facilities are slightly more vulnerable. The predicted cost of repairing the wind damage to the water treatment works damaged by the 2005 Cumbrian storms was over £100 000. However this structural damage appears not to have affected the operation of the facility (McDonald & Yerkess 2005). It is noteworthy that no other sites were affected. The combination of low exposure and low probability of the function of the site being affected means this vulnerability is not considered by the model. In contrast, a flooded water treatment works will be shut down immediately for safety reasons and the electrical components of pumping stations are vulnerable to flooding (Bassett, 2014 *pers. comm.*). This model therefore concentrates on the potable water infrastructure's vulnerability to flooding (Figure 4.36)

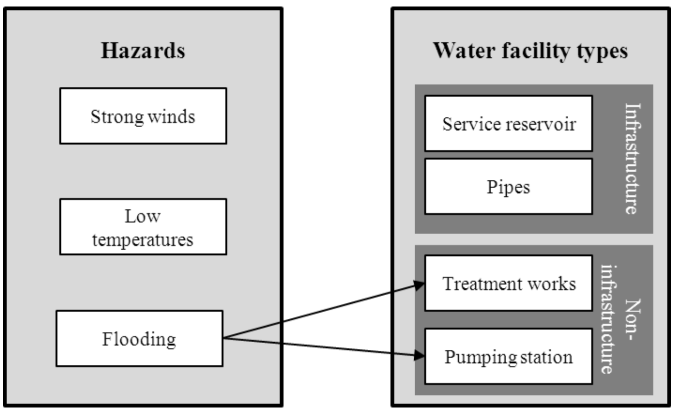


Figure 4.36 Initial assessment of water infrastructure vulnerabilities

Source, Input, Process & Output - Flooding of water treatment works

The precautionary approach to flooding at water treatment works is both to minimise the risk of contamination and to protect the health and safety of staff (since underground chambers could be hidden by the flood water). This is supported by HAZUS-MH which defines the functionality threshold depth of an open treatment works as 0ft (FEMA 2012b). The fragility curve is therefore simple:

$$P(fault|d) = \begin{array}{lll} 0 & ; & d < 0.01 \\ 1 & ; & d \geq 0.01 \end{array} \qquad 4.24$$

Where:

d = inundation depth (m)

P(fault|d) = the fault rate given inundation depth d

Source & Input – Flooding of pumping stations

A literature review identified only the technical manual for HAZUS-MH (FEMA 2012b), which appears inconsistent with UK experience. Empirical information is equally scarce; a review of one water company's incident log for the past 10 years found no relevant reports of flooded water facilities (apart from one set of river intake pumps which stopped operating when the ultrasonic gauge which controlled them was submerged). The following section describes how a fragility curve was produced using the combination of a photographic survey of pumping stations and expert opinion from within the project sponsors.

Two pieces of information are required:

i. The depth of water required to enter a pumping station.
ii. The depth of water within the pumping station which will cause failure.

Depth of water is required to enter the building

HAZUS-MH assumes that the entrances to below ground pumping stations are three feet (0.9 metres) above ground level. However experience of UK pumping stations suggests that entry points are rarely more than a foot above ground level and can often be at ground level (Figure 4.37).

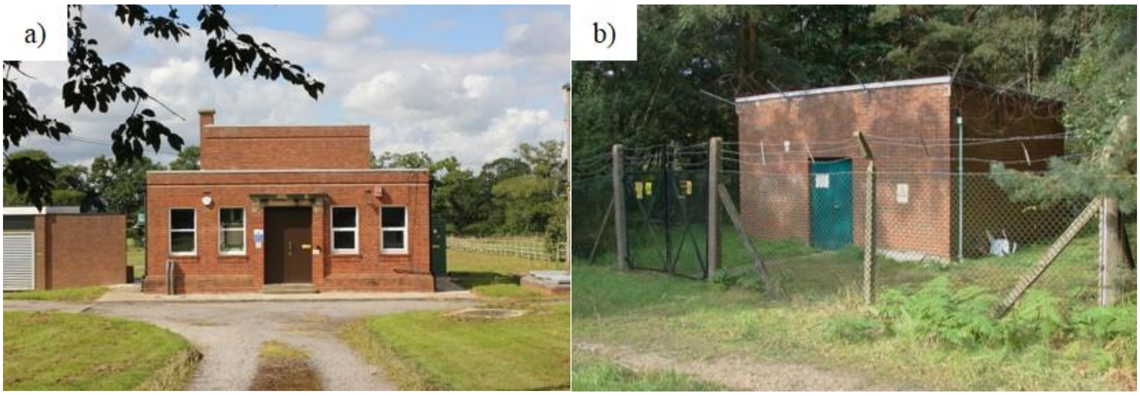


Figure 4.37 Example UK pumping stations (Hunt 2012, Brock 2015). The doorstep at a) is approximately a foot above ground level and the entrance to b) is slightly below ground level.

UK specific data is obtained using photographic evidence from Google Street View and Geograph.org.uk and known dimensions such as the British Standards for brickwork (Ibstock 2010). A survey of 50 sites was taken working alphabetically through one of the project sponsors' databases (Figure 4.37).

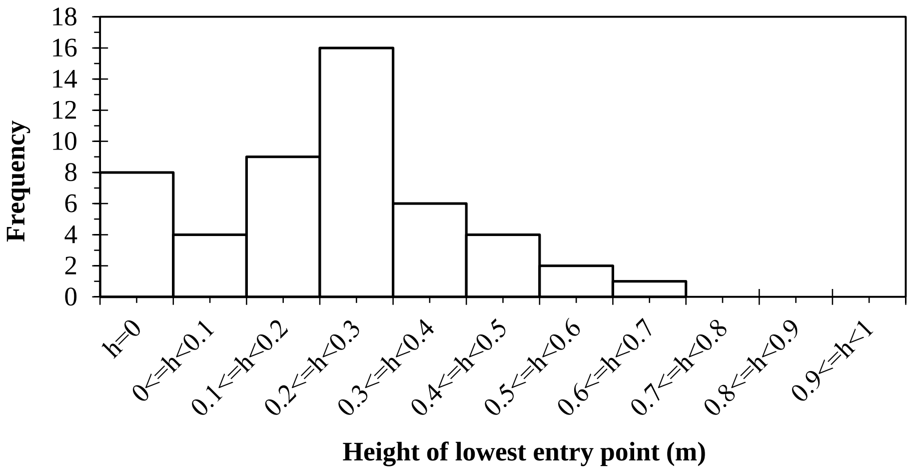


Figure 4.38 The height of lowest ingress points at 50 UK water pumping stations.

The results suggests that the entry point to 16% of pumping stations are level with the surrounding ground and ingress heights at the remaining stations are best approximated by a Gumbel distribution. These two pieces of information combined create an equation summarising the heights of ingress points at UK pumping stations:

$$h = \begin{matrix} 0 & ; & X \leq 0.16 \\ 0.186 - \ln(-\ln Y) \cdot 0.109 & ; & X > 0.16 \end{matrix} \qquad 4.25$$

Where:

h = height of ingress (m)

X and Y = uniformly distributed random variables between 0 and 1

Depth of flooding to cause failure

The lowest ingress point was a doorway in all but one of the 50 surveyed pumping stations. Therefore it is assumed that the floor level corresponds with ingress heights and the internal depth can be calculated from this level.

Pumping stations can be divided into two types:

i. The majority are above ground level, typically within a kiosk or small building.

ii. In a smaller number of cases the pressure in the network is insufficient to reach ground level. Therefore the pump is located at the bottom of a ‘dry-well’.

An experienced Principal Engineer suggested that 70% of the company’s water pumping stations fall into the first category. This is the best arrangement because it simplifies maintenance and reduces the number of confined spaces. Then 15% of pumping stations are of a dry well type whilst the remaining 15% are ‘oddballs’, for example integral to treatment works or large raw water transfer pumps (Carlo 2014. *pers. comm.*). The latter category is impossible to characterise because it is so varied. As a result it is omitted to leave an 82%-18% split between the two groups.

The fragility of below grade pumping stations can be characterised very simply. The dry well in which the pump is located is lowest point within the building, therefore any water which enters the facility fills this area and submerges the pumps causing them to fail:

$$p(fault|d_i) = \begin{matrix} 0 & ; & d_i = 0 \\ 1 & ; & d_i > 0 \end{matrix} \qquad 4.26$$

Where:

d_i = internal inundation depth (m) $\quad$ $P(fault|d_i)$ = the fault rate given internal inundation depth d_i

Above ground pumping stations are more complicated. HAZUS-MH (FEMA 2012b) places the functionality threshold for above grade pumping stations at four feet (1.2 metres). This is plausible but FEMA do not provide any supporting information about how this value is reached. Therefore it is supplemented with information from UK water industry standards and further expert opinion:

- The Water Industry Mechanical and Electrical Specifications (WIMES) standardise the requirements for water industry electrical installations within the UK. Included within these are minimum and maximum heights for the low and medium voltage switchgear which would be in pumping stations (Table 4.16).

Table 4.16 Maximum and minimum heights for UK water industry switchgear components

	Minimum height for operator interfaces	**Maximum height for operator interfaces**	
Low Voltage	0.3 m	2 m	Marlow (2014)
Medium voltage	0.3 m	1.9 m	Marlow (2011)

- The lead sponsor's three standard designs for control kiosks place the lowest electrical equipment at 300mm in two cases and 600mm in the third (United Utilities standards STND/11/052, STND/11/051 & STND/11/052).
- The experts from the industrial sponsors were very reluctant to quantify their judgements but provided useful information:
    - One estimates if water reached "knee-high" then 60 to 70% of pumping stations would fail.
    - The other stated that facilities exposed to a metre of water had a high probability of failure – this was interpreted as a 90% probability.

The knowledge gathered from HAZUS-MH, the WIMES standards, standard designs and expert judgement is summarized in Figure 4.39. Figure 4.39 shows that a Weibull distribution with the lower boundary set at 0.3m to reflect the WIMES specifications (Equation 4.27) is a good fit to the collected information.

$$P(fault|d_i) = \; 1 - e^{-\left(\frac{d_i}{0.192}\right)^{0.714}} \qquad 4.27$$

Where:

d_i = internal inundation depth (m)

$P(fault|d_i)$ = the fault rate given inundation depth d_i

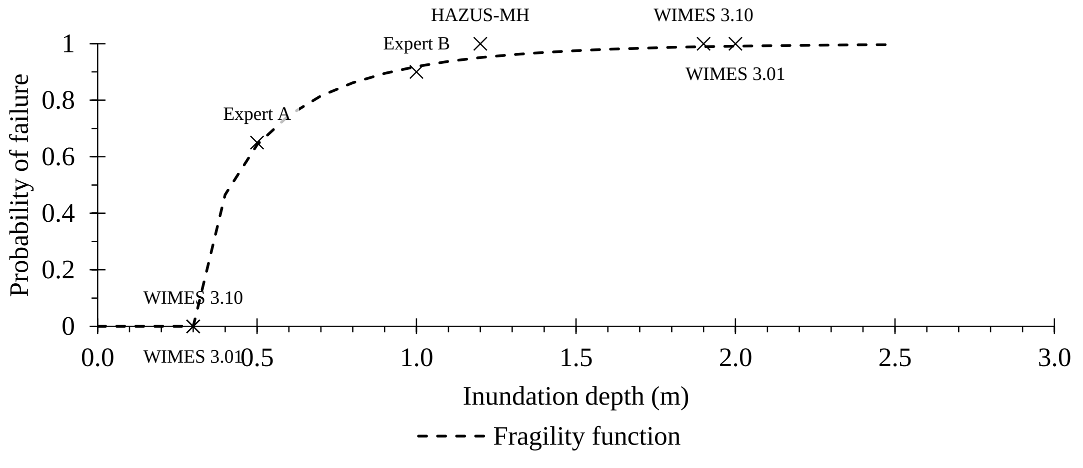


Figure 4.39 Summary of information gained on the vulnerability of pumping stations to flooding

Process – Flooding of pumping stations

The height of entry point (Equation 4.25) and depth required to incapacitate the pumping station (Equations 4.26 & 4.27) were combined into a single fragility curve through Monte Carlo sampling. The algorithm in Table 4.17 was repeated 10,000 times to create a large sample of failure probabilities given random flood depths (Figure 4.40). A number of data points indicate failure at very low depths; these correspond to below grade pumping stations with low ingress points. Equally a number of facilities do not fail even at high inundation depths due to high entry points, the impact of this resistance diminishes as the depth increases until failures is almost certain at depths greater than 2m.

Table 4.17 Algorithm for the generation of failure probabilities at random inundation depths

1.	An inundation depth between 0 and 5 m is sampled at random	$d = U(0, 5)$
2.	Equation 4.25 is used to randomly sample the height of the facility floor	$h = \begin{matrix} 0 & ; X \leq 0.16 \\ 0.19 - \ln(-\ln Y) \cdot 0.11 & ; X > 0.16 \end{matrix}$ $X = U(0, 1) \;\; Y = U(0,1)$
3.	The internal inundation depth is calculated	$d_i = d - h$
4.	The type of pumping station (above or below ground) is determined at random	$Type = \begin{matrix} Above\ ground & ; & W > 0.18 \\ Below\ ground & ; & W < 0.18 \end{matrix}$ $W = U(0,1)$
4.1	If the pumping station is above ground then Equation 4.27 is used to determine the probability of failure.	$P(fault\|d_i) = \begin{matrix} 0 & ; d_i = 0 \\ 1 - e^{-\left(\frac{d_i}{0.192}\right)^{0.714}} & ; d_i > 0 \end{matrix}$
4.2.	If the pumping station is below ground then Equation 4.26 is used to determine the probability of failure.	$p(fault\|d_i) = \begin{matrix} 0 & ; & d_i = 0 \\ 1 & ; & d_i > 0 \end{matrix}$

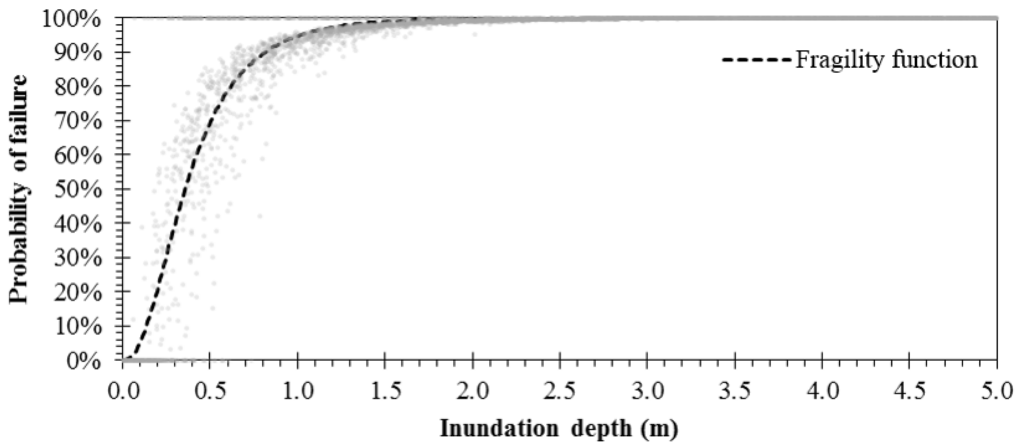


Figure 4.40 Probability of failure given flood depth for pumping stations where the type (above or below ground) and ingress height were selected at random

Output – Flooding of pumping stations

Statistical software (Minitab) was used to fit a range of distributions to the results of the Monte Carlo simulation. A three-parameter lognormal distribution had the lowest Anderson-Darling statistics so is selected as the best fit. The function outlined in equation 4.28 and shown in Figure 4.40 is therefore adopted as the fragility curve for pumping station exposed to flooding.

$$p(fault|d) = \Phi\left(\frac{\ln(d + 0.0705) + 0.8507}{0.5667}\right) \qquad 4.28$$

Where:

d = inundation depth (m)

P(fault|d) = the fault rate given inundation depth d

4.3.5 Connection for all fragility functions

Each fragility curve is used in the same way. At each time step the model takes the relevant hazard values from the time series created in Section 4.2. The fragility curves are used to establish the probability of failure for each infrastructure facility in this time step and then these probabilities are compared with samples from a uniform distribution between zero and one to simulate facility failures. The effect of failed facilities is calculated using the network models described in Section 4.5.

4.4 Facility Response – Recovery Times

Conventional Catastrophe Modelling and Performance Based Engineering Design approaches only consider structural failure. However, the time taken to recover is crucially important to infrastructure customers. This is emphasised by the presence of ‘response and recovery’ in the Cabinet Office definition of resilience. The following section outlines the statistical distributions used to sample recovery times in the model. As with the previous section, each output is used in the same way so a separate subsection at the end of section describes the connection of these components to the rest of the model.

4.4.1 Method of producing highways facility recovery times

Table 4.18 SIPOC table for the method of producing highways facility recovery times

Source	Highways Agency Command and Control incident management system.
Input	Lane impact duration of incidents between 01/01/2009 and 31/12/2013
Process	Fit a statistical distribution to the event durations
Output	A distribution from which random recovery times can be sampled

Source & Input

The Highways Agency incident data used to form the fragility curves (Chapter 4.3.1) also details incident durations.

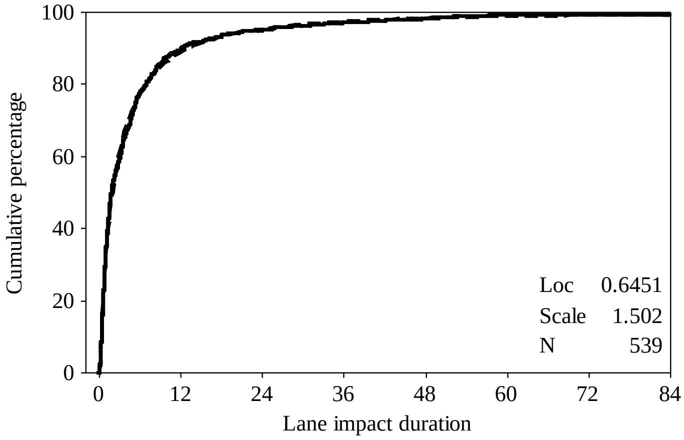
Process

The incidents are categorised according to their cause (strong winds, snow/ice/freezing rain, and floods/heavy rainfall) and Minitab statistical software is used to fit statistical distributions to the duration of incidents in each category.

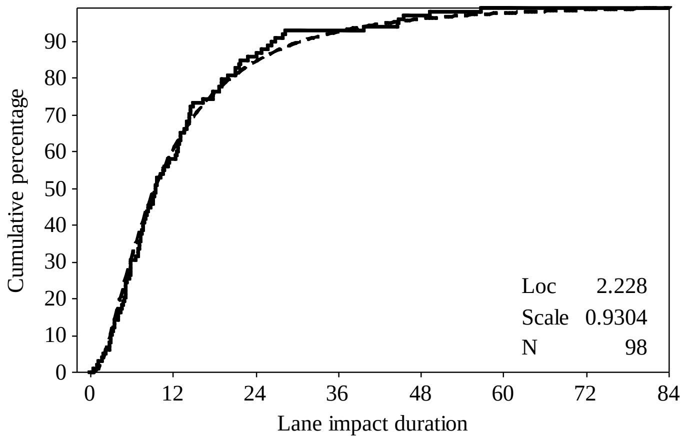
Output

Figure 4.41 shows that in each case a lognormal distribution provides a good fit to the recorded incident durations. The skewed distribution indicates that most incidents are resolved quickly but a small number have a prolonged impact on the network. The differences between the sectors are slightly unexpected with heavy rainfall and flooding showing the quickest recovery times; this is indicative of the short duration of intense rainfall events and the effective drainage of main roads. In contrast, incidents due to strong winds take the longest to recover reflecting the longer duration of storms and the difficulties associated with recovery such as dangerous conditions for staff and the potential for multiple simultaneous events across the network.

a) Heavy rain / flooding



b) Strong winds



c) Low temperatures

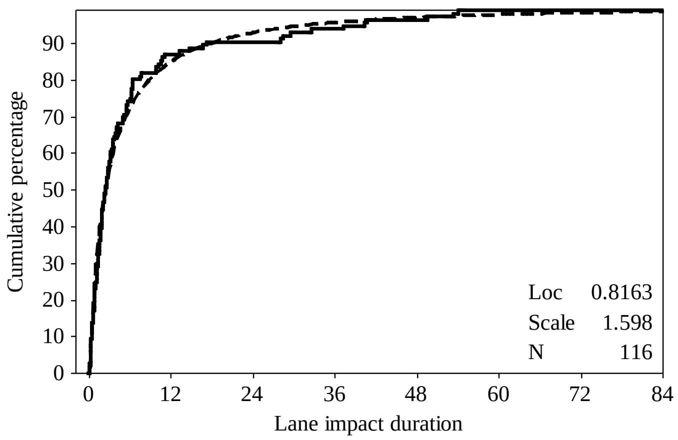


Figure 4.41 Lognormal distribution fitted to the durations of highways incidents caused by a) heavy rain / flooding, b) strong winds, and c) low temperatures

4.4.2 *Method of producing electricity facility recovery times*

Table 4.19 SIPOC table for the method of producing electricity facility recovery times

Source	• Published reviews of historical faults data • Industry standards for resilience
Input	Statistical information on observed and likely recovery times
Process	Fit a statistical distribution to the event durations
Output	A distribution from which random recovery times can be sampled

<u>Source & Input</u>

A number of studies review the recovery times for electricity infrastructure damaged by severe weather:

- Chow et al. (1996) find times range between 0 and 500 minutes.
- Maliszewski & Perrings's (2012) sample has a mean recovery time of 99 minutes and maximum of 330 minutes.
- Reed (2008) proposes that recovery times follow a gamma distribution and provides the parameters for the events she studied (Table 4.20).

Table 4.20 Gamma distribution parameters for outage duration (in hours) (Reed 2008)

Storm	Sample mean	Sample variance	Gamma shape	Gamma scale
January 1993	31.8	556.9	17.53	1.81
November 1995	4.23	7.80	1.85	2.29
November 1996	7.31	28.9	3.96	1.85
December 1996	15.0	158.5	10.55	1.43
Mean	14.5	188.0	8.47	1.85
Median	11.2	93.7	7.26	1.83

The UK electricity industry standard for security of supply (Engineering Recommendation P2/6) also specifies recovery times for substations. The requirements become more stringent as the number of customers dependent on the substation increases (Table 4.21). This is reflected in how the electricity companies operate their networks; small substations have little or no redundancy whereas large sites have manual or automatic switches to bring in alternative supplies almost immediately.

Table 4.21 P2/6 Requirements for each demand group (from Blake & Taylor 2010, p463)

Class of supply	**Range of group demand (GD)** *	**First circuit outage**	**Second circuit outage** †
A	Up to 1MW	In repair time (GD)	No requirement
B	Over 1 – 12MW	i. Within 3 h (GD minus 1 MW) ii. In repair time (GD)	No requirement
C	Over 12 – 60 MW	i. Within 15 min (Smaller of GD minus 12 MW and 2/3 GD) ii. In repair time (GD)	No requirement
D	Over 60 – 300 MW	i. Immediately (GD minus up to 20 MW) ii. Within 3 h (GD)	i. Within 3 h (for GD greater than 100 MW, smaller of GD minus 100 MW and 1/3 GD) ii. Within time to restore arranged outage (GD)
E	Over 300 – 1,500 MW	Immediately (GD)	i. Immediately (All customers at 2/3 GD) ii. Within time to restore arranged outage (GD)
F	Over 1,500 MW	Seperate regulations	

* Group demand (GD) is the maximum demand of the network which the substation supplies. For primary substations and above these are available from the DNO's LTDS.

† A fault which occurs in one circuit when another nearby is unavailable due to maintenance.

<u>Process</u>

It is clear that there is no consensus on the likely duration of power outages. Chow et al. (1996) and Maliszewski & Perrings (2012) find that supplies are typically restored within a couple of hours, but their samples only include normal conditions. On the other hand, Reed (2008) finds more lengthy disruption. The UK standards lie in between.

This model follows the approach taken by Reed and models recovery times using a gamma distribution, defined by the median of the parameters found by Reed (Table 4.20). Selecting the worst case is arguably pessimistic but this is the best available information: it is derived from outages caused by severe weather and gives a probabilistic relationship which can be applied in a transparent way. The alternatives do not specifically record severe weather and only provide point values.

Output

The distribution from which recovery times are sampled is shown in Figure 4.42.

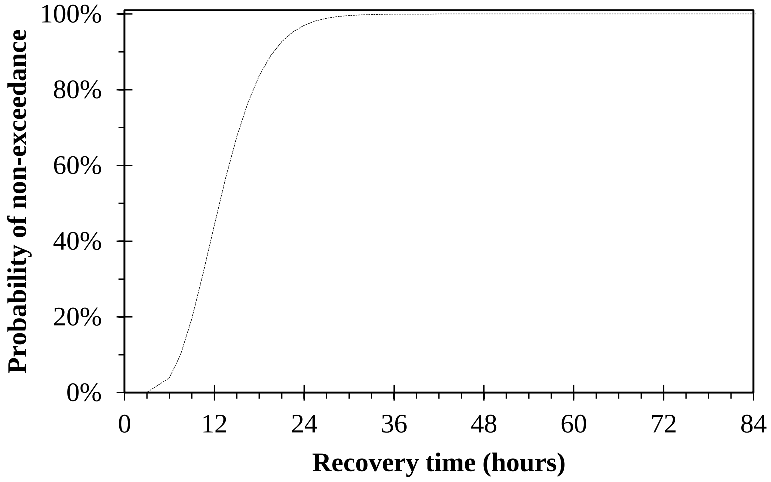


Figure 4.42 The gamma distribution (shape: 7.25, scale: 1.83) used to sample recovery time for electricity network components

4.4.3 Method of producing telecommunications facility recovery times

Table 4.22 SIPOC table for the method of producing telecommunications recovery times

Source	• Published reviews of historical faults data • Industry standards for resilience
Input	Statistical information on observed and likely recovery times
Process	Fit a statistical distribution to the event durations
Output	A distribution from which random recovery times can be sampled

Source & Input

The study of telecommunications restoration times is in a similar position to electricity networks; innovative methods for rapidly restoring service are an active area of research but there is only limited information of typical outage times. A literature review found three studies which detail average restoration times:

- Kuhn (1997) observes that the average duration of outages caused by 'acts of nature' is 828 minutes (13.8 hours). However, his data only includes outages longer than 30 minutes and affecting more than 30 000 customers.

- Snow et al. (2013) find the average outage is 3.3 hours. Their sample is larger – it includes all local exchange outages longer than two minutes – but does not distinguish between different failure causes.
- BT Openreach hired Deloitte in 2013 to investigate fault frequency and repair times. They find that, for fault types whose occurrence is correlated with weather, the mean task time is 3.8 hours.

Notably none of the above includes any information on the spread of recovery times. The only information available were regulations which oblige BT Openreach to repair 80% of faults within two days (Ofcom 2014). As they set an intermediary target of 70% from 2014-2016 it is inferred that Openreach is currently operating within the 70-80% range as they move towards the 2016 target.

Process

The difference between Kuhn's results and the other studies is striking but not inexplicable. The distributions of recovery times for the other infrastructure sectors have been positively skewed and his data excludes outages shorter than 30 minutes. Therefore the mean will be markedly higher because the many low values have been missed. Notably, Kuhn also only includes outages affecting more than 30 000 people. Large events are likely to have a longer recovery time as the number of faults is likely to be higher.

The times provided by Deloitte may also be an underestimate for the purposes of this model. They only consider faults between the exchange and the customer so overlook the potentially severe impacts of exchange loss. They also only count the engineer's task time, not the total outage experienced by the customer. However, Snow et al.'s results are not subject to these assumptions and correspond closely with Deloitte's analysis.

The Deloitte value of 3.8 hours is chosen as the mean recovery time. Whilst it corresponds closely with Snow et al.'s value it is preferred because it specifically accounts for severe weather.

Information on the shape of the distribution is very limited because there is only the constraint that 80% of faults should be fixed in two days. It is impossible for a distribution to satisfy this constraint and have a mean of 3.8, therefore the mean is fixed and a distribution is found which maximises the probability of an outage lasting longer than 48 hours. Both lognormal and gamma distributions were considered and a gamma distribution with a shape parameter of 0.037 and scale parameter of 102.7 returned the highest 80th percentile. At 97.7% this value is still very high but it represents the mathematical limit.

Output

Figure 4.43 shows the distribution from which recovery times are sampled.

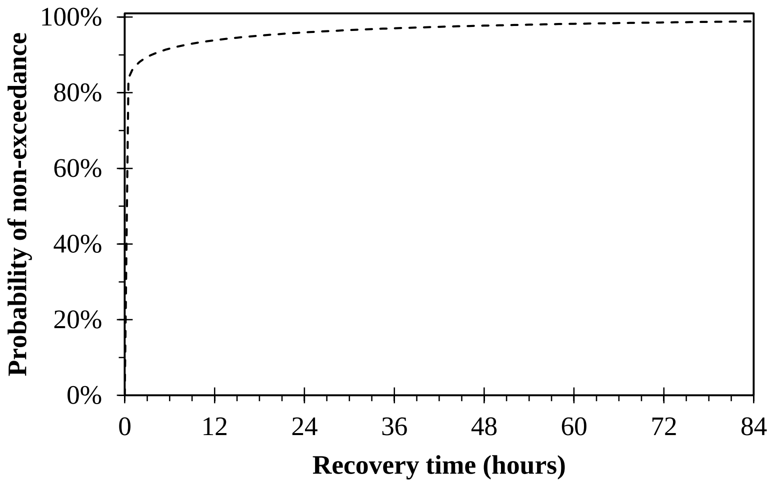


Figure 4.43 Gamma distribution (shape: 0.037, scale: 102.7) used to sample recovery time for telecommunications network components

4.4.4 Method of producing potable water facility recovery times

Table 4.23 SIPOC table for the method of producing potable water facility recovery times

Source	• Published reviews of historical faults data. • Industry expert knowledge.
Input	• Anecdotal information on past failures. • Expert opinion on asset recovery times.
Process	Fit a statistical distribution to the event durations.
Output	A distribution from which random recovery times can be sampled.

Source & Input

Of the four infrastructure sectors there is least information about the recovery times of potable water infrastructure. A literature search found only one source, a report from a pump engineering firm about their efforts in aiding the recovery efforts after Hurricane Sandy. Parsons (2013) record that the hurricane affected more than 30 pumping stations and they also state that they restored temporary services to more than 30 pumping stations within 48 hours. Therefore it is assumed that almost all pumping stations can be returned to service in 48 hours. This assumption is supported by experts within the project sponsor.

One of the sponsoring companies has recently assessed the criticality of all their major mains. They use a hydraulic model to assess how many customers are affected if the downstream area loses supply for 24 hours. Conversations with company experts also converged on this time period; suggesting that in most cases a pump could be replaced or over-pumping installed within 24 hours.

Process

A gamma distribution has been the best fit for recovery times in two of the three other infrastructure sectors. Therefore a gamma distribution is chosen where the 50th percentile is 24 hours and the 99th percentile is 48 hours.

Output

The resulting distribution is shown in Figure 4.44. It is a reasonable curve and is coherent with the industry expert's knowledge. However, it is based upon very limited data so should be used with caution. Further work to support the expert opinion with observed data would greatly increase confidence in the output.

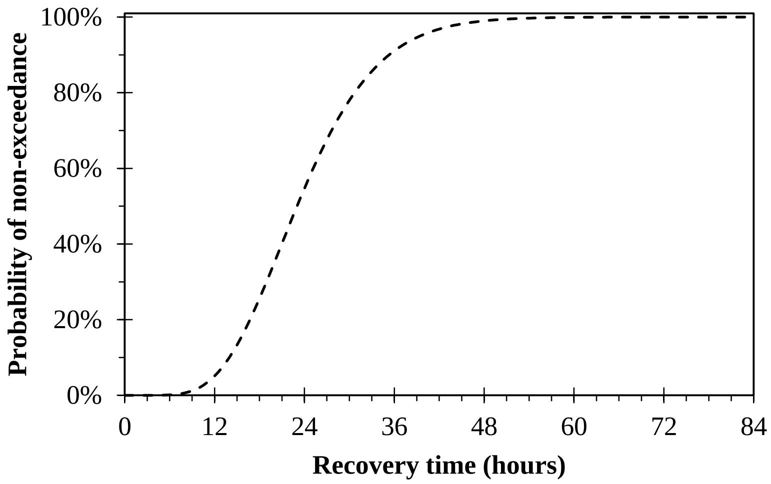


Figure 4.44 Gamma distribution (shape: 8, scale: 3) used to sample recovery times for water network components.

4.4.5 Connection

In the event of failure, a recovery time is sampled at random from the relevant distribution and fed into the model.

In Chapter 4.2.4 periods with normal weather conditions were removed from the hazard data to improve the models efficiency creating a risk that a failure in one event may carry over into the next. To eliminate this risk all facilities are returned to their initial operating state whenever the model encounters non-consecutive time steps.

4.5 Network Analysis

The next step is to assess how the loss of facilities, or structural integrity in PBD terminology, affects the performance of the system. This is achieved through network models which assess how connectivity and flows in the respective infrastructure networks are affected by individual facility failures.

4.5.1 Method of simulating the impact of road closures

Table 4.24 SIPOC table for the method of simulating the impact of road closures

Source	• Ordnance Survey maps. • Google Maps journey planning tool. • Time series of weather values. • Fragility curves (Chapter4.3). • Recovery time distributions (Chapter 4.4.1).
Input	• Shape of the road network in the area. • Normal journey times between points. • Weather conditions at each time step. • The vulnerability of facilities to the weather conditions. • A distribution of times taken to recover from failures.
Process	i. Identify failed facilities. ii. Sampling closure duration from appropriate distribution. iii. Calculate of new journey times if any roads are closed.
Output	The time taken to reach each highways node at each time step, depending on the weather conditions.
Connection	• Each infrastructure facility is allocated to its nearest highways node. • The journey time to reach the facility determines how quickly repairs can start on failed facilities.

Source & Input

The highways network is represented as a series of nodes and links. Each link represents a motorway, 'A road', or one of the local roads connecting water treatment works to the strategic network and the nodes represent the junctions between them. This data is easily obtained from the Ordnance Survey or other map providers. The journey time along each link is calculated by planning a journey in Google Maps between the two nodes it links.

Process

Facility failure

Chapter 4.3 developed fragility curves which describe the impact of different hazards on highways links. Combining these with the hazard time series produces the expected failure rate per kilometre at each time step. Closed links are identified by Monte Carlo sampling; the failure rate is multiplied by the each link's length and the result is compared with a random sample from a uniform distribution between zero and one.

Facility recovery

The duration of a failure is determined by sampling at random from the distributions developed in Chapter 4.4.1.

Failure impact assessment

A simple routing algorithm (Dijkstra's algorithm) is used to assess the impact of closed links. This uses an iterative process to efficiently identify the least cost route from one node in the network to every other node. Costs could be financial or any other metric but the target in this case is the shortest journey time. Journeys are assumed to start at one node, typically representing the main depot or warehouse. In reality, an engineer's location will depend upon their home location and the location of their previous task. However, this is too variable to capture in the model so a single point is used.

Output

The time it will take to reach each highways node conditional upon on the weather conditions.

Connection

Each infrastructure facility is associated with its nearest highway node. For linear assets (e.g. transmission lines) the node closest to the midpoint is used. The model delays the start of repairs until the engineers can reach the facility. It also recalculates when necessary to account for quicker routes becoming available as roads re-open.

4.5.2 Method of simulating the impact of electricity infrastructure failures

Table 4.25 SIPOC table for the method of simulating the impact of electricity infrastructure failures

Source	• Distribution network operator (DNO) Long term development statement. • Expert knowledge on network operation. • Time series of weather values. • Fragility curves (Chapter 4.3.2). • Recovery time distributions (Chapter 4.4.1).
Input	• A hierarchical model capturing the structure of the electricity network and describing which nodes can feed the critical nodes. • Weather conditions at each time step. • The vulnerability of facilities to the weather conditions. • A distribution of times taken to recover from failures. • The time to reach each facility at each time step depending on the weather conditions.
Process	i. Identify failed facilities. ii. Sampling closure duration from appropriate distribution. iii. Assess cascading effects of facility failure.
Output	The availability of power at each substation at each time step, depending on the weather conditions
Connection	Infrastructure facilities which require power are linked to either their dedicated substation or the nearest secondary substations

Source

The Distribution Network Operators (DNOs) who operate the local electricity networks are required to publish a Long Term Development Statement. This includes geographical and schematic diagrams detailing the structure of the electricity network. An understanding of a typical network's configuration and its operation in an emergency was obtained through detailed conversation with former employees of DNOs.

Input

Power companies use a range of voltages to create an efficient network. This results in a radial network where nodes belong to four distinct levels (Table 4.26). The analysis of the network reflects this hierarchical structure. The failure of a substations or transmission lines affects the nodes below them, unless these nodes can be fed by redundant links from other higher order facilities.

Table 4.26 Electricity distribution network substation types

Substation type		**Input voltage**	**Output voltage**
Grid Supply Point	GSP	400kV	132kV
Bulk Supply Point	BSP	132kV	33kV
Primary Substation	1°ry	33kv	11kV or 6.6kV
Distribution Substation	-	11kV or 6.6kV	230v

Two factors determine a substation's ability to feed another in the layer below: i) the existence of a physical connection between them; and ii) the availability of sufficient capacity. The schematics in the DNO's Long Term Development Strategy show the physical connections but network capacity requires further interpretation.

400kV, 132kV & 33kV networks

Engineering Recommendation P2/6 requires that large substations – such as these – should have at least two incoming feeds (though they can be from the same or different substations) (Charlesworth 2007). Therefore it is assumed that the 400kV, 132kV and 33kV networks are not constrained by capacity; the higher substation can feed the lower so long as there is connection between them.

Modelling the 6.6/11kV network

At the 6.6 / 11kV level, networks consist of feeders radiating out from the 33kV substation (Haggis 2006). These lines terminate at a 'normally open point' where they are connected to the end of another feeder which started from either the same or another primary substation (Figure 4.45a). In the event of a fault the faulty section can be isolated and the majority of 6.6/11kV substations back-fed via the alternative route (Figure 4.45b).

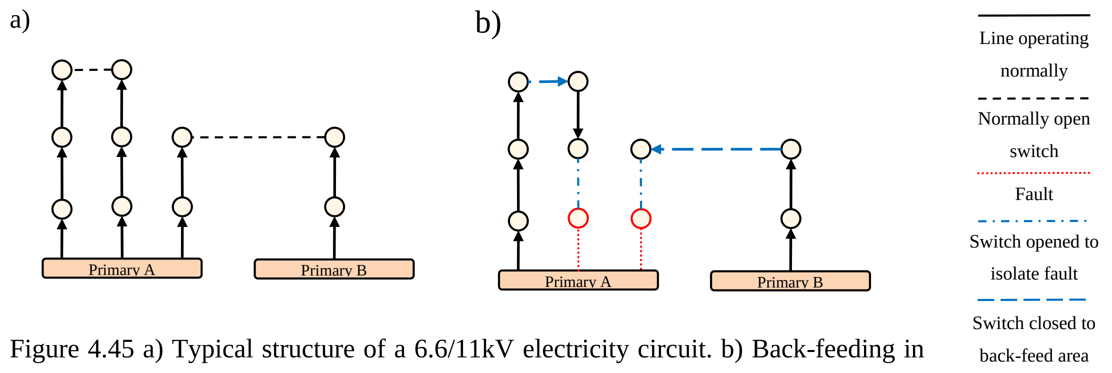


Figure 4.45 a) Typical structure of a 6.6/11kV electricity circuit. b) Back-feeding in 6.6/11kV circuits following faults

In reality, the networks do not form simple circuits like those shown in Figure 4.45 because there are cross-connections between loops to improve resilience. If capacity is ignored long twisting paths could be used to connect almost any pair of substations. This is not realistic so some form of capacity constraint is needed.

In the absence of the detailed information needed to build an accurate physical model the increase in flow relative to normal operations is used to judge whether a link is over capacity. This assumption is logical given the cost of extra capacity and is taken by other studies into network vulnerability including Motter & Lai (2002), Crucitti et al. (2004) and Hernandez-Fajardo & Duenas-Osorio (2013).

These studies vary the safety margin between normal flows and capacity limits to explore how this affects the resilience of the network. In contrast, this study requires the safety margin for the specific network in question. Experienced engineers indicated that networks are typically run at 80% of the design capacity. They also have the ability to run at 120% of the design capacity in emergencies. Therefore they individual components can operate at a level which is 150% above their normal operating state (Slavin 2014, Booth & Mutunono 2015 *pers comm.*).

To interpret this in the context of the network, secondary substations are first allocated to their nearest primary substation. Then an estimate is made of which parts of the network could be cross-fed from other sources:

i. The network is divided into nodes which represent parts of the network which can be isolated from their neighbours. This means that if there is a fault within a node then all substations within it would be disconnected. Meanwhile, if there are the requisite connections and capacity in the network, supplies to other nodes can be re-routed around this failed node.

ii. In most cases the boundaries of nodes are defined by the ability to isolate a line from the busbar at a ground-based substation.

   a. This isolation could be achieved automatically, by radio controlled switch, or manually. These details could be insignificant because the storage capacity of water networks protects it from short term power losses but they could be crucial if, for example, travel disruption prevents manual isolation. These details are too complex to include in the model but the sponsors may want to engage with DNOs on the arrangements at substations critical to their operations.
   b. Pole- or pad-mounted transformers cannot be isolated so easily. These are most common in remote parts of the network where there are stand-alone breaker switches to isolate sections of the network.
   c. Tee-d connections were also included as nodes. Connecting three nodes together directly would indicate an arrangement of strength when the reality is a single point of failure.

iii. The shortest route, in terms of the number of nodes traversed, from each secondary sub-station to every primary substation was calculated using Dijkstra's algorithm.

iv. It is assumed that 'normally open points' are at the midpoint of the route between two primary substations. This is a logical assumption because it is preferable to balance loads evenly between primary substations (Haggis 2006).

v. By adding the route length to the supply primary in normal conditions (l_n) to the route length to a potential alternative supply (l_a), and finding the midpoint (m) the boundaries of their normal supply zone are established.

$$m = \frac{l_n + l_a}{2} \qquad 4.29$$

Where:

m = midpoint

l_a = length to potential alternative supply.

l_n = length to supply point in normal conditions.

vi. The 150% capacity rule is applied to calculate the boundary of what can be supplied if the network is rezoned.

The resulting network is different from the traditional networks used by many studies. Rather than representing a physical connection between nodes, each edge in the network signifies an ability to supply the downstream node. Normally studies wait until after they have identified failures to test if the remaining infrastructure has the capacity to support the increased load. This is computationally intensive and limited by the information available to the researcher. Making an assessment of network capacity implicit in the structure of the model alleviates these issues.

An area for future improvement is how the capacity is estimated. In this study the distance from the primary substation is used as a proxy for network capacity, assuming that there is the capacity to supply 50% further than normal. Hernandez-Fajardo and Duenas-Osorio (2013) use a measure called betweeness-centrality which assesses how many routes between nodes pass through each node. This is a better proxy for flow so it is recommended if the work is replicated.

Process

Facility failure

The electricity network has two failure modes; substation flooding and wind damage to transmission lines (Figure 4.22).

The process for substation flooding is very simple. The probability of failure at the appropriate flood depth is read from the fragility curve developed in Chapter 4.3 and a Monte Carlo sampling determines whether the facility is operational.

Chapter 4.3 also develops curves to show the fragility of transmission lines to strong winds in both normal and cold conditions. To use these curves, which give the fault rate per kilometre, the length of each link within the electricity network is required. For the 400kv, 132kv, and 33kv networks the length of each link can be measured from the geographic plans in the DNO's LTDS.

The 6.6 / 11kv circuits, however, are too intricate and densely packed to measure accurately. Therefore the measured transmission line lengths for high voltage lines in the case study described in the next chapter are plotted against the straight line distance between the two nodes (Figure 4.46). The correlation between true length and straight line distance is strong and a relationship fitted by least squares regression suggests the former is 42% greater than the latter. Therefore the straight line distances to the 6.6 / 11kv substations are measured and multiplied by 1.42 to estimate the true length.

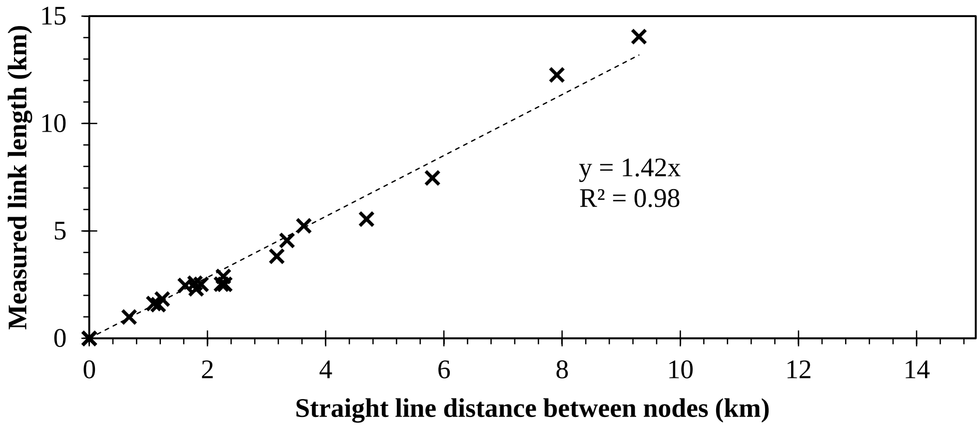


Figure 4.46 A regression relationship fitted between the straight line distance between two substations and the length of the connecting transmission lines provides a good fit.

Facility recovery

The time taken to repair the fault is determined by sampling at random from the distributions developed in Chapter 4.4.2. The start of this repair is delayed until the facility can be reached by road.

Failure impact assessment

The hierarchical structure of the electricity network means that a series of logic gates can be used to assess the impact of failed facilities (Figure 4.47). The result is similar to a fault tree but it cannot be described as one because of the interdependence of events and upstream cross-connections. Assessing the impact of failures in this way does not consider network capacity explicitly but includes it implicitly in the network structure.

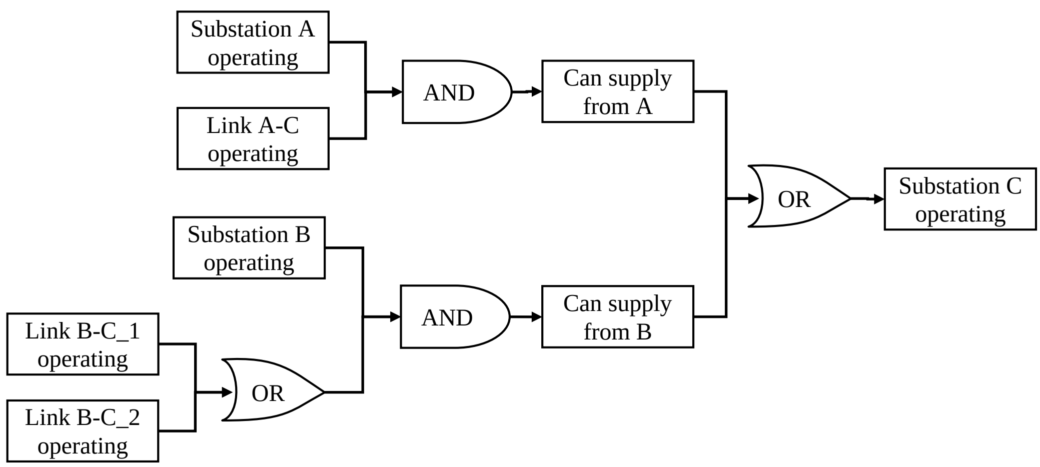


Figure 4.47 Illustration of electricity network failure impact assessment

Output

The operation of secondary substations is most important because they supply the water and telecommunications facilities. If one of these substations stops operating - either due to their own failure or due to the loss of supply from upstream – it is captured by the model and passed through to the relevant dependent facilities in the other networks.

Connection

The majority of water facilities have their own substation which is labelled on the DNO’s LTDS. Where this is not the case they are assumed to be connected to the nearest 6.6/11kv substation.

Critical infrastructure facilities normally connect to multiple substations to increase their resilience. Therefore each telephone exchange is mapped to the two nearest substations and connected to both.

4.5.3 Method of simulating the impact of telecommunications infrastructure failures

Table 4.27 SIPOC table for the method of simulating the impact of telecommunications infrastructure failures

Source	• SamKnows Telephone Exchange Search. • Ordnance Survey mapping. • Water company asset database.
Input	• Direct links between water facilities connected by radio link. • Links between water facilities and telephone exchanges. • Weather conditions at each time step. • The vulnerability of facilities to the weather conditions. • The performance of related electricity substations at each time step. • A distribution of times taken to recover from failures. • The time to reach each facility at each time step depending on the weather conditions.
Process	i. Identify failed facilities. ii. Sampling closure duration from appropriate distribution. iii. Assess cascading effects of facility failure.
Output	The availability of connections between pairs of water facilities at each time step, depending on the weather conditions.
Connection	Water facilities which lose connection continue to operate in the same mode as when communications are lost, regardless of the need to increase or decrease output.

Source

Telephone exchanges were identified using the exchange mapping service offered by SamKnows (https://www.samknows.com/) which provides details on the locations of telephone exchanges and the areas they cover (Figure 4.48). Locations were cross checked against Ordnance Survey maps to confirm the precise location. The water company's asset database holds information on the telemetry outstations attached to their facilities including their location and type (e.g. fixed line or radio link).

Input

Most messages between water network facilities are transmitted through one of two means: via radio links or via the Public Switched Telephone Network (PSTN). GPRS (i.e.

mobile telephone networks) is now widely used for logging flows and pressures within the distribution networks but fixed line or radio links at service reservoirs and pumping stations typically predate this technology.

Figure 4.48 Example exchange map from www.samknows.com

Radio links

Radio links are represented as single links between transmission and receiver nodes. The performance of telephone lines and exchanges becomes irrelevant as messages are communicated directly.

Public Switch Telephone Network (PSTN)

The structure of the PSTN is more complicated. The structure is hierarchical with a number of layers as shown in Table 4.28 and Figure 4.49. This is similar to the electricity network but differs in two regards:

i. The source node is not at the head of the network. Each message begins at a low order node, travels up the hierarchy as far as necessary and then down a different branch to reach its destination.
ii. There is less redundancy in the local network because every customer is fed by their own line from the exchange; if this wire fails they are disconnected.

Table 4.28 Telephone exchange types in BT's Public Switched Telephone Network

Exchange type		Number in case study area	Number in BT's network (Valdar 2006)	
Trunk exchange	DMSU	0	80	
Wide area tandem	WAT	0	20	Tandems reduce loads on the DMSUs by creating shortcuts between local exchanges.
Junction tandem	DJSU	0	15	
Local exchange	LE	5	800	LE's can also be joined directly to handle local calls.
Remote concentrator unit	RCU	Unknown	5,200	
Telemetry outstation		28	-	

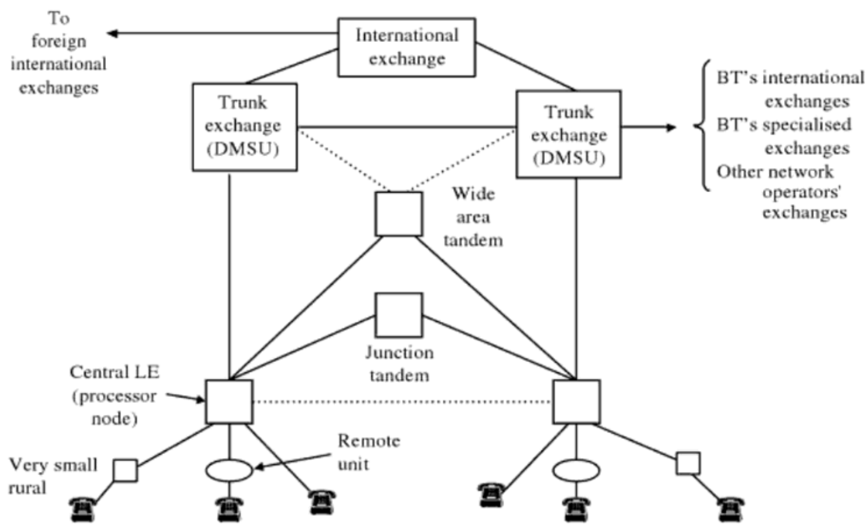


Figure 4.49 BT's public switched telephone network (from Valdar 2006)

The growth of digital technology is making the hierarchical structure of telecommunication networks less distinct because equipment such as tandems and remote concentrator units allow information to follow shortcuts between branches (Svendsen & Wolthusen 2007). Notwithstanding, this study assumes that the network follows a traditional hierarchical structure. No information could be found on the specific structure of particular local telecommunications networks and Svendsen & Wolthusen suggest that a hierarchical structure is still representative of much of the existing infrastructure.

Information on connectivity between the exchanges is equally lacking. This is not a significant shortfall since pairs of source and receptor nodes are invariably close together so connect to the same exchange. Equally, it is apparent from Figure 4.49 that the PSTN system is highly redundant above the level of the local exchange. Therefore the case study assumes that connections between exchanges are invulnerable.

Alternative power supplies

All BT exchanges are equipped with alternative power supplies (Coppinger 1990, EC-RRG no date). The model uses 98.4% as the probability of standby generators starting when required is; this is the mean of the values reported by three published studies on generator reliability (Smith et al. 1990, Grasselli 1994 and Du et al. 2003). Experience in the water industry suggests this may be too high - for example, Andrews (2006) claims 50% of Thames Water's generators did not start when required during the 1987 storms – but there was no robust evidence to support a lower value.

The availability of power at telemetry outstations is assumed to equal the availability of power to the wider facility.

Process

Facility failure

Chapter 4.3 identified that telecommunications networks are vulnerable to two hazards: the flooding of exchanges and wind damage to overhead telephone lines. As with other networks, failures are determined by Monte Carlo sampling

The failure rate of the lines is proportional to their length. As previously noted, the average length of a UK connection is 3.34km (Williamson et al. 2008) but this provides no information about variability in the vulnerability of facilities; remote facilities are expected to be more vulnerable because they are further from telephone exchanges. A search for locally specific information was unsuccessful so the regression relationship fitted for electricity connections (Figure 4.46) was again applied to the straight line distances between exchanges and outstations.

Telephone exchanges can also fail if they lose power. If power is lost at both of the associated substations then Monte Carlo sampling is used to check whether the alternative power supplies start successfully.

Facility recovery

Repairs do not begin until the facility can be reached according to the journey times calculated in Chapter 4.3. The repair time is then determined by sampling at random from the distributions developed in Chapter 4.4.

If a power cut causes an exchange to fail then it recovers quicker because the equipment only needs to be reset, not repaired. Once engineers reach the facility it is estimated that this will be completed within one hour.

Failure impact assessment

The lack of redundancy within the local PSTN system, and assumption of an invulnerable high level network, makes assessing the impact of facility loss very simple. Each connection between two water facilities is treated individually and marked as failed if any of the components on this route fail (Figure 4.50, Figure 4.51 and Figure 4.52).

Output

Lost contact between a pair of water facilities is noted against the facility whose operation is controlled by this information.

Connection

The loss of connection does not prevent the operation of the relevant water facility so it would be inappropriate to mark it as failed immediately. Instead the model notes the loss of communication and prevents the facility changing its mode of operation. For example, if a set of pumps are running to fill a service reservoir and the signal is lost then they will continue to operate even when the reservoir is full. More importantly, if there is no signal the pumps will not turn on until the link is restored, even if the reservoir empties.

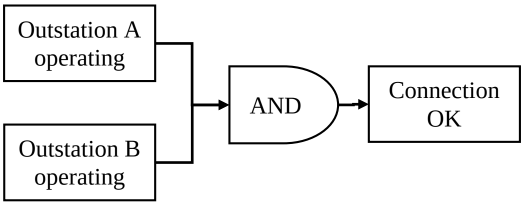


Figure 4.50 Impact assessment for a radio link between two water facilities.

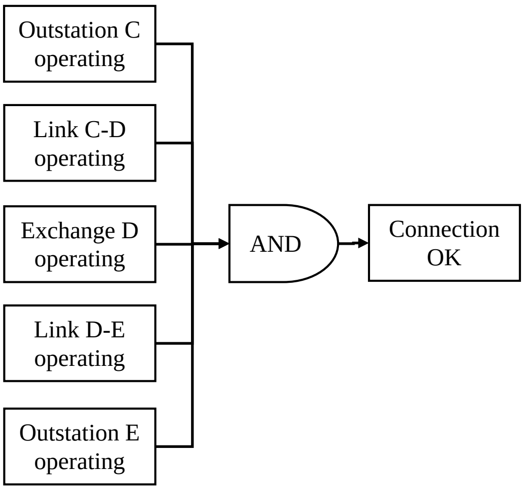


Figure 4.51 Impact assessment for a connection between two water facilities which share the same local exchange.

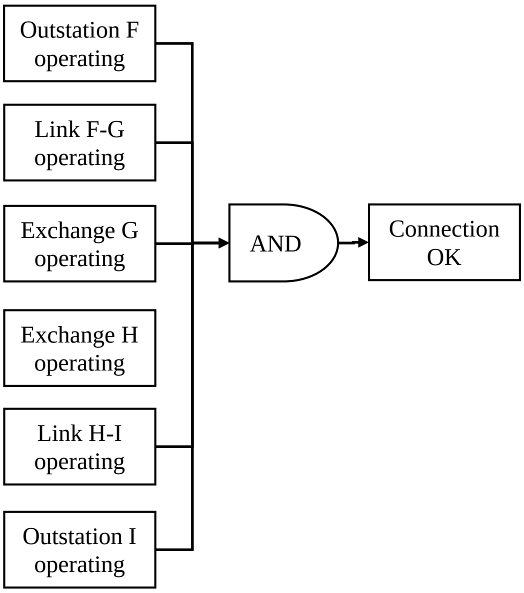


Figure 4.52 Impact assessment for a connection between two water facilities attached to difference local exchanges

4.5.4 Method of simulating the impact of potable water infrastructure failures

Table 4.29 SIPOC table for the method of simulating the impact of potable water infrastructure failures

Source	• Water company regional trunk mains model. • Water company schematics. • Water company asset database. • Water company expert knowledge.
Input	• A hydraulic network model of the case study area. • Weather conditions at each time step. • The vulnerability of facilities to the weather conditions. • The performance of relevant electricity substations at each time step. • The performance of relevant telecommunications links at each time step. • The availability of alternative power supplies at each site. • A distribution of times taken to recover from failures. • The time to reach each facility at each time step depending on the weather conditions.
Process	i. Identify failed facilities. ii. Sampling closure duration from appropriate distribution. iii. Assess the impact of failed on network pressures.
Output	The water pressure at each node, and therefore which nodes have an adequate water supply.

Source

The industrial sponsor's regional trunk mains model and network schematics are the main source of information on the water network. Other sources, such as production output reports, company asset databases and the expertise of company staff, were also consulted.

Input

Water network model

The hydraulic network model is a simplified version of the company's regional trunk mains model. The benefits of this simplification are twofold: i) it makes is easier to present the results clearly; and i) it reduces the time taken for the analysis to run.

The model is constructed in EPANET 2.0 and composed of a number of components:

- Each telemetry link between two facilities is represented by large diameter pipes connecting a reservoir to a node with a small demand (Figure 4.53). The pressure at this proxy node represents the availability of the telemetry link.

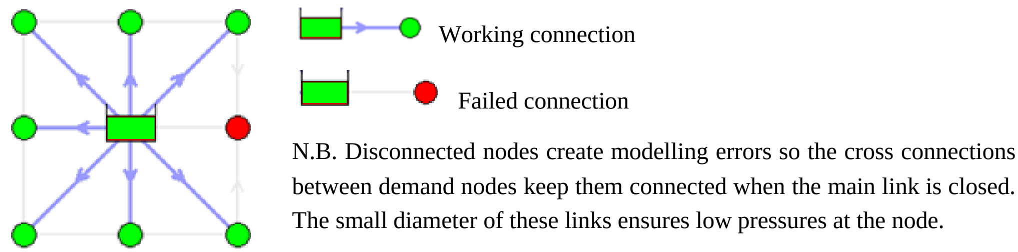


Figure 4.53 Representation of telemetry links

- Reservoirs feed the treatment works. In the case study discussed in the following chapter this supply is continuous because each water treatment works has at least one gravity source but, if required, the method for raw water pumping stations is identical to network pumping stations.
- Water treatment works are represented as control valves which open or close to reflect the operation of the treatment works.
- Service reservoirs store a volume of water to smooth out imbalances in supply and demand. They are assumed to be 75% full at the start of the simulation. Thereafter they refill depending on the level inside them and the number of pumps feeding them. The correct control philosophy can be followed if available. Table 4.30 sets out the rules followed in the case study where this information was not available.

Table 4.30 Service reservoir level controls

Number of pumps available	**Service reservoir level**				
	1st pump trigger level	**2nd pump trigger level**	**3rd pump trigger level**	**4th pump trigger level**	**All pumps off**
1	50%	-	-	-	95%
2	75%	50%	-	-	95%
3	25%	50%	75%	-	95%
4	12.5%	25%	50%	75%	95%

- The pumping stations in the network can be divided into two groups. The first group maintain the water levels in service reservoirs so their operation is governed by the rules such as those in Table 4.30. Note, however, that these changes are only implemented if the pressure is normal at the node representing the telemetry link between the service reservoir and pumping station. The second group pump directly into the network so are controlled by the pressure at the critical monitoring point in the area, typically the highest point.

- Each node in the model represents either a significant junction between trunk mains or a collection of District Metered Areas (DMAs). These are discrete areas used by water companies to measure demand and represent a group of customers.

EPANET, in its basic form, is a demand driven model and therefore not designed for the analysis of networks where nodes lose their water supply. It assumes that the demand at a node will always be met and therefore when a node cannot be supplied it receives a low or negative pressure (Gupta & Bhave 1996, Sivakumar & Prasad 2014). This is not realistic and, as Figure 4.54 shows, can affect the wider network.

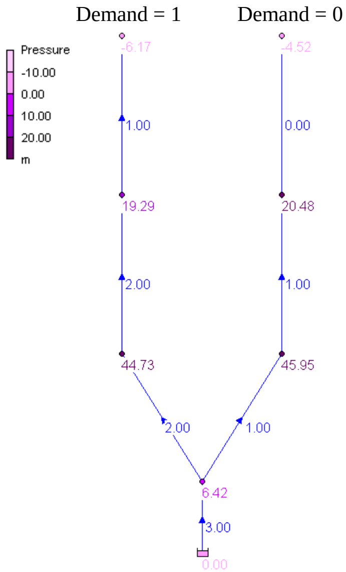


Figure 4.54 The effect of negative pressures on the network. Both arms of the network are identical and produce pressure deficient conditions at the distal node. Note how the node which still demands water lowers the pressure in other nodes on the left hand arm. Text in blue shows the flow through each pipe in MLD and text in purple shows the pressure at the node.

A number of alternative approaches have been proposed including adjusting nodal demand in response to low pressure and recalculating flows (e.g. Bhave 1981, Germanopoulus 1985) and the systematic addition and removal of reservoirs or activation and deactivation of emitters to identify pressure deficient nodes (e.g. Ang & Jowitt 2006, Rossman 2007). However, these approaches have two weaknesses. Firstly, they significantly increase the computational cost of the analysis because flows have to be recalculated multiple times for each time step (Wu 2007, Ang & Jowitt 2007). This is acceptable for modelling short period or very simple networks but incompatible with this model’s requirement to consider the impact of many events on a complex network. Secondly, they require modifications to the source code of EPANET (Sivakumar & Prasad 2014) and this is beyond the scope of this research.

This research therefore uses EPANET in its basic form to identify the most likely impacts of failures. It is accepted that the results will not be entirely accurate but, given that it will be applied to trunk mains models and the focus is on high level patterns rather than property specific assessment, the effect on achieving the project aims will be limited.

Alternative power supplies

The water company’s asset database lists standby generators at only the two larger water treatment works. The reliability of these generators is set at 98.4%, the same as the telecommunications infrastructure. As discussed above, water industry experience suggests that this value is high but it is the only robust value which is available.

Process

Facility failure

Water facilities are only vulnerable to the flooding of pumping stations and water treatment works. The probability of failure given the depth of water is read from the fragility curve developed in Chapter 4.3.4 and Monte Carlo sampling determines whether the facility is operational.

If power is lost at the substation which feeds a facility then the model first checks whether there is a standby generator. If there is, it tests whether a random number between zero and one is smaller than 0.984 (the starting reliability). If this is true then the site continues operating normally. If there is no alternative supply, or it does not start, then the site stops operating.

A proxy node represents each telemetry link between two water facilities (Figure 4.53). If this connection is lost then the pipe connecting the proxy node to the reservoir closes and the pressure at the node falls. Before the model makes any changes to the operation of pumps or treatment works it checks the pressure at this proxy node. If the pressure is below the set threshold it does not make the change (Table 4.31).

Facility recovery

Like electricity and telecommunications facilities, the time taken for water facilities to return to service is a combination of the time taken to reach the site and the time taken to implement the repair.

Each water facility is associated with the nearest highways node and the outputs from the highways model are used to determine the journey time to a failed facility.

The model uses two different repair times:

i. If the facility fails independently the repair time is a sample from the distribution of water facility repair times.
ii. If the failure is caused by the loss of power the facility is repaired in one hour. This reflects the time taken to reset the equipment and restart the plant. Simple equipment such as pumps may restart quicker but this is the shortest time step in the model. Some facilities will also restart automatically when power is restored but over the winter of 2013-2014 a number of incidents occurred when these systems failed to operate correctly.

The recovery of telemetry links occurs as soon as cause of the failure is repaired and the connection is restored.

Failure impact assessment

There are two types of controls in EPANET: rule-based and simple.

In this model, rule-based controls are used to dictate the day-to-day operation of the network and to capture the effects of lost telemetry connections. They are fixed parts of the model and do not change. In the example in Table 4.31:

- Node 11 is the service reservoir
- Pump 1 is the pumping station
- Node 139 is the node representing the telemetry connection between the service reservoir and pumping station

The first condition in the rule (lines 2 and 6) refer to the water level in the service reservoir and determines how the pump should respond. The second condition of the rule (lines 3 and 7) refer to the availability of the telemetry connection; if the pressure is below the normal level it prevents the rules being implemented.

Table 4.31 Example rule-based controls

```
RULE 1
IF NODE 11 PRESSURE  ABOVE 9
AND NODE 139 PRESSURE ABOVE 95
THEN PUMP 1 STATUS IS CLOSED

RULE 28
IF NODE 11 PRESSURE  BELOW 5
AND NODE 139 PRESSURE ABOVE 95
THEN PUMP 1 STATUS IS OPEN
```

Simple controls are used to effect the facility failures and subsequent recoveries so they change each time the model is run. The first part of the model, in Microsoft Excel, outputs a list of controls (Figure 4.30). Each one simply instructs a link, representing a pump or control valve, to open or close depending on whether the facility is operational. Once this list is copied into EPANET the model can be run in the usual way.

Table 4.32 Example simple controls

```
LINK 197 0 AT TIME 11
LINK 203 0 AT TIME 11
LINK 187 0 AT TIME 12
LINK 197 1 AT TIME 12
LINK 200 0 AT TIME 12
LINK 201 0 AT TIME 12
LINK 203 1 AT TIME 12
LINK 187 1 AT TIME 13
LINK 195 0 AT TIME 13
LINK 200 1 AT TIME 13
LINK 201 1 AT TIME 13
LINK 195 1 AT TIME 14
```

Output

The EPANET model records the operation of each facility and the pressure at each node at each time step of the simulation. This can either be viewed within the software or extracted for analysis.

Connection

Nodes which experience pressures below zero are identified as failed by the model and passed through to the Customer Impact Analysis.

4.6 Customer Impact Analysis

The final step of Performance Based Design and Catastrophe Modelling is an analysis of the losses incurred as a consequence of the damage experienced. This means translating information about system component failures into meaningful information for the decision maker

Source & Input

Two pieces of information are required.

i. The total time for which each demand node experiences negative pressures. This is taken from the output of the water network model described above.

ii. The number of properties affected by each failure. This is based on the baseline flow into each demand node available from the company schematics and the natural correlation between the number of customers and demand. A rule of thumb used within the industry is that one megalitre serves 2000 properties (Clucas 2012 *pers. comm.*). Figure 4.55 confirms this by plotting demand against property counts for the district metered areas in Greater Manchester and shows that the average property uses 504 litres per day. Therefore the base demand of each node in the hydraulic model (in megalitres per day) is divided by the gradient of the line in Figure 4.55 (0.0005) to estimate the property count.

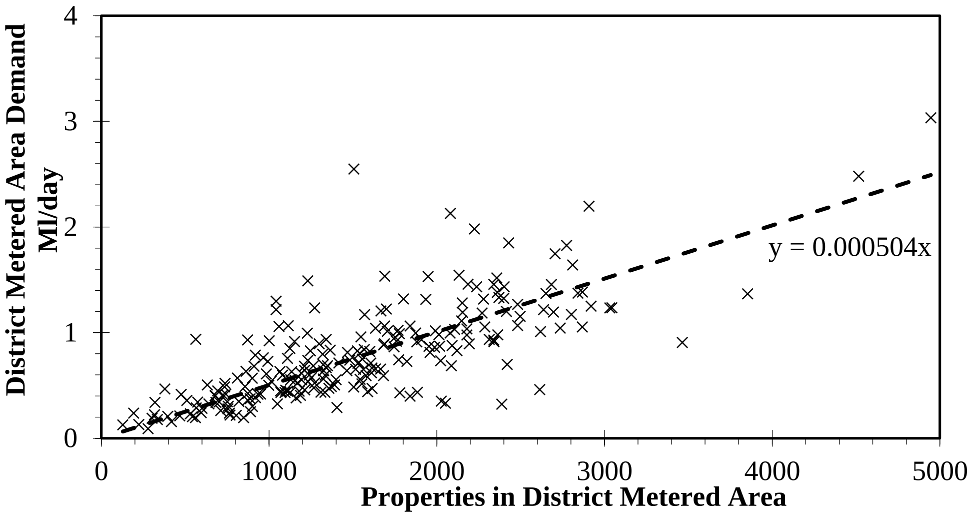


Figure 4.55 Regression of District Metered Area (DMA) metered daily demand against number of properties. 25 DMAs with large industrial demand were identified as outliers and removed from the analysis.

Process & Output

The hours lost and number of properties are multiplied together to give the property hours lost at every node. These can either be summed as a metric for the system as a whole or compared to understand how the vulnerability varies across the region.

4.7 Summary

This chapter has outlined the components of a model for risk assessments due to infrastructure interdependency; this is summarised on the following page. Figure 4.56 outlines how each component connects together and a more detailed schematic is included on the A3 sheet in Appendix A.

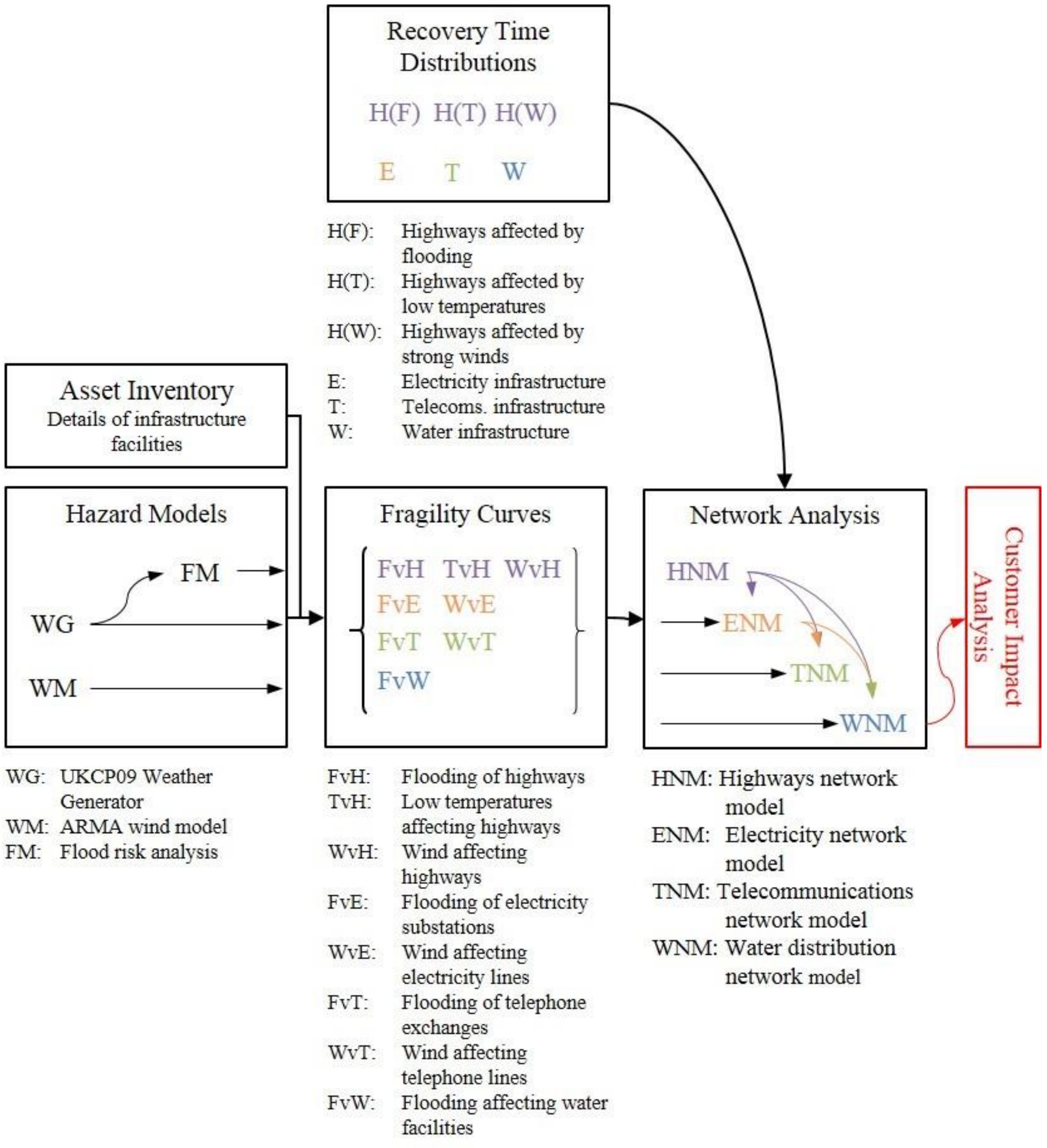


Figure 4.56 Model integration

i. A combination of UKCP09 Weather Generator output and a purpose built wind model produces a time series of values for the three hazards identified in Chapter 3 (temperature, rainfall and strong winds). A further step uses Environment Agency flood maps to convert rainfall intensities to flood depths at the location of individual facilities.

ii. A library of fragility describes the impact of these hazards on four key sectors of the UK national infrastructure (road transport, electricity, telecommunications and water). Where possible, the curves are based upon published sources (e.g. the effects of wind on electricity transmission lines) or empirical data from infrastructure providers (e.g. the effect of temperature and wind on road transport) and distributions describing likely recovery times for failed facilities. Where an extensive search has not found this data, curves are based upon reports of historical events and the judgement of experts.

iii. The literature is also used to define a set of distributions which describe the expected recovery times for failed facilities in the four sectors.

iv. Network models are used to simulate the effect of individual facility failures on the behaviour of the system. These models also capture the effects of interconnections between sectors, for example, the telephone exchanges' dependence upon power and pumping stations' dependence upon telephone exchanges.

    The network models vary according to the character of the sector: a simple routing algorithm is used for the highways; preliminary analysis of networks breaks the electricity and telecommunications network down into simple logical relationships; and EPANET is used to model flows in the water network.

The outputs from EPANET can be used to estimate the number of minutes without supply per property over a given time frame (e.g. 1 000 years). This metric allows internal comparison to identify high risk areas of the network and external comparison with the company's regulatory commitments to make decisions about the level of the risk.

Chapter 5. Model 1: Case Study

The previous chapter developed a model to assess the vulnerability of water services to failures in three other sectors (road transport, electricity and telecommunications) due to the impact of three natural hazards (low temperatures, heavy rainfall, strong winds). This chapter applies this model to a network serving approximately 175 000 people in Northern England; this case study is outlined in the first section of the chapter.

The second part of the chapter examines the results of the analysis including verification that the model is operating correctly and partial validation by comparison with the water companies' performance targets. The roles of different water network configurations, different hazards and different external sectors are also assessed. The final section discusses whether these results are valuable to infrastructure providers.

5.1 Case Study Data

5.1.1 Location

Two neighbouring DMZs were identified which met the following criteria for a suitable case study area:

i. The topography of the area creates geographical boundaries around the area which limit the number of external connections in and out of the networks to a few infrastructure corridors.

ii. It contains an interesting mix of water infrastructure facilities which demonstrate a range of interdependencies. It is anticipated that this area will have a high level of risk due to the number of booster pumping stations in the water network.

iii. The population of approximately 175 000 people in 78 000 properties is large enough that failures will cause significant disruption.

Working with real data means that the area and assets cannot be identified and any geographical information has been omitted from this thesis.

5.1.2 Infrastructure Networks

The figures over the following pages show the structure of each of the infrastructure networks. Key facilities are labelled to allow cross-comparison between the networks.

The diagonal pattern of major infrastructure facilities reflects the where the population is concentrated. Unfortunately the use of real data makes it impossible to include a geographical map but the telephone exchanges give a good impression of the town centres. There are two particularly noteworthy features of the networks:

i. Unlike the other networks, a number of water facilities are on higher ground away from the central valley. This reflects the use of gravity to supply the lower areas, and the need to pump water up to rural communities.

ii. In the road, electricity and water networks there appear to be few connections between the majority and the north-western part. This suggests that this area could be easily isolated and therefore be more vulnerable.

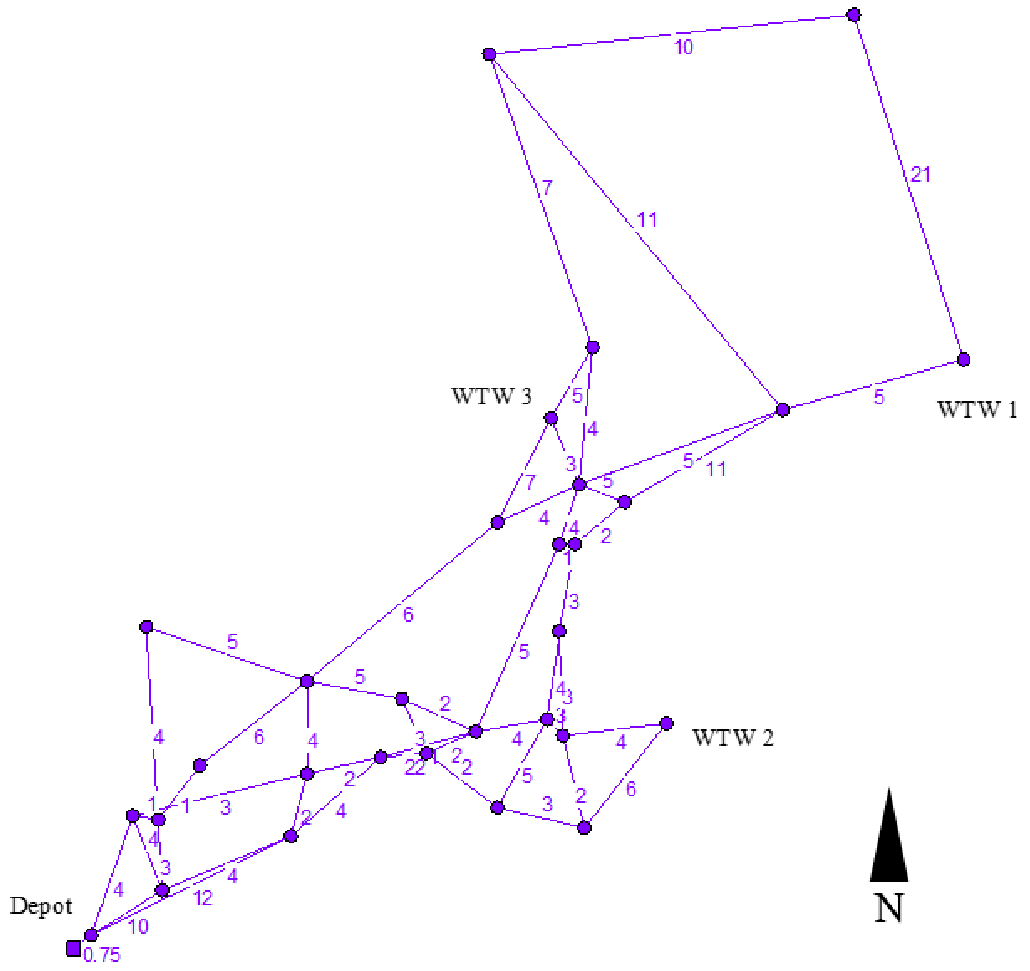


Figure 5.1 Case study highways network, labelled with the journey time in minutes for each link in normal conditions. The depot from which journeys start is shown in the south west and the three water treatment works are shown to ease cross-referencing with other networks.

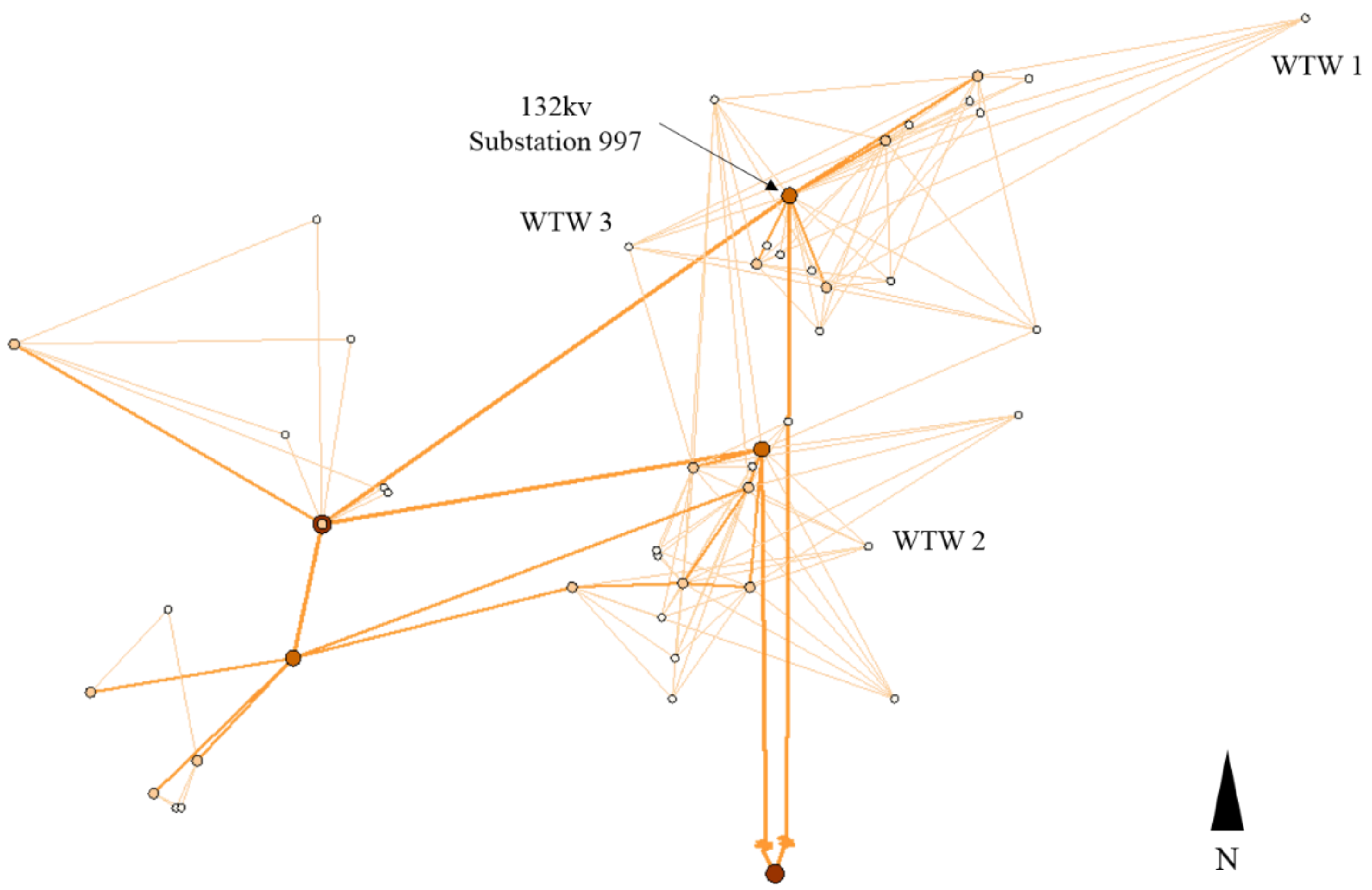


Figure 5.2 Electricity network (only the 34 secondary substations which feed water or telecommunications assets are shown.). The major substation exposed to flooding (Figure 5.23) is highlighted.

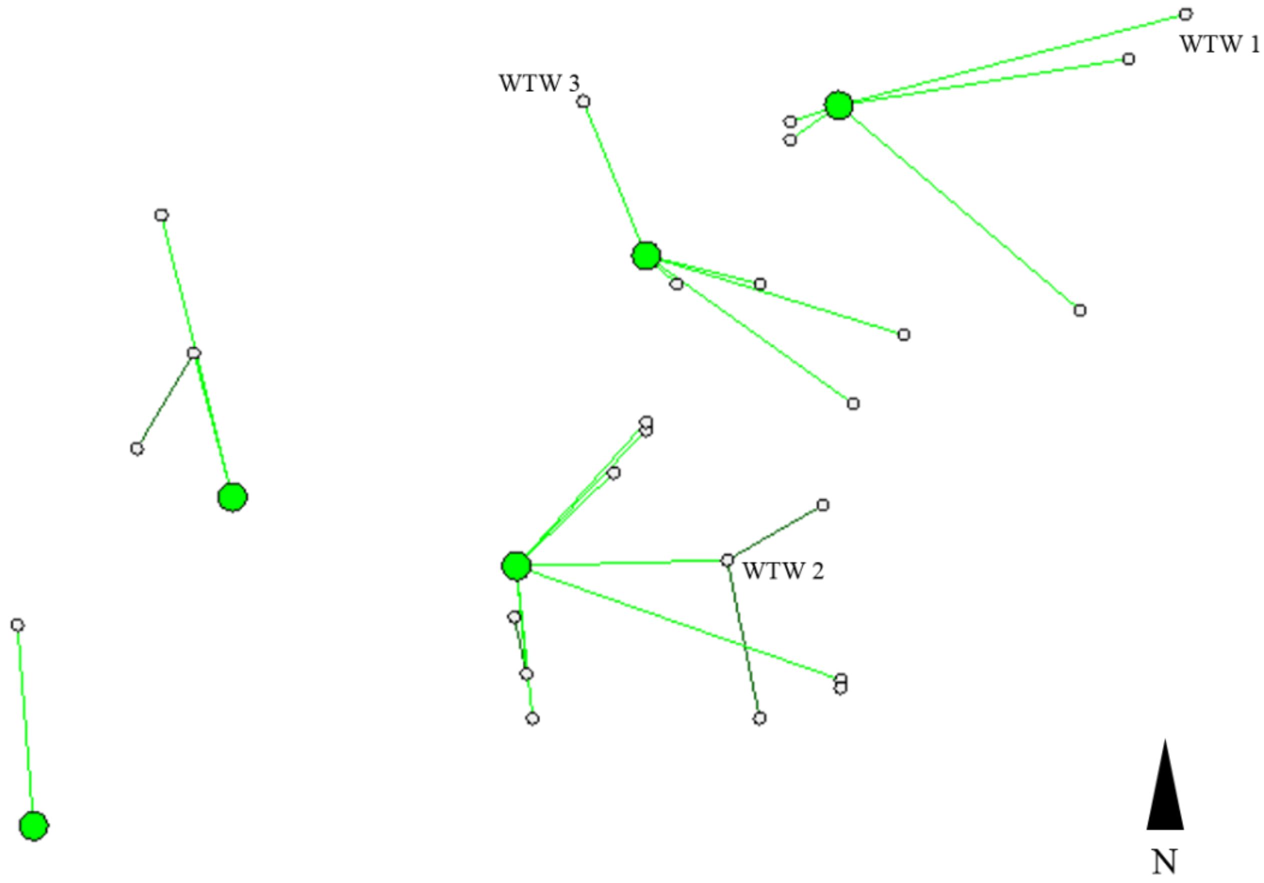


Figure 5.3 Telecommunications network. The connections between exchanges are not shown because no information could found on the local structure. It is assumed that this level of the network is invulnerable (see Chapter 4.5.3)

Telephone Exchange o Telemetry outstation — Fixed line connection — Radio link

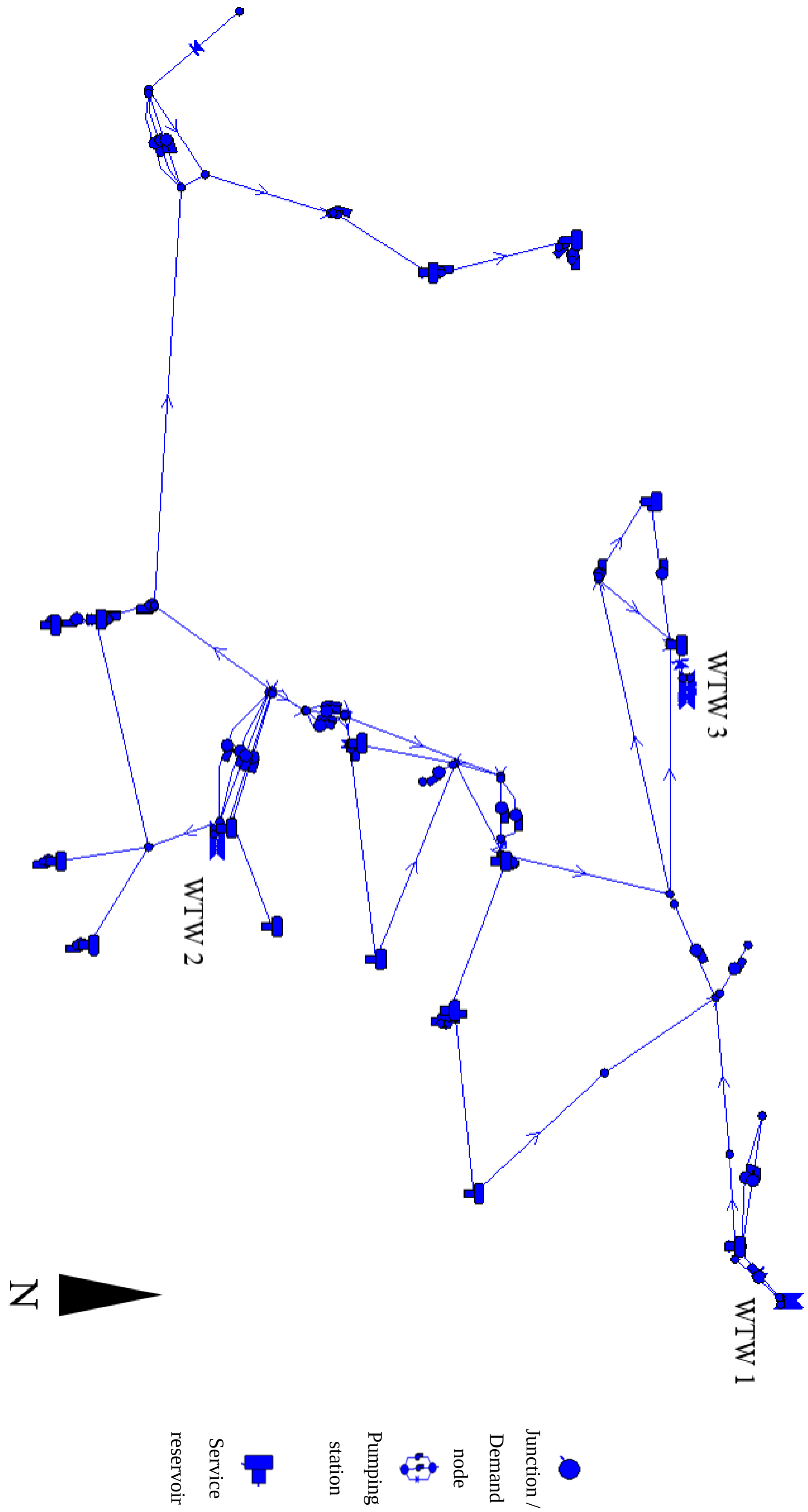


Figure 5.4 Geographical diagram of the water network. For more clarity, a schematic representation of the network is shown in Figure 5.5

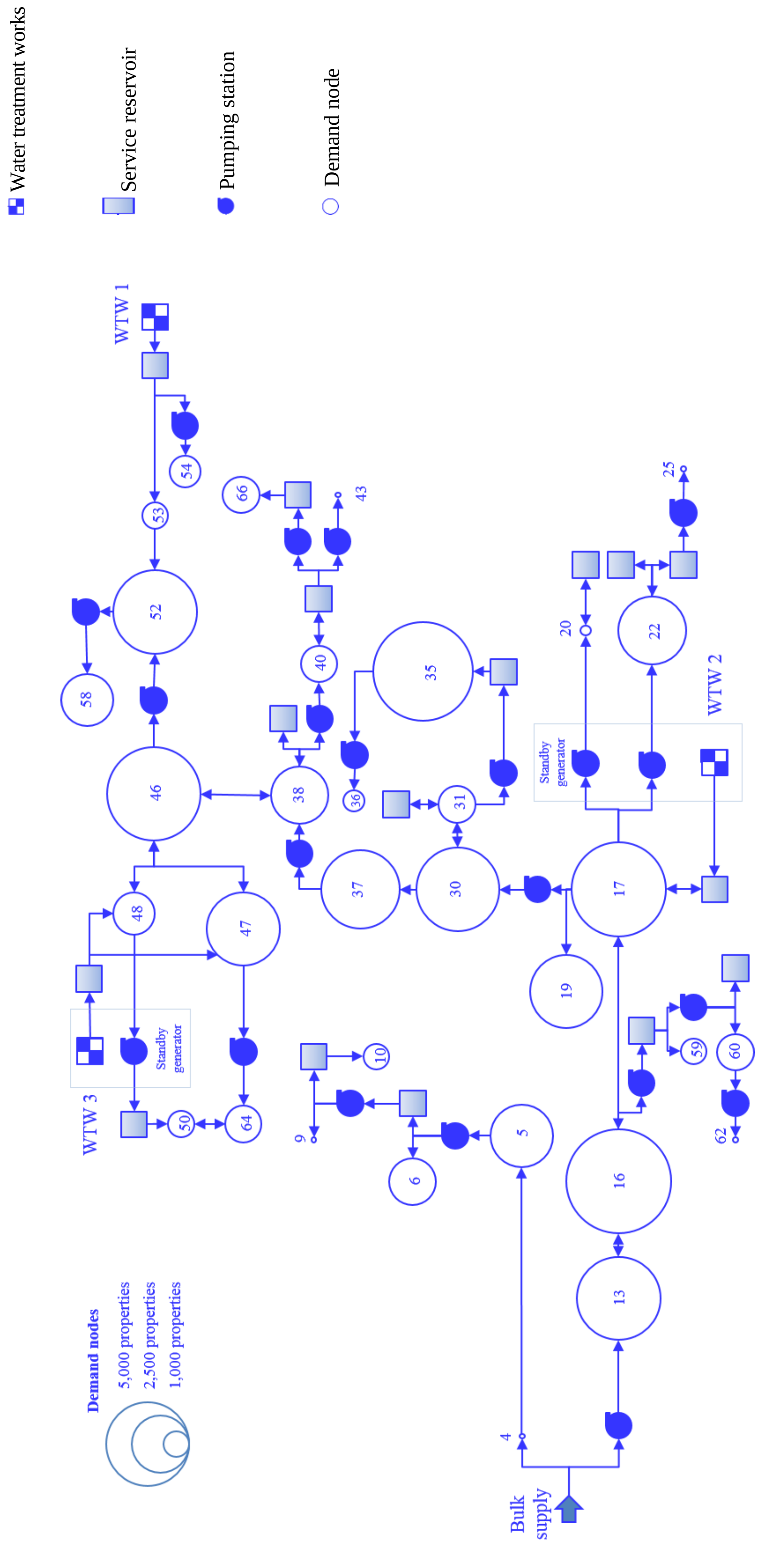


Figure 5.5 Schematic diagram of the water network

5.1.3 Hazard Model

The model was run using a 1 020 year long time series of hourly hazard values; all other parts of the model operate to the same hour long time step.

UKCP09 Weather Generator

The grid square at the centre of the area was selected and the data downloaded.

ARMA wind model

The nearest appropriate weather station was selected and the wind speeds extracted from the MIDAS data set. The intention was to use data from the period between 1980 and 2010 to fit the model but, as Figure 5.6 shows, the years between 1994 and 1999 contained an anomalous number of zero values. Whilst 1995 and 1996 are known dry years, and consequently could be associated with prolonged stable weather patterns, this pattern is not replicated consistently at other nearby locations. The most likely explanation is instrument or recording error so these six years are removed from the data set and replaced by extending the period by three years in both directions.

Using the month of January as an example, Figure 5.7 to Figure 5.11 illustrate the process steps described in Chapter 4.2.3.

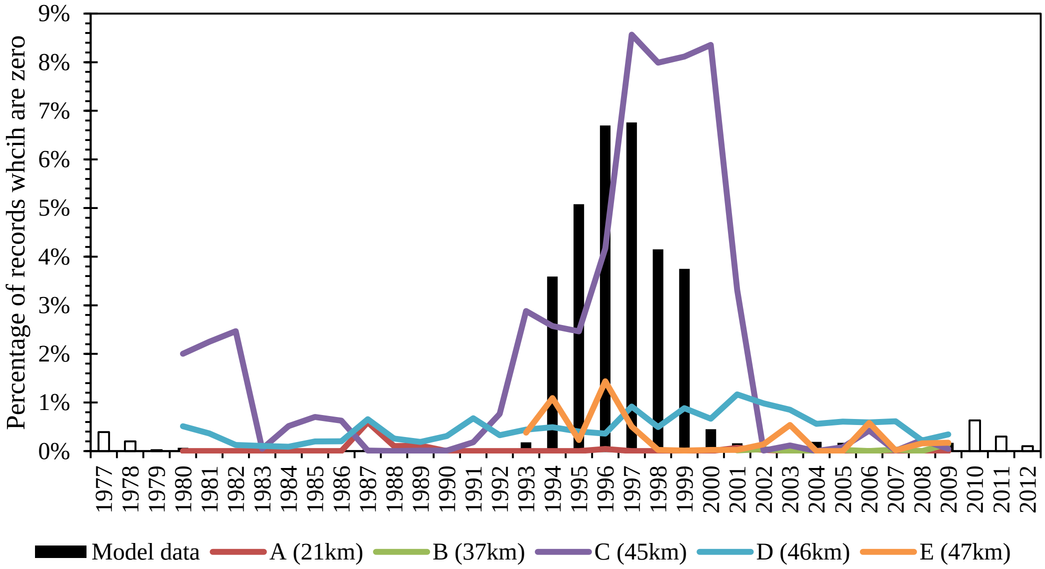


Figure 5.6 The record of observations at the weather station used to fit the model (black bars) has a large number of zero values between 1994 and 1999. Comparison with five surrounding weather stations (coloured lines) shows that this is not representative of a wider pattern, therefore these six anomalous years are replaced by extending the record three years in both directions (hollow bars).

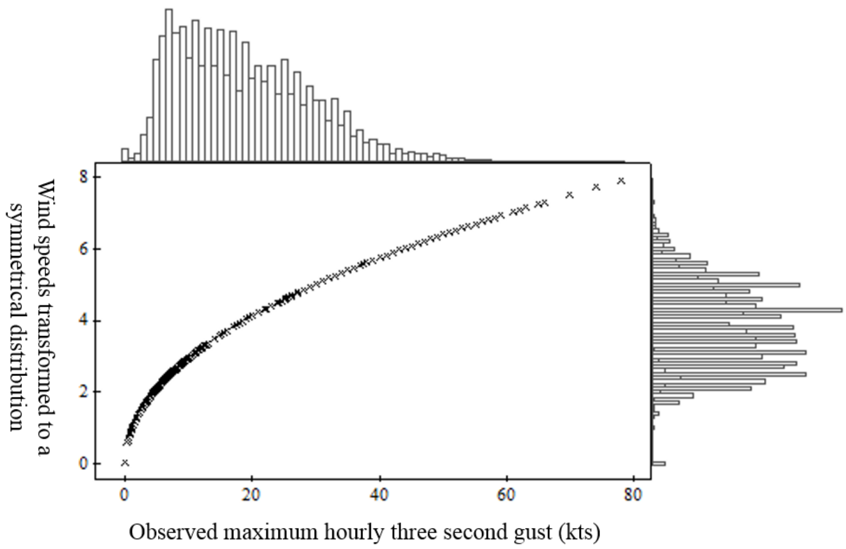


Figure 5.7 The histogram on the x-axis shows that the observed wind speeds follow a Weibull distribution. Torres et al. (2005)'s approach of raising the wind speed by a power chosen to minimise the asymmetry (Equation 4.3) is used to transform this skewed distribution to the more balanced distribution shown on the y-axis. The curve shown in the figure reflects the power used, for the month of January this is calculated as 0.48 (Equation 4.4). Note that zero wind speeds (below the detection threshold of the equipment) mean the transformed distribution is not entirely symmetrical.

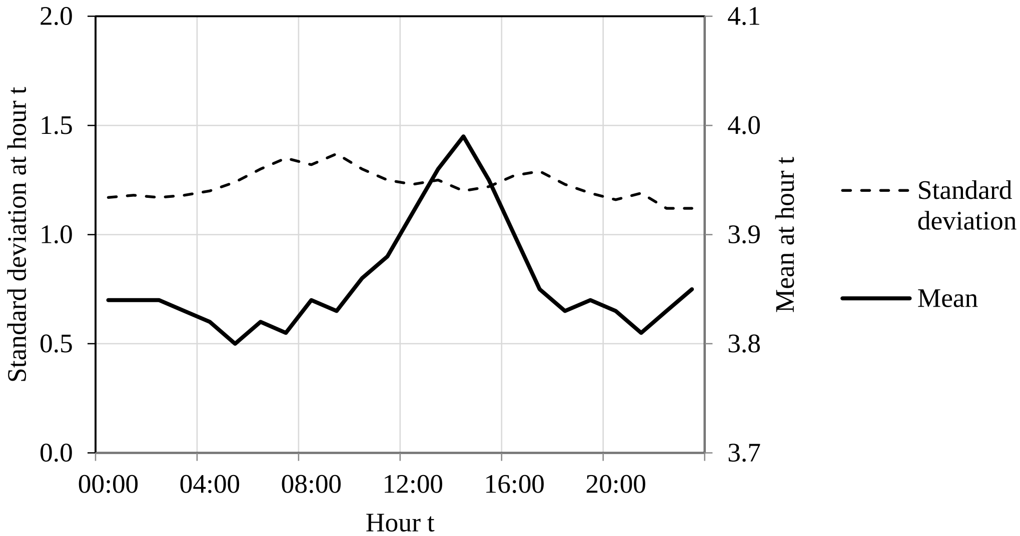


Figure 5.8 Diurnal variation in mean and variance standard deviation of the maximum three second gust wind speed. The standard deviation is largely constant but the average wind speed shows a distinct pattern with a peak in the mid-afternoon (note, however, the shortened axis).

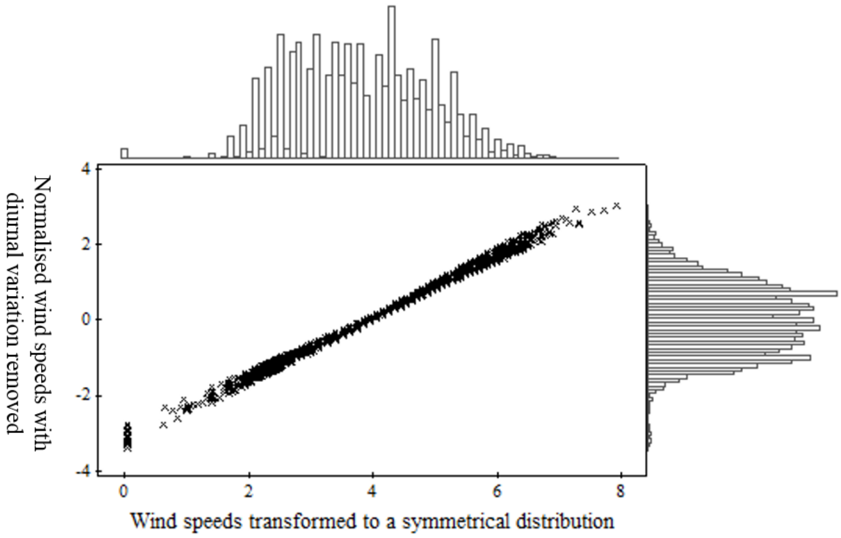


Figure 5.9 Removal of diurnal variation. The histogram on the upper axis is the same as the upper axis in Figure 5.7. Normalising the data using the values in Figure 5.8 (Equation 4.5) produces the distribution shown on the right hand axis. The result is closer to a normal distribution than the original distribution.

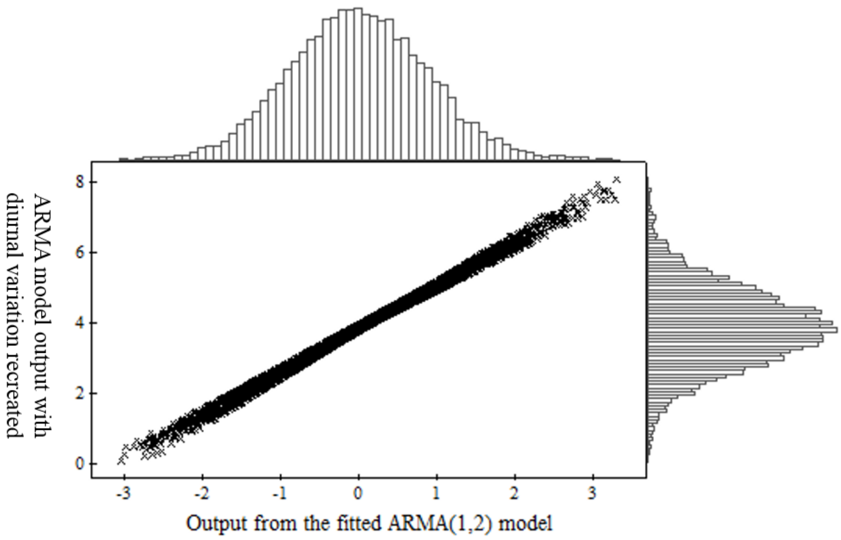


Figure 5.10 The BIC values identify an ARMA(1,2) as the best fit for the month of January. The x-axis shows the outputs of the ARMA model and the effect of re-instating the diurnal variation is shown on the y-axis.

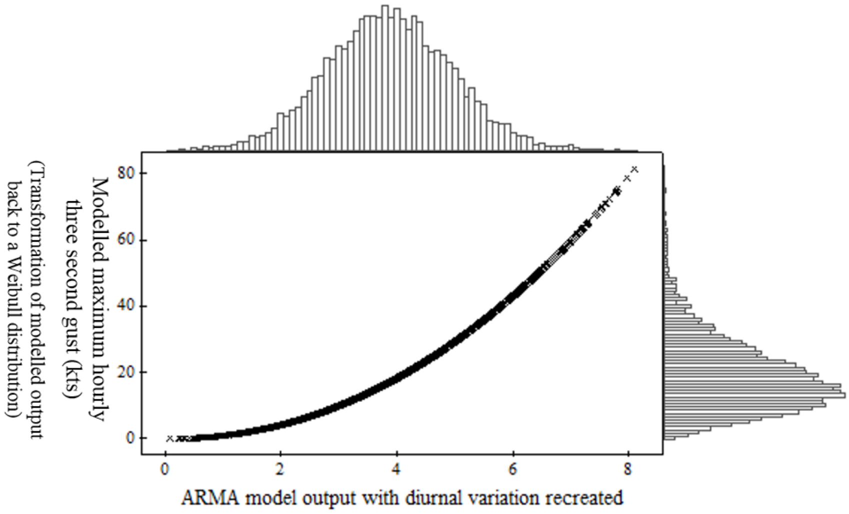


Figure 5.11 Synthetic wind speeds (shown on the y-axis) are created by taking the results which reincorporate the diurnal variation (shown on the x-axis, which is equivalent to the y-axis in Figure 5.10) and applying Equation 4.11 to return them to a Weibull distribution.

The output from the model is promising; Figure 5.12 shows that the overall distribution of the modelled values is a very close match to the observed data. A study of the autocorrelation and partial autocorrelation (Figure 5.13 and Figure 5.14) of the two data sets suggests the model may slightly underestimate the persistence of wind speeds over longer periods but it is nonetheless accurate within 12 hour period.

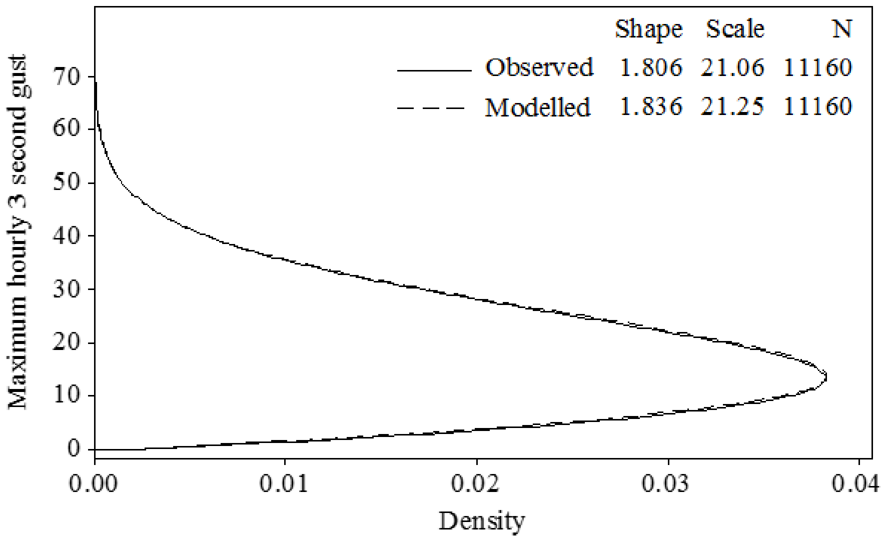


Figure 5.12 A comparison of the distributions of observed and modelled maximum hourly 3 second gusts shows a strong fit between the observed and modelled data set.

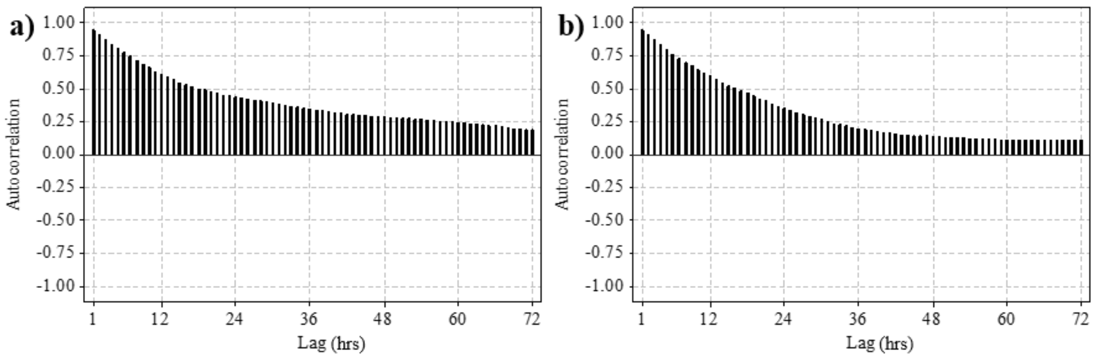


Figure 5.13 Autocorrelation of observed (a) and modelled (b) three second gust wind speeds.

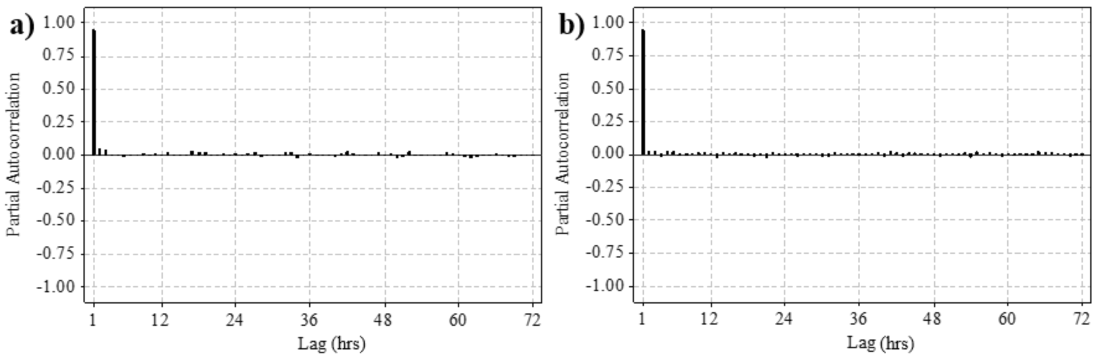
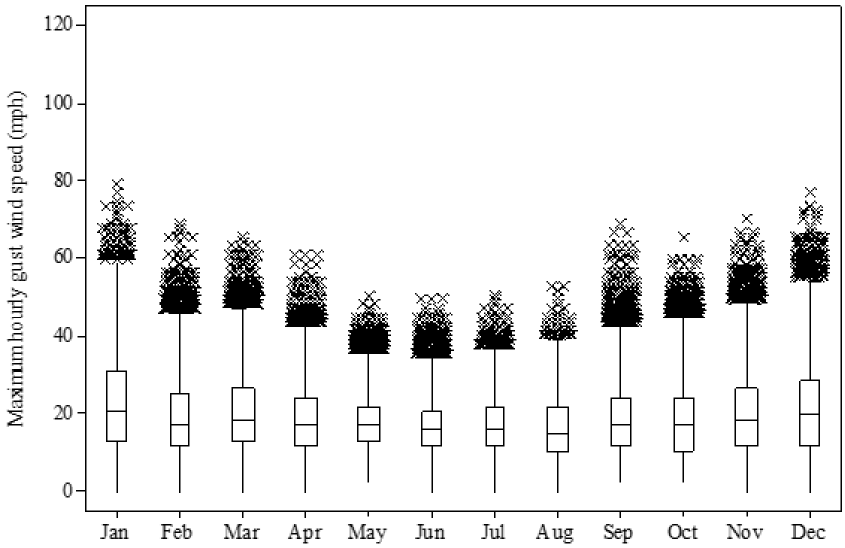


Figure 5.14 Partial autocorrelation of observed (a) and modelled (b) three second gust wind speeds.

Figure 5.15 compares the model output with the data set aside to validate the model. For 10 of the 12 months the correspondence is strong. In November there is one unusually high value but this is not concerning given that this is a stochastic model. The month of May is a greater concern with a number of anomalous values. Further investigation revealed that the division of May wind speeds by alternate years had created two substantially different data sets (Figure 5.16) and the low median and extreme values shown in Figure 5.15 are the result of the high positive skew in the calibration data.

a)



b)

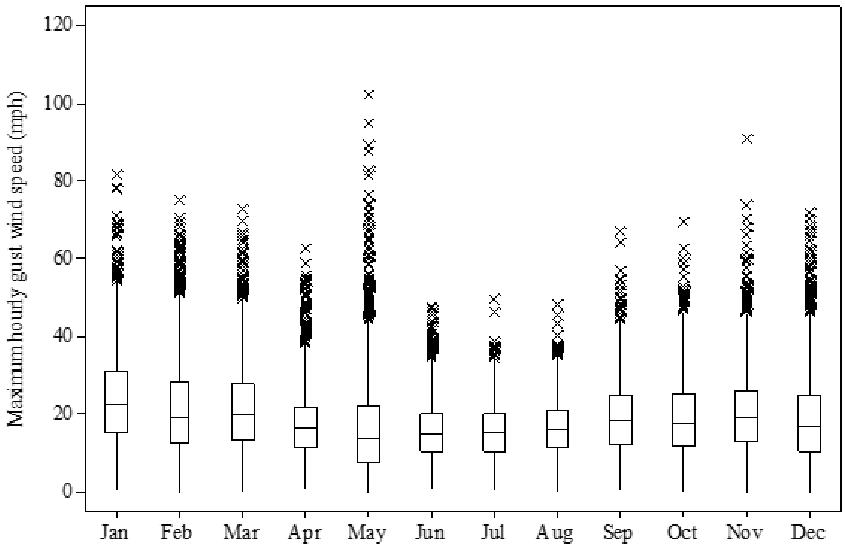


Figure 5.15 Monthly box plots showing a) the observed validation data, which was not used to fit the model, and b) the synthetic wind speeds produced by the model. Outliers (shown as crosses) are defined those which exceed the upper quartile by more than 1.5 times the interquartile range. The clusters in a) reflect the limited resolution with which wind speeds are recorded whereas the model outputs continuous data. Note how the model produces a number of very large values in the month of May.

There is no reason to give the validation data precedence over the calibration set but the May results are noticeably inconsistent with the surrounding months and the annual cycle. To resolve this anomaly the model calibration was repeated for May using a combined data set of both the calibration and validation data. It is accepted that this prevents the statistical validation of this month’s values but the consistency with surrounding months and the annual cycle of wind speeds suggests considerable improvement (Figure 5.17). Further improvement may be possible but it is outside the scope of this research.

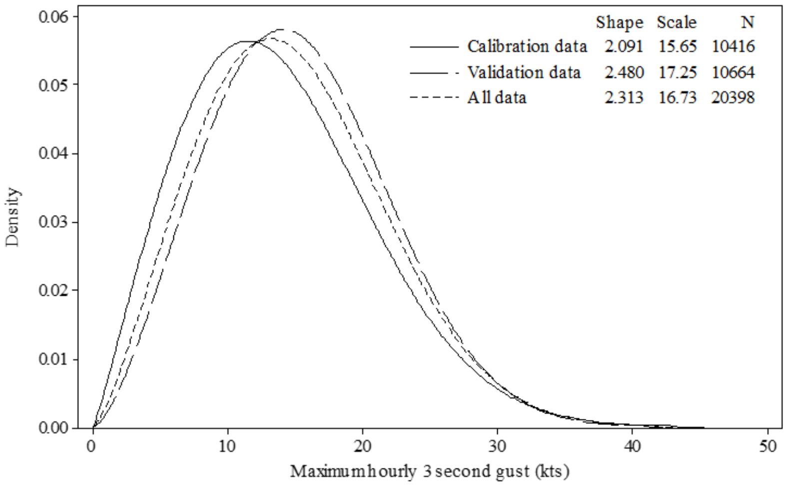


Figure 5.16 Different distributions of wind speeds in the calibration and validation data sets for the month of May

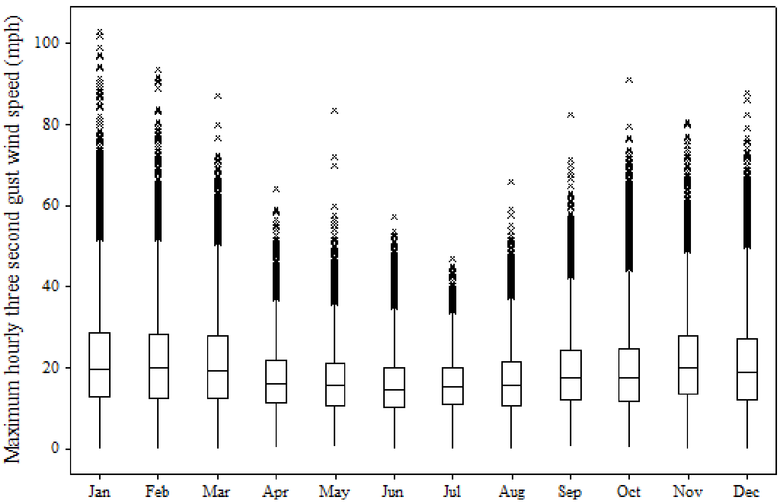


Figure 5.17 Monthly box plots for a 30 year sample of synthetic wind speeds. When the combined calibration and validation data is used to fit the model there are only three outlier values which exceed the surrounding months.

The parameters of the resulting models are summarized in Table 5.1 and the figures on the following pages show further results from this revised model. In general the model performs well; it captures both seasonal variation (Figure 5.18) and matches the distribution of the validation data (Figure 5.19). It is noted that, relative to the validation data, the very highest winds tend to be stronger in the modelled data than the validation data set (Figure 5.20). Whilst Figure 5.21 shows that this difference is small (it only equates to a 1% overestimation of 100 year return period event rising to 2% for a 1000 year return period event) the implications should be considered alongside the results.

Table 5.1 Parameters of monthly ARMA models for the generation of a synthetic time series of maximum hourly 3 second gust wind speeds

Month	**m**	**ARMA type**	**Autoregressive parameters**			**Moving average parameters**		
		(p,q)	**1st**	**2nd**	**3rd**	**1st**	**2nd**	**3rd**
January	0.48	(1,2)	0.961	-	-	- 0.056	- 0.031	-
February	0.50	(1,1)	0.962	-	-	- 0.061	-	-
March	0.43	(1,3)	0.956	-	-	- 0.096	- 0.031	0.032
April	0.35	(1,2)	0.945	-	-	- 0.093	- 0.045	-
May	0.31	(1,1)	0.940	-	-	- 0.132	-	-
June	0.33	(2,1)	1.208	- 0.249	-	- 0.395	-	-
July	0.50	(1,2)	0.939	-	-	- 0.130	- 0.042	-
August	0.38	(1,1)	0.940	-	-	- 0.108	-	-
September	0.42	(1,2)	0.956	-	-	- 0.086	- 0.039	-
October	0.37	(1,1)	0.949	-	-	- 0.075	-	-
November	0.47	(1,1)	0.954	-	-	- 0.100	-	-
December	0.48	(1,1)	0.958	-	-	- 0.058	-	-

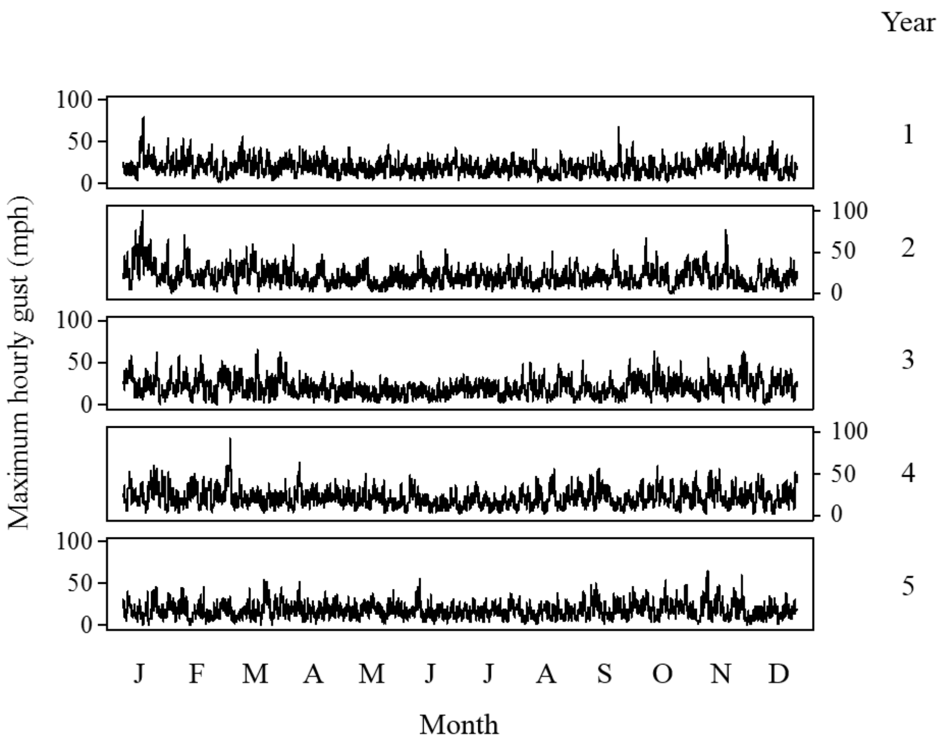


Figure 5.18 Five annual times series of maximum three second gust wind speeds

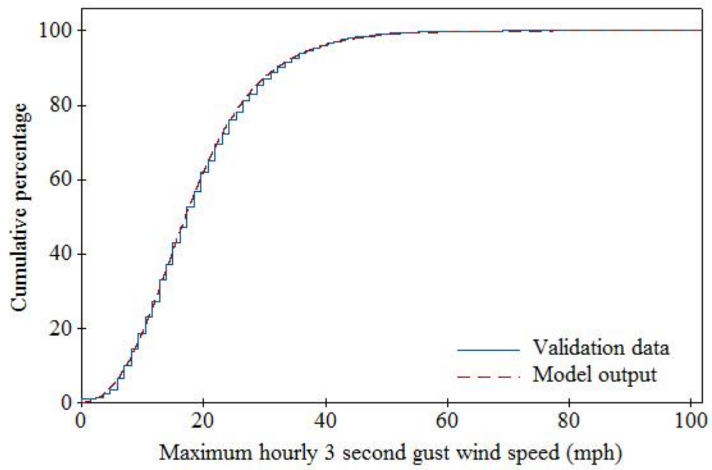


Figure 5.19 Comparison of the distribution of maximum gust wind speeds in a 32 year synthetic time series produced by the model and those in the 15 year time series retained for validating the model.

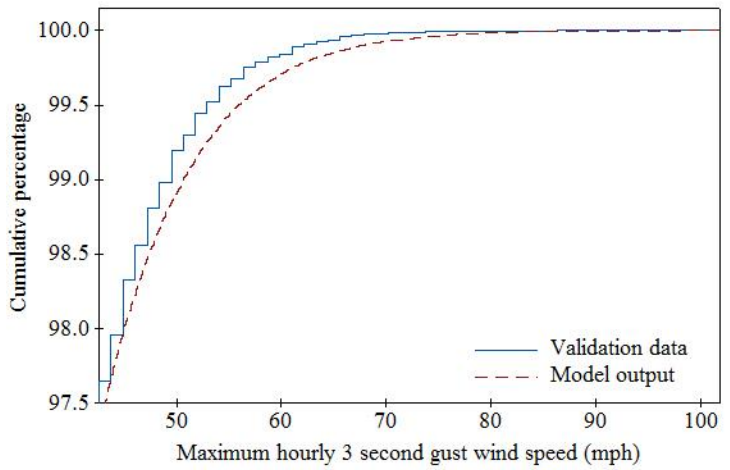


Figure 5.20 Comparison of validation data and model outputs at high wind speeds.

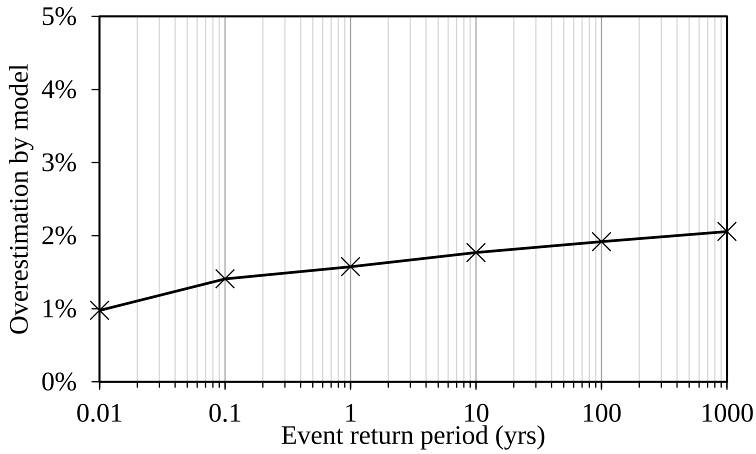


Figure 5.21 Difference between validation and modelled distributions at different return periods

Time series of hazard values

Figure 5.22 shows the time series of hazards for the first year. The one year return period threshold is crossed four times and the hazard values are captured. Meanwhile, the model steps over the intervening time periods which are unlikely to cause significant failures. This time series is used in combination with the flood risk assessment discussed in the following section and the fragility curves developed in Chapter 4.3 to identify failed facilities.

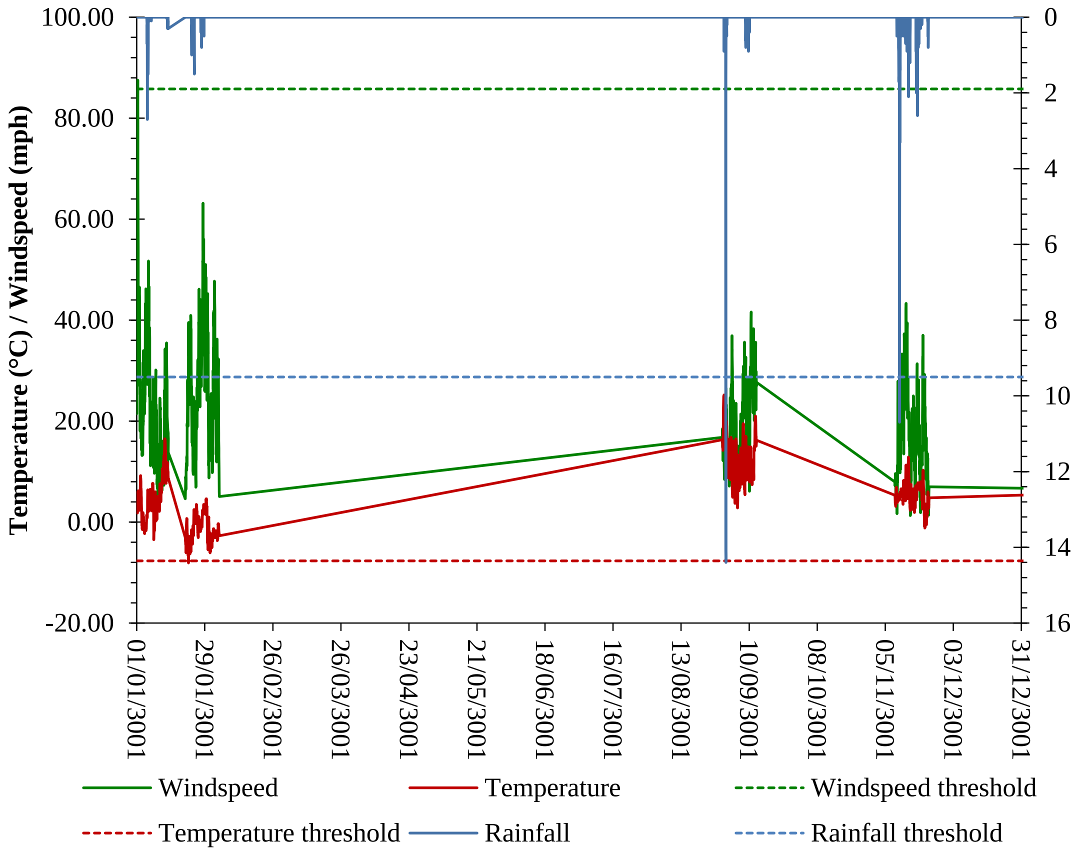


Figure 5.22 The first year of the hazard time series. Values for all three hazards are captured on the four occasions when one of the hazards crosses the one year return period threshold. The first is triggered by high winds on 5th January, the second by low temperatures on 23rd January, the third by heavy rain on 31st August and the fourth by further heavy rain on 10th November. Note that the horizontal axis follows the UKCP09 Weather Generator's convention of using the third millennia to avoid confusion with real dates.

Flood risk assessment

Figure 5.23 shows the estimated flood depths for each of the infrastructure facilities in the case study area. There are notable differences in the exposure of different sectors. Only three water facilities experience flooding and the inundation depths are low (<0.04m) even in a 100 year return period event. In stark contrast, many of the highways links are exposed to flooding, with some predicted to flood to depths of over a metre. The pattern for the electricity and telecommunications sectors is mixed with a limited number of sites exposed to a moderate level of flooding. Of particular note is Substation 997, a major bulk supply point, which floods to a depth of 42cm in a 20 year return period event. This could represent a significant vulnerability if there is no redundancy in the network.

It is also interesting to note that the predicted flood depths at facilities do not increase uniformly with increased return periods. At some sites (e.g. Highways Link 5) the relationship between return period and flood depth in exponential; at others (e.g. Highways Link 57 or Substation 997) the rate of increase slows considerably. This reflects local geography and the ponding of flood water behind obstacles; when the height of this obstacle is reached it spills over into another area so the level does not build further

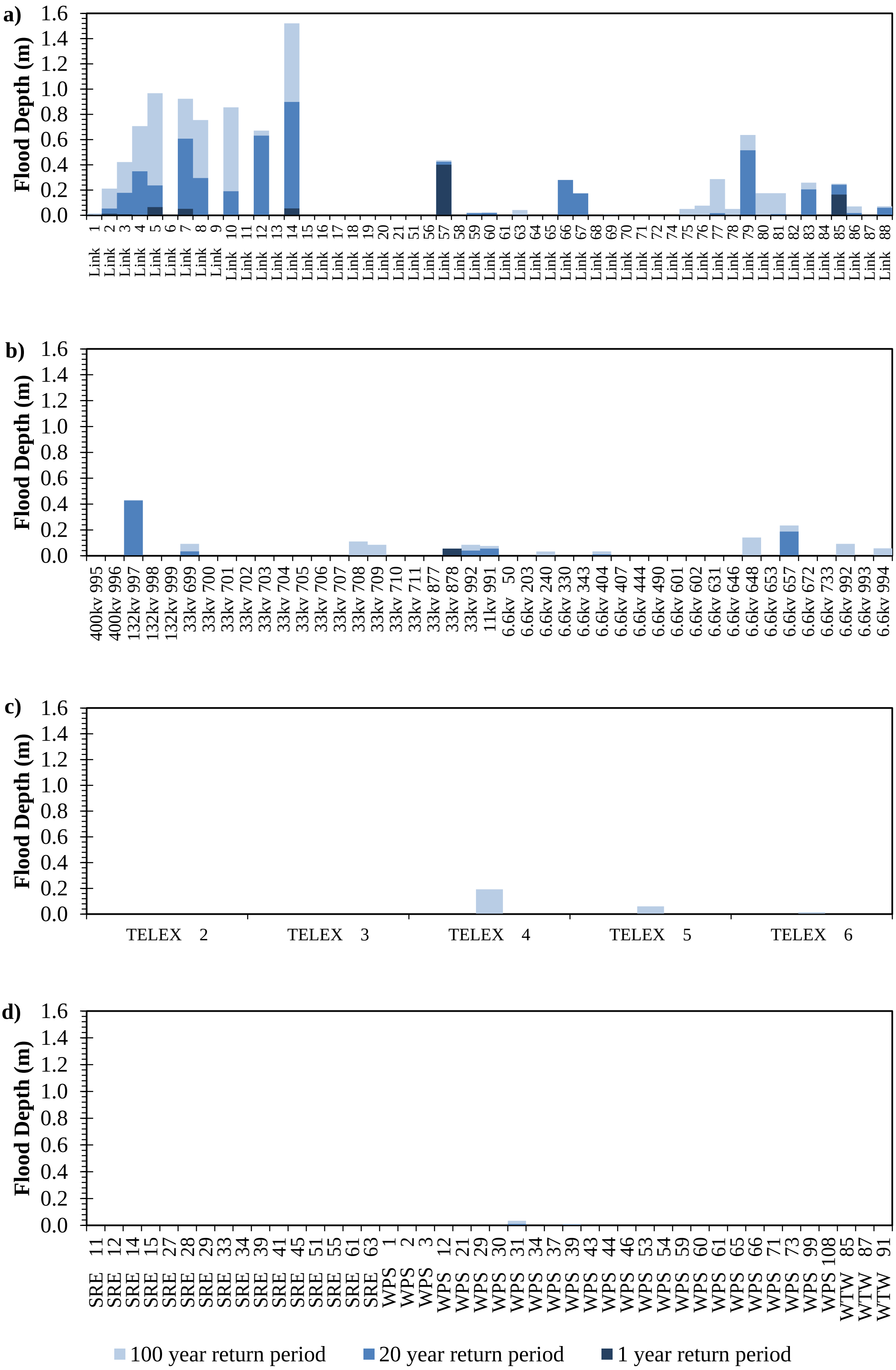


Figure 5.23 Estimated flood depths at a) highways, b) electricity, c) telecommunications and d) potable water facilities in the case study area at 1, 20 and 100 year return period events.

5.2 Results

The Introduction identified that infrastructure providers require methods which:

i. Provide quantitative information which decision makers can use to make evidence based decisions.

ii. Identify where their systems are vulnerable and hence where to direct efforts to reduce risk.

iii. Be practicable to implement in an industrial context.

This section assesses the model outputs against the first two criteria. An assessment of the balance between realism and complexity, and whether the model is manageable in an industrial context, is reserved for the subsequent discussion section.

5.2.1 Can the outputs be used to support decision making?

Chapter 3 established that the construction of the model should be followed by a process of verification and validation:

i. Verification is the process of checking the model's internal logic. Essentially, is it doing what it was intended to do?

ii. Validation assesses whether it accurately represents the target phenomena.

<u>Verification - Do events unfold in a realistic way?</u>

Verification is achieved by stepping through individual events in the time series and exploring how they evolved. This section gives an example of one event where a severe wind storm which causes two separate loss-of-supply events. The chain of events is shown in Figure 5.24.

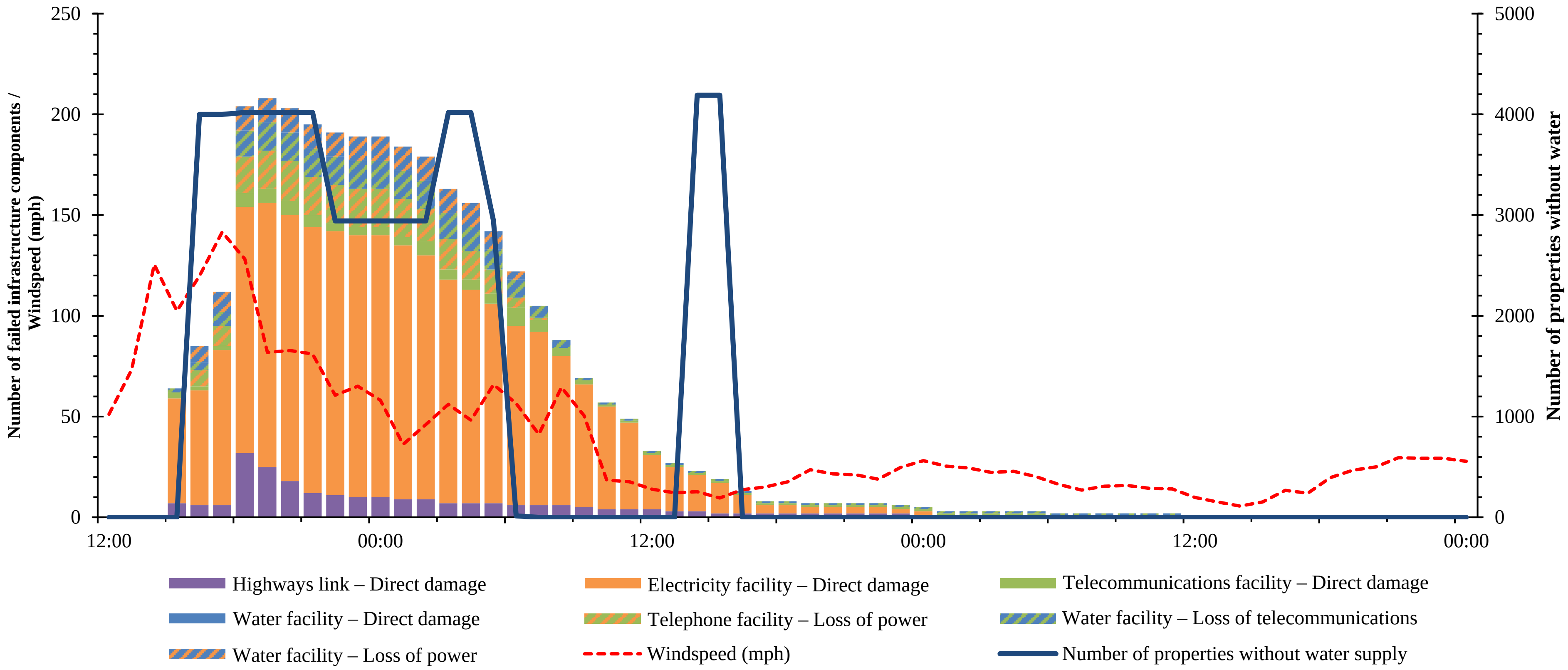


Figure 5.24 Timeline of the impacts caused by an extreme windstorm. The number of failed electricity lines (orange bar) increases with the growing intensity of the storm (dotted red line) until at its peak 122 separate facilities have failed. However, the initial impact in the water sector occurs earlier when power is lost to eight water facilities (blue bar with orange hatching) and approximately 4 000 properties lose their water supply (blue line). The wind speeds subside through the evening but the number of failed facilities only decreases slightly. The number of properties without supply drops to 2 900 overnight before rising again in the early morning. At 06:00 the number of water facilities without power drops and water supplies are restored to all properties. There remains, however, one water facility without a telecommunications link (blue bar with green hatching); this is the cause of the further interruption to 4 100 properties' water supply seven hours later (see Figure 5.27).

The critical factor in the initial impact is the failure of both of the lines which connect the 132kv Bulk Supply Point (BSP) in the north east of the area to the National Grid. This completely isolates this area (Figure 5.25) and almost 4,000 properties fed directly from five pumping stations lose supply immediately. This echoes Yazdani and Jeffrey's (2011) concept of 'bridges'; connections between parts of the network whose loss can isolate large areas (see Chapter 3.2).

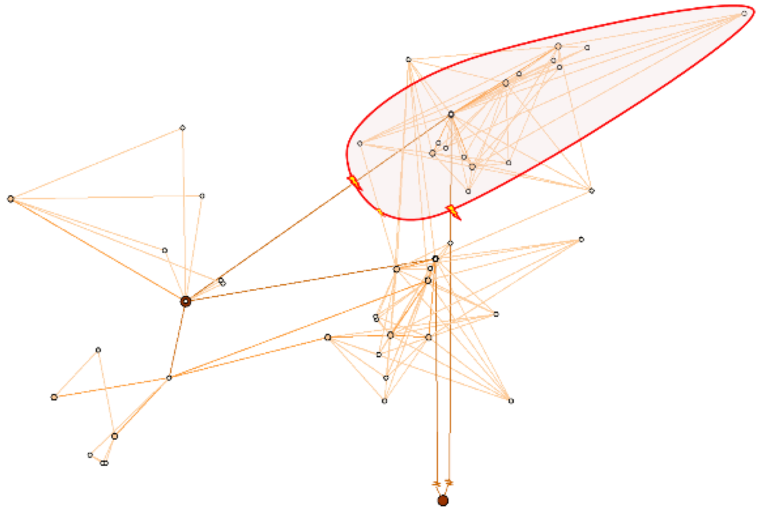


Figure 5.25 Damage to the two 400kv transmission lines causes power to be lost in the north east of the area

Closer examination reveals that the temporary drop in the number of customers affected overnight is due to lower demand allowing 1,000 properties to be fed via a cross-connection to a service reservoir (Figure 5.26). The capacity of this cross connection is limited so as demand increases again in the morning the supplies are lost.

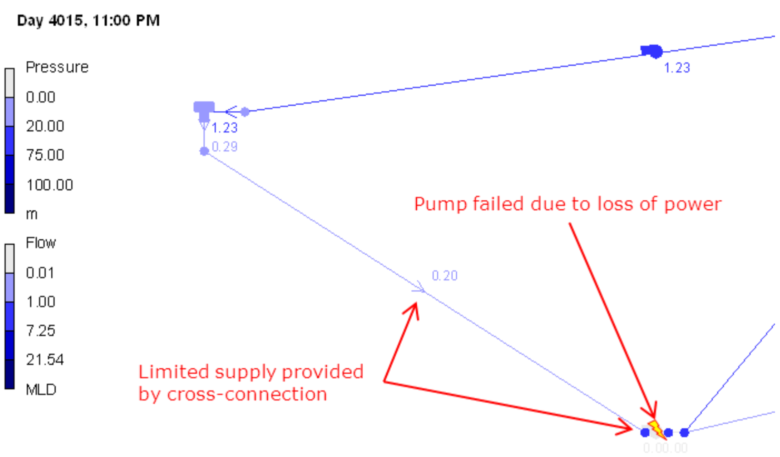


Figure 5.26 When pressures drop overnight one node can be supplied via a cross-connection

The restoration of supplies overnight has important implications for regulatory penalties. Whilst more customers may contact the company because their supply is interrupted twice, the impact on the customer minutes without supply metric falls by 7 530 minutes. Given that the company has approximately 3.2 million customers, the AMP6 penalties and rewards could equate to £12 200. The direct effect of customers regaining supply accounts for only 71% of this benefit. The remainder, more interestingly, is gained because the interruption to supply in the morning only last two hours and the metric counts interruptions longer than three hours.

Initially the damage to electricity infrastructure makes damaged telecommunications infrastructure irrelevant. However, Figure 5.27 shows it is critical factor in a second interruption which occurs a number of hours later.

Notably, the increase in journey times to reach the damaged infrastructure appears to be insignificant. At the storm's peak the journey times increase by an hour but they drop again in the following time step as roads re-open.

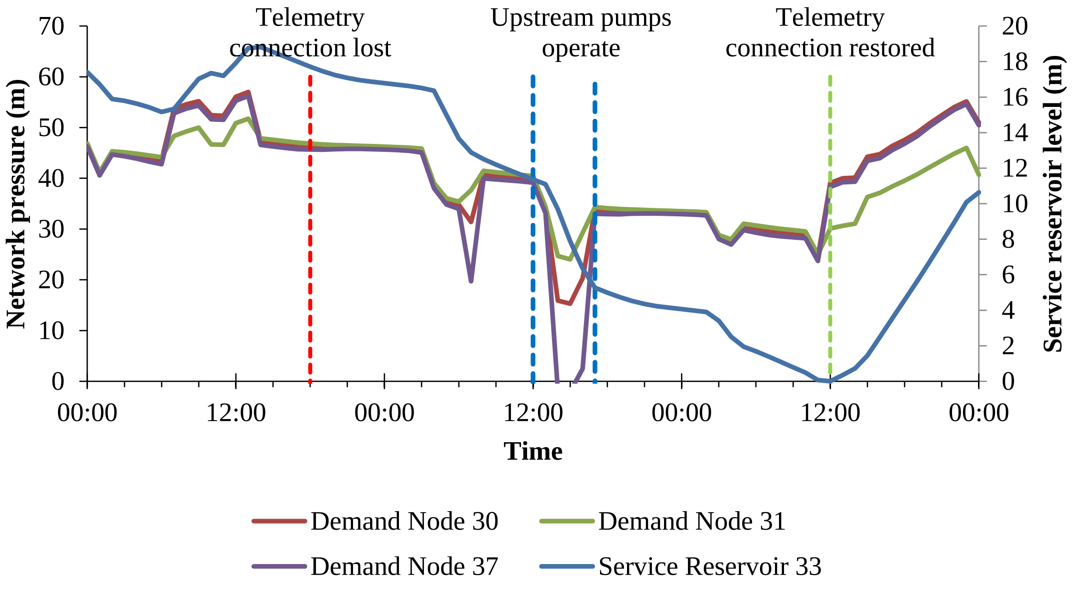


Figure 5.27 Long repair times for telecommunications infrastructure leads to loss of supplies. A telemetry connection is lost at 18:00 on the first day meaning that a pumping station does not switch on to replenish the supplies in Service Reservoir 33. This connection is repaired almost immediately after the reservoir runs dry at midday on the third day and hence there is no impact at this point. Meanwhile, however, power is restored to Pumping Station 34 which pumps water from Node 31 to another reservoir. The telemetry for these facilities is still operating and the level in the reservoir is low so Pumping Station 34 automatically starts at midday on the second day. The extra demand, combined with the low level in Reservoir 33, causes the pressure in the local network to drop. Nodes 30 and 31 experience low pressures and supplies are lost to the 4 200 properties in Node 37 at the furthest point of the network.

Verification is an iterative process and it has been repeated for different events through the time series of events until no further issues are identified. Verification of a model can never be exhaustive as a new combination of inputs could reveal a further issue (Carson 2005) but there is confidence that the major and consequential issues have been resolved.

Validation - Is the magnitude of the modelled risk plausible?

Chapter 3 established that there is no empirical data with which to validate the model outputs and the model's validity must be established at a component level. Therefore the construction of each component has been carefully described in Chapter 4.

Notwithstanding, Chapter 2 discussed how most water companies have customer minutes lost due to interruptions longer than three hours, or variants thereof, in their "Measures of Success" for the 2015-2020 asset management period. The modelled minutes lost per property per year for events longer than three hours is 10.5 minutes and Figure 2.10 compares this with the AMP6 performance commitments for UK water companies.

Figure 5.28 plots the distribution of annual property hours lost values with the AMP6 commitments for average property minutes lost made by the water companies in England and Wales. They cannot be compared directly as the performance commitments include all interruptions, not just those caused by third party infrastructure failures. Nonetheless, the figure presents an opportunity to benchmark the results and also reveals interesting patterns.

The results indicate that, whilst there is no impact in approximately 80% of years, there remains a substantial risk of regulatory penalties. Furthermore, the rise in frequency of annual scores between 20 and 45 average minutes lost per property suggests that, when an event occurs, the threshold for penalties is likely to be exceeded by a high degree. United Utilities and Yorkshire Water's caps on their penalties protect them from this risk but, in contrast, Severn Trent's potential penalty is unlimited and therefore they are more exposed. It is important to note that these results represent only one case study area whereas the performance commitments refer to entire businesses; on one hand hazards are likely to affect neighbouring areas simultaneously but equally the averaging effect across the whole company is likely to reduce scores.

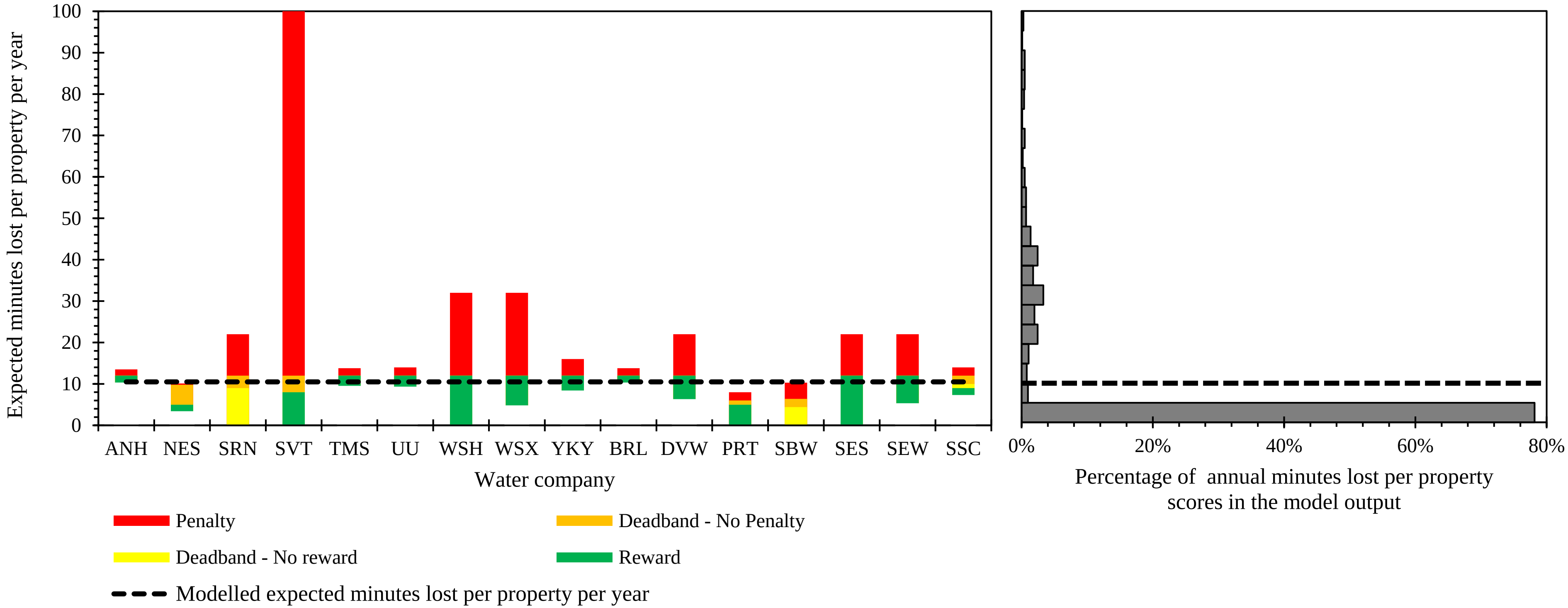


Figure 5.28 Left hand panel: The expected property minutes lost per year calculated using the model compared with the PR14 penalties, deadbands and rewards for interruptions to supply (data from Ofwat 2014c). Right hand panel: the distribution of annual property hour lost values from the model showing that in many years (78%) there is no impact but when there is an impact it is typically large and there is a high probability of regulatory penalties. Notes that in 1.6% of the modelled years the average minutes lost per property exceeds 100; the maximum is 532.

ANH: Anglian Water (including Hartlepool), WSH: Dŵr Cymru / Welsh Water, NES: Northumbrian Water (including Essex and Suffolk Water), SVT: Severn Trent Water, SWT: South West Water, SRN: Southern Water, TMS: Thames Water, UU: United Utilities, WSX: Wessex Water, YKY: Yorkshire Water (including York), AFW: AffinityWater, BRL: Bristol Water, DVW: Dee Valley Water, PRT: Portsmouth Water, SBW: Sembcorp Bournemouth Water, SEW: South East Water, SSC: South Staffordshire Water (including Cambridge Water), SES: Sutton and East Surrey Water

The occurrence of events in only approximately one year in five highlights the difficulty of validating the results of the model. UK water companies have only collected data on property minutes lost for the last three years (since 2012) so the record is too short to provide any meaningful comparison. Using the companies' performance commitments is arguably more reliable because they reflect the careful consideration of industry experts.

The comparison with companies' performance commitments indicates that the model output are likely to be an overestimate. The mean annual property hours lost is only slightly below their performance commitments and failures due to dependency on third party infrastructure only make up a proportion of this score.

There are a number of potential explanations:

i. The company targets are regional averages. This case study area was chosen for its dependency on pumping and therefore its vulnerable to failures in third party infrastructure is likely to be higher than average.

ii. The model does not include the ability of staff to reconfigure the network and supply customers from other areas and this is an important component of the network's resilience.

iii. The use of a demand driven model does not capture fully the performance of the water network in pressure deficient conditions. This may lead to overestimation as nodes with a negative pressure will still be drawing water from the network.

iv. It was noted above that the wind model can produce extreme wind speeds. Therefore catastrophic failures affecting large parts of the system may be more likely.

v. There is more general uncertainty around parameters used in the model which could affect the outputs.

The latter three are most relevant to the development of an effective model. Ideally some form of uncertainty analysis would be used to understand the impact of these concerns on the overall model output.

5.2.2 Does the model identify the contribution of different factors to the overall risk?

Figure 5.29 shows that risk is not evenly distributed across the network; instead a small number of nodes carry the majority of the risk. One node, Node 58, contributes over 40% of the total. Meanwhile, half of the nodes – representing 66% of customers – never lose supply. The high risk nodes are obvious targets for interventions to reduce risk, and their identification by the model indicates it could be a successful aid to decision making.

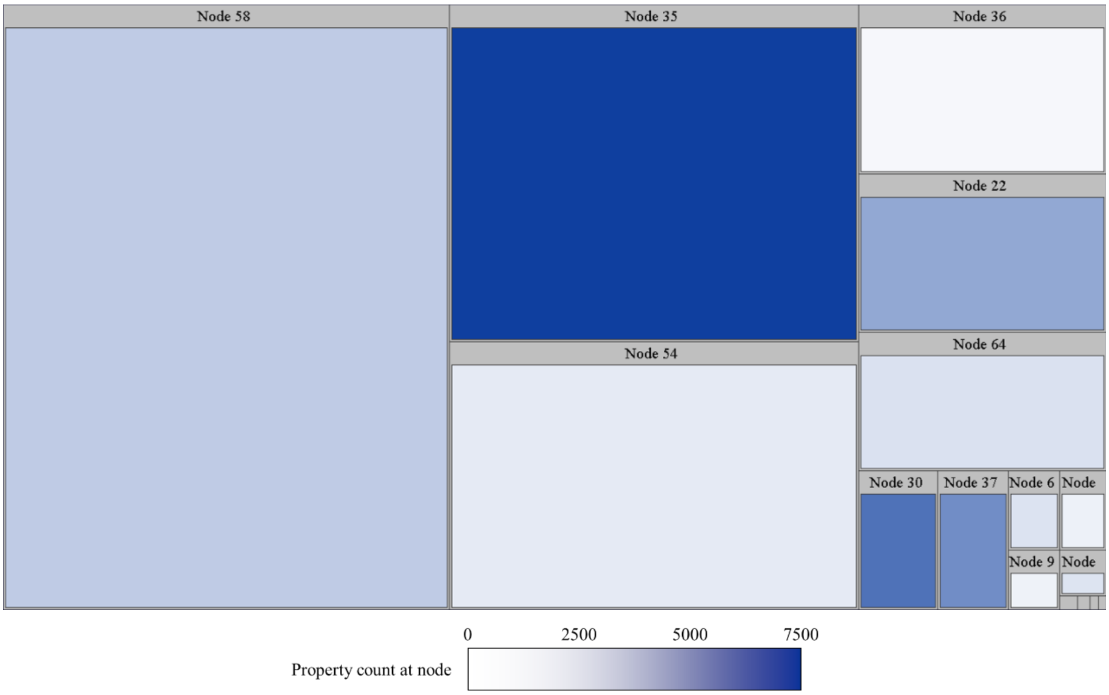


Figure 5.29 A tree map showing the contribution of each water network node to the total number of customer minutes lost; the size of the square is proportional to that node's contribution. Note how three nodes make up over 50% of the total risk.

The next step is understanding why these high risk nodes are less resilient. Figure 5.30 plots the number of properties at each demand node against the frequency with which the model predicts they lose supply. It shows a clear pattern; nodes with more frequent interruptions tend to have fewer properties and nodes with high properties counts are affected less frequently. Notably, with the exception of Node 58, the most vulnerable nodes appear to follow a Pareto curve and there are no nodes in the upper right hand corner. This implies that the structure of the network already acts to manage the risk in accordance with an unconscious risk appetite.

Do differences in the structure of the water network influence the risk?

Figure 5.31 shows that the majority of the customers who never lose supply are in high population nodes along the major trunk mains. By contrast, the nodes which lose supply most frequently tend to be directly associated with pumping stations. Table 5.2 explores this further by categorising the demand nodes into three groups: those fed by gravity directly from a source; those fed by gravity from a service reservoir; and those fed directly by pumps.

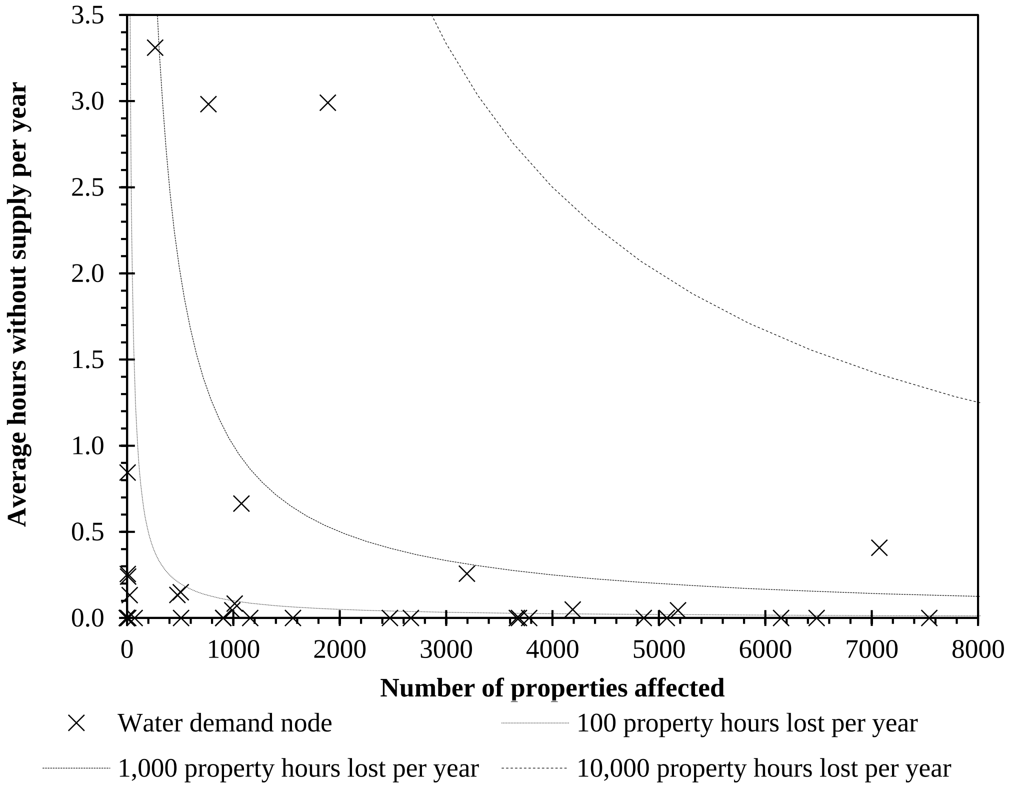


Figure 5.30 The risk due to external infrastructure dependency at each demand node. The horizontal axis shows the number of properties within the node (i.e. the consequence) and the y-axis shows the annual average number of hours the node is without supply in 1 020 year simulation (i.e. the likelihood of failure)

Table 5.2 The effect of different supply arrangements on the number of hours properties are without supplies

	Number of properties (percentage of total)	**Annual average hours without supply**	**Annual average customer hours lost**
Nodes fed by gravity from a WTW or aqueduct	41 900 (54%)	0	0
Nodes fed by gravity from a service reservoir	33 300 (43%)	0.123	4 096
Nodes fed directly by pumps	2 940 (4%)	1.77	5 203

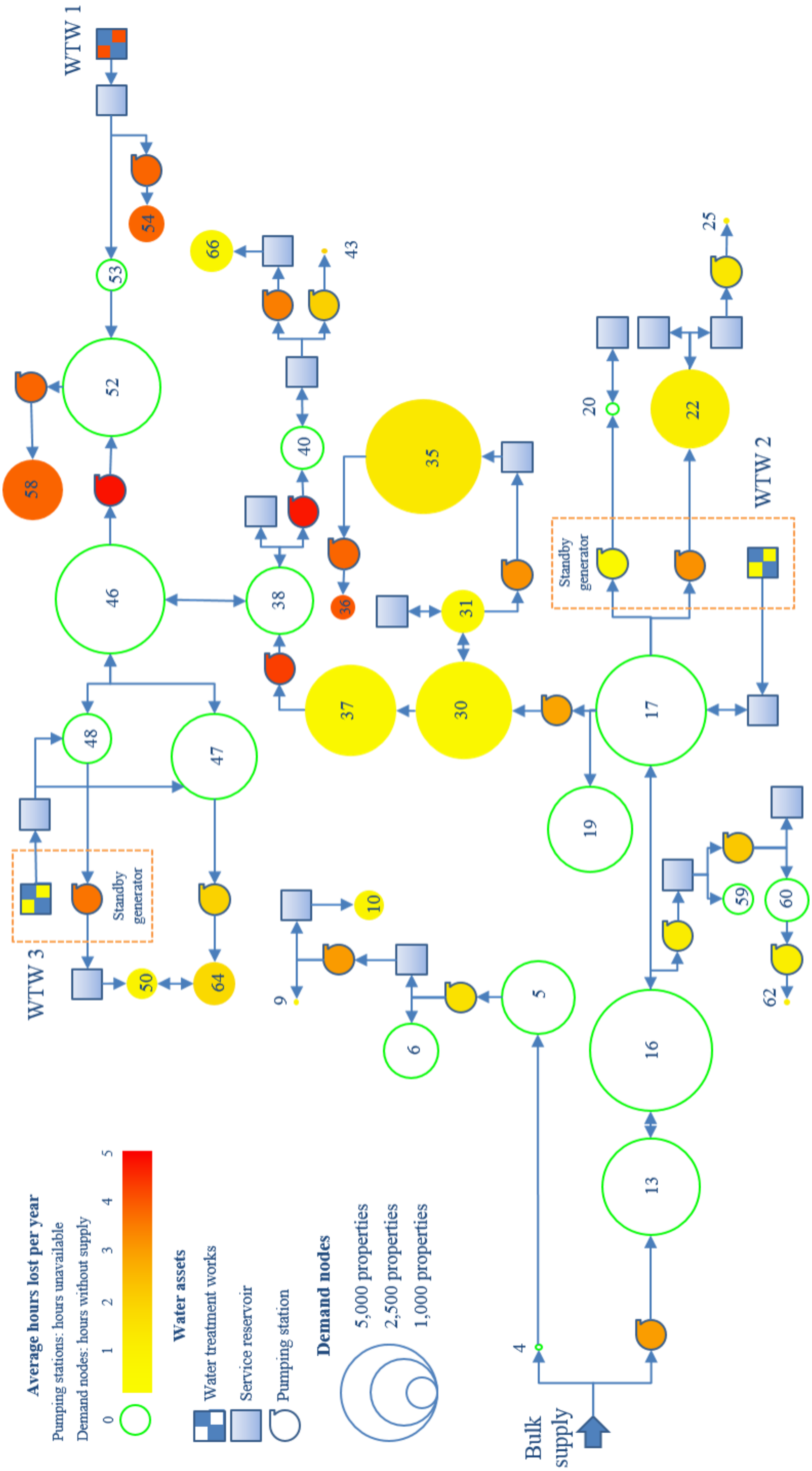


Figure 5.31 Network schematic showing the variability in risk. The labels attached to each node refer to the Node ID.

The nodes fed directly from sources never fail, despite three of the four sources depending on power (the fourth being the bulk supply from the aqueduct). It appears that the combination of standby generation and the storage in contact tanks is sufficient protection against even the most extreme events. It should be noted, however, that Chapter 4.5 expressed concern over the value used for the reliability of standby generators since there is a disparity between the peer-reviewed data and industry experience.

The annual average customer hours lost for the other categories are broadly comparable but the balances between likelihood and consequence are very different. Nodes fed directly from pumping stations fail frequently but affect few properties; nodes with service reservoirs fail rarely but affect many. This is partly because, as Figure 5.31 shows, directly pumped nodes are typically on the fringes of the network and therefore in less populous areas. However, the more meaningful interpretation lies in how the risk of supply interruptions has influenced the evolution of the network. If a larger population is vulnerable to pumping station failures then constructing a service reservoir to provide some emergency storage is a logical response. Therefore only small populations, where the investment in emergency storage is less beneficial, remain directly dependent on pumps. The service reservoirs are effective at reducing the frequency of failure but many properties are affected if supply is interrupted.

Can the contribution of the different hazards be identified?

Identifying the causes of failures is difficult because the model successfully represents the interactions of the complex system. It would be necessary to analyse each incident in detail to determine precisely which hazard causes a node to lose supply. This is incompatible with the resources available to infrastructure providers so a programme was written to identify which hazards had caused infrastructure facility failures since the start of each event. The start of an event was identified whenever a time step in which a facility failed followed a time step where all infrastructure facilities were operating normally.

Therefore Figure 5.32 does not necessarily show which hazards *caused* the customer to lose supply. Instead it shows which hazards caused facility failures in the hours before the customer lost supply. Whilst individual hazards dominate, it may nonetheless over-estimate how many failures occur as result of simultaneous hazards.

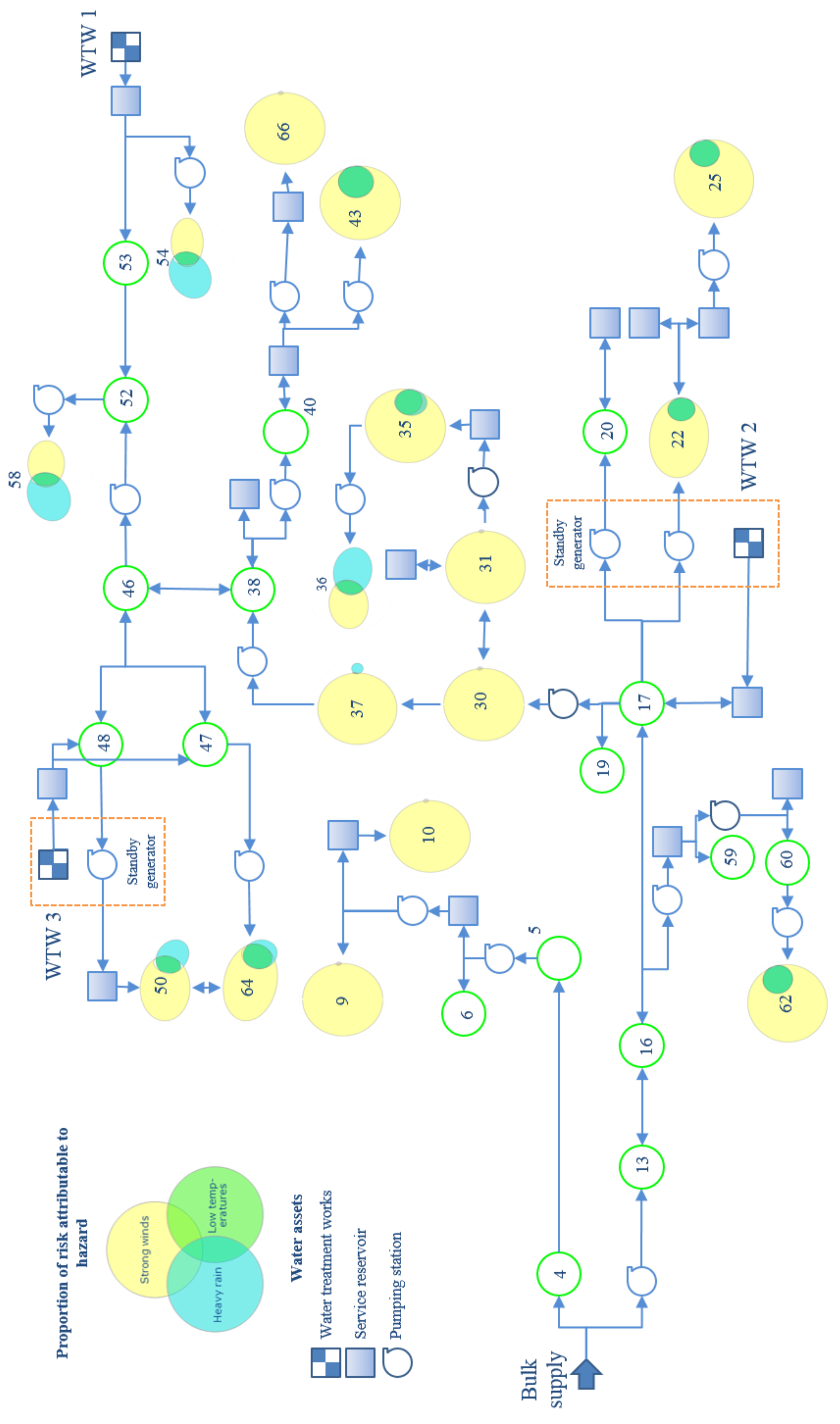


Figure 5.32 Network schematic attributing customer impact to hazards.

Timestep	Description
26316	i. Wind damage to a telephone line cuts the connection with one pumping station while simultaneously two roads are flooded. ii. Access to the telephone line is not affected and it is repaired within an hour and there is no onward affect. iii. In the following timestep a major substation is flooded causing 2918 customers to lose their water supply for 14 hours. The method for assigning failures to hazards means that this is associated with the strong winds though they are entirely independent;
355394	i. Wind damage to an electricity line occurs at the same time as two roads are closed by flooding, but the roads do not affect access to the damaged line. ii. Redundancy in the electricity network means the failure of this single line does not have any further effects.
402113	i. The road to one of the treatment works is flooded at the same time as wind damage to a telephone line disconnects a pumping station. ii. The dependent service reservoir empties over the following 13 hours, at which point 7336 customer lose water for 13 hours until the telephone line is repaired. iii. However, this prolonged repair is unrelated to the closed road and the event would have had the same impact regardless of the flooding.

For example, concurrent strong winds and heavy rain accounts for a small proportion of the risk but closer inspection reveals that the effects of the two hazards were not connected in any of the three events where they occurred simultaneously (Table 5.3). When the disruption is properly apportioned to the cause 70% is due to strong winds and 30% due to flooding, indicating that strong winds are again the dominant factor.

A much larger portion of the risk is assigned to the combined effect of all three hazards. This is almost entirely due to ice accumulation on overhead lines, in which case strong winds remain the primary cause of asset failures. The cold temperature and moisture are significant because they increase the vulnerability of the lines but the faults are not necessarily indicative of particularly extreme cold or heavy rain because ice accumulation is predicted whenever there is any rainfall and the temperature is below 2.5°C.

Strong winds occur uniformly across an area but the local geography means that flooding is concentrated in particular locations. Figure 5.32 shows that the spatial variation in the exposure of facilities is replicated in the risk to customer’s water supply despite the risk passing through multiple infrastructure sectors. Failures related to strong winds occur at all vulnerable nodes but heavy rain only affects five nodes. It is noticeable that the vulnerability is concentrated in the north of the area despite Figure 5.33 to Figure 5.36 showing that electricity, telecommunications and highways facilities across the entire region are exposed to flooding. The difference lies in the criticality of the facilities affected and the redundancy of the network.

This section has demonstrated that the model can apportion the impact of infrastructure failures to different hazards. Moreover it has shown that, whilst the local geography affects which facilities are exposed to hazards, the structure of the infrastructure network is equally important to the probability of the failure affecting customers.

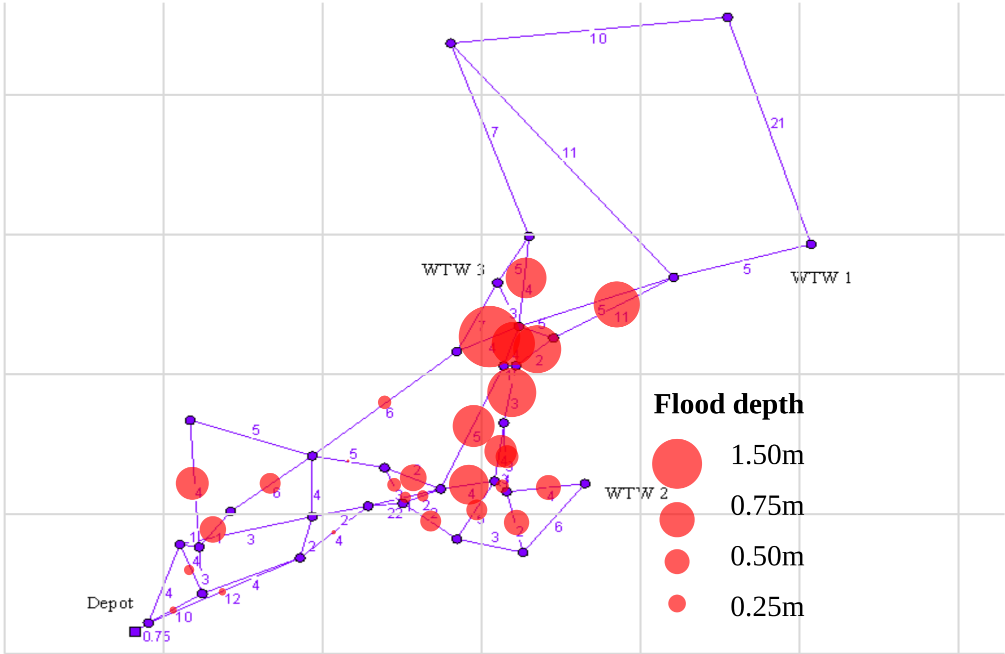


Figure 5.33 Flood depths for each highways link in a 100 year return period flood event. Note that many roads are flooded but the exposure is greatest in the centre of the region where most links flood to considerable depths. The links to and from WTW 3 may be particularly critical because they offer a bypass around this area.

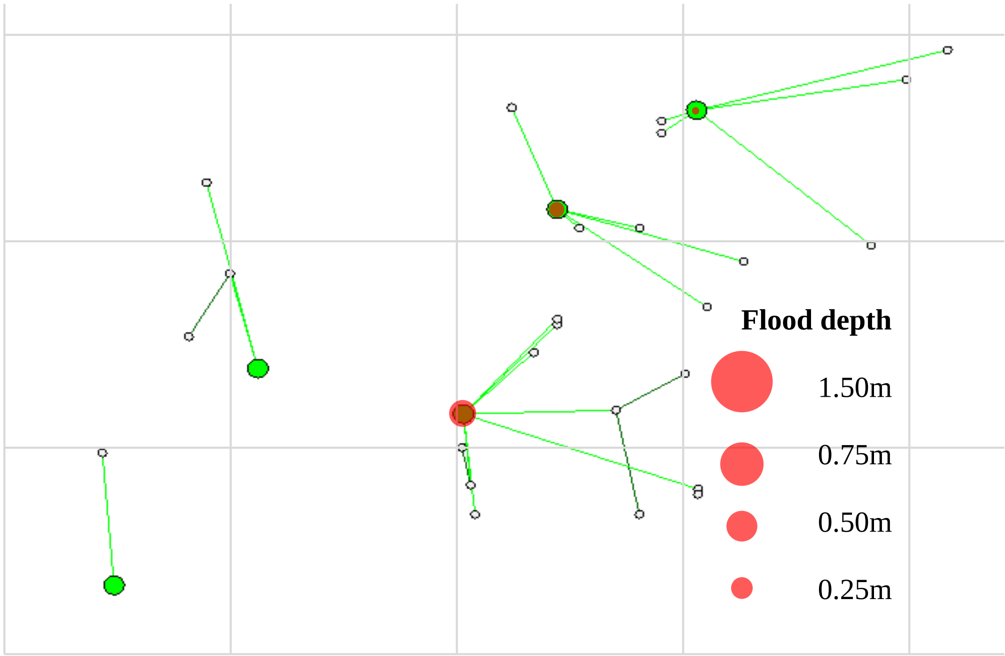


Figure 5.34 Flood depths at each telephone exchange in a 100 year return period event. The exposure is generally low; two exchanges do not flood and one only floods to a very low level. However the central exchange, which serves many water facilities, floods to a depth of approximately 0.5m.

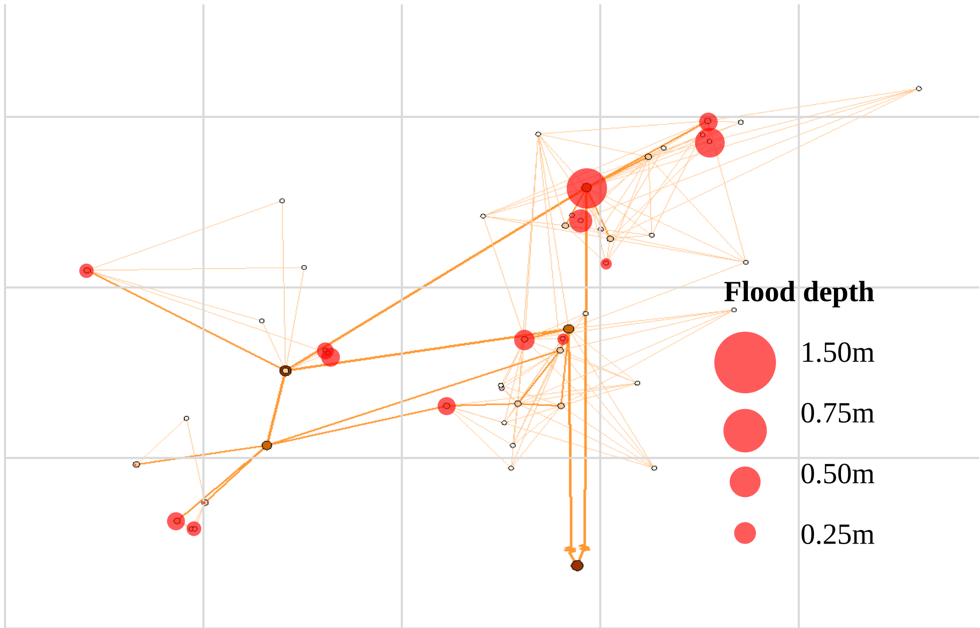


Figure 5.35 Flood depths at electricity substations in a 100 year return period event. A number of secondary substations are exposed to a depth of around 0.5m. Most notable is the bulk supply point towards the north of the region; it is a critical asset because few of the local primary substations have alternative sources and it floods to a depth of approximately one metre.

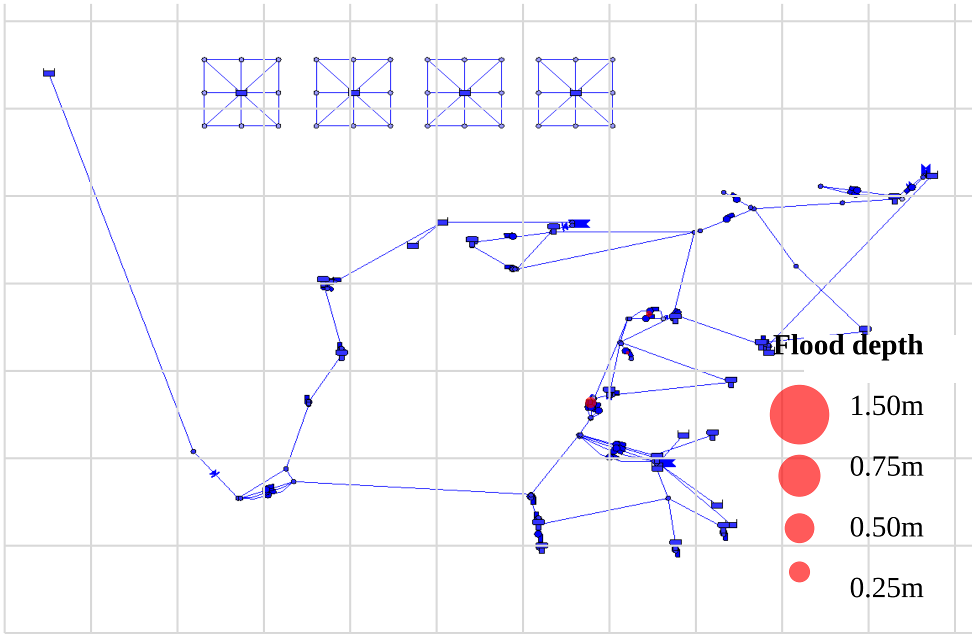


Figure 5.36 Flood depths at water facilities in a 100 year return period flood event. The exposure is low with only two pumping stations exposed to flooding and low depths in these two cases

Can the model identify which sector the risk is coming from?

The patterns discussed in the previous section are closely tied to the vulnerability of the electricity network and the consequent impacts on the water sector. It is therefore logical to ask whether particular sectors are more important than others.

Notably, no demand nodes lost water as a direct result of the hazards affecting water facilities. Figure 5.36 shows that two pumping stations are exposed to flooding but the more northerly, which only floods to a depth of 0.01m in a 100 year flood event, does not fail during the 1 020 year time series. The more southerly pumping station fails once but the storage in the service reservoir prevents this failure from affecting customers. This resilience cannot necessarily be generalised to all water networks as other areas, particularly those which are low and flat, may have a greater number of more critical pumping stations exposed to flooding. However, it indicates that the vulnerability of the potable water network is relatively low.

Figure 5.37 shows the risk at each node attributed to each individual or combination of infrastructure sectors. Note that, as in Figure 5.32, risk is attributed according to which sectors have caused infrastructure failures since the start of the event. Therefore it does not necessarily follow that a failure in that sector caused the property to lose water supply.

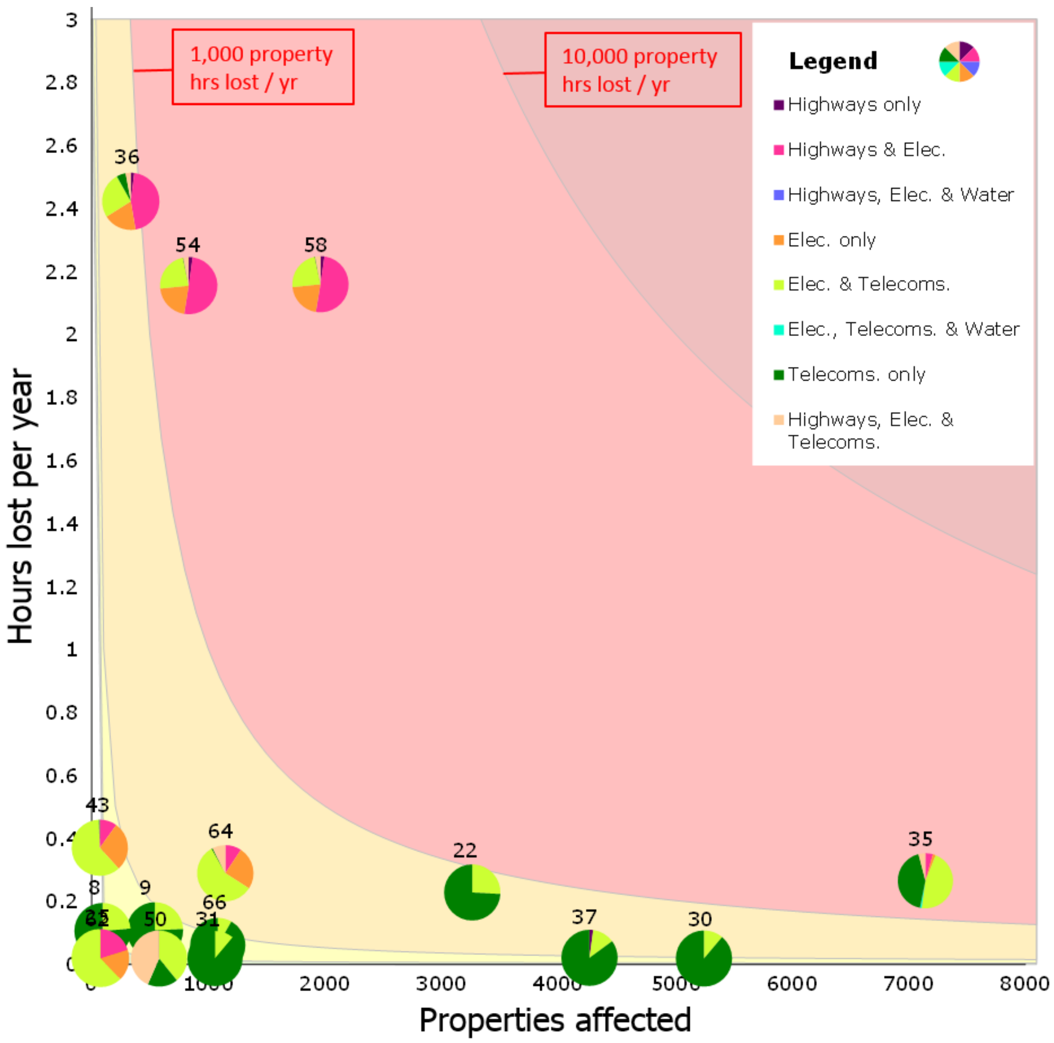


Figure 5.37 The attribution of risk to different sectors. Each pie chart represents one demand nodes in the water network, only those which fail during the simulation are shown. The number of properties supplied by each node is shown on the x-axis and the frequency of failure on the y-axis. The pie charts represent the proportion of the risk apportioned to each combination of sectors. The number above each pie charts indentifies which node it represents. The graph shows that Nodes 35, 54 and 58 should be the priorities for risk reduction strategies

It was previously noted that the demand nodes can be divided into three groups: i) those which never fail, ii) those which fail rarely but affect many customers, and iii) those which fail frequently but only affect a few customers. Figure 5.37 provides further support for the argument that service reservoirs protect large groups of customers whilst smaller groups of customers remain vulnerable. Moreover it shows that, as a consequence, different customers are vulnerable to failures in different sectors.

Nodes which depend directly upon pumping stations are the most reliant upon a continuous supply of electricity. This is evident for Nodes 36, 54 and 58 in Figure 5.37; in each case roughly 50% of the risk is attributed to the combination of highways and electricity and over 40% of the remainder is attributed to either electricity in isolation and electricity and telecommunications.

In contrast, Nodes 22, 37, 30 and 35 are supplied from service reservoirs and their failures are almost exclusively related to failures in the telecommunications network. It was suggested above that a large population at a node can justify the construction of a service reservoir to reduce the likelihood of customers losing supply. In this regard, Figure 5.37 shows that they were successful; if they failed as frequently as nodes 36, 54 and 58 then they would represent an intolerable risk to the company. More interestingly, Figure 5.37 shows that the provision of a service reservoir shifts the dependence from the electricity network to the telecommunications network. This is logical because, without telemetry systems, the relevant pumping stations are unaware that the service reservoirs are empty.

It is also noteworthy that, whilst the failures at Node 35 are mainly linked to telecommunications failures, a small proportion of the risk is linked to events where no telecommunications facilities fail. Similarly a small proportion of the risk to Node 36 is linked to telecommunications failures, not electricity facility failures. This can be explained by their position in a chain of pumping stations and service reservoirs (Figure 5.38); a long power cut to Pump 34 may cause Service Reservoir 34 to empty even if the telecommunications network is still operating. Similarly, the operability of the Pumping Station 37 is irrelevant if a telecommunications failure causes Service Reservoir 34 to empty. The cumulative effect of the vulnerability of a number of facilities may explain why these two nodes fail slightly more frequently than comparable nodes in Figure 5.37.

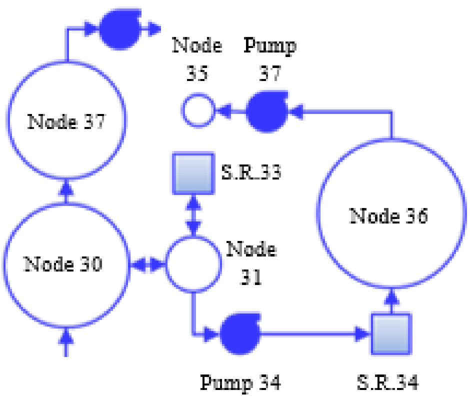


Figure 5.38 Nodes 35 and 36 form part of a chain of pumping stations, service reservoirs and demand nodes

Figure 5.37 is an effective way of communicating the risk allocated to different sectors at different nodes but it only identifies which sectors failed during each event, not whether they caused or contributed to the event. To gain a fuller understanding the model is re-run with an identical hazard time series and random number seed but different combinations of the three sectors are made invulnerable to the hazards and failures in other sectors. The aggregate results for all nodes, weighted by property count, are shown in Figure 5.39.

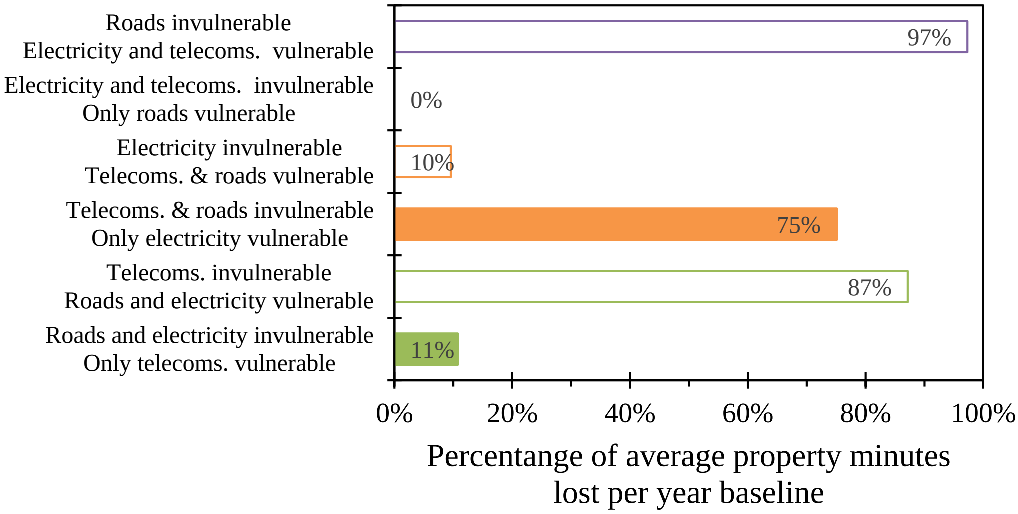


Figure 5.39 The effect of making different combinations of infrastructure sectors invulnerable to hazards compared with the baseline scenario where every sector is vulnerable. When the highways infrastructure is made invulnerable the risk drops by only 3% but, in contrast, an invulnerable electricity network reduces the risk to 10% of the baseline value. The complementary scenario where all other sectors are made invulnerable also indicates that the electricity network is significant but in this case the risk only falls by 25%. The telecommunications sector in isolation only contributes 11% of the baseline value.

The absence of failures when only the road sector was vulnerable is consistent with the design of the model; no facilities rely upon roads to operate so it does not have a direct effect. Nonetheless road closures can exacerbate the impact failures because they affect the recovery times of other infrastructure facilities. This is apparent in the fall in the risk when the sector is made invulnerable. The relatively small size of this reduction contradicts many of the reviews of historical events which often cite difficulties reaching sites as contributory factors (e.g. Horsfall et al. 2005, McDonald & Yerkess 2005). It questions whether the transport disruption materially affects the impact of an event, or whether the impact would be significant regardless but those involved in the event are more aware of the travel disruption because it affects them directly.

The significant impact of the electricity sector suggests that the resilience of the electricity network is pivotal to the overall resilience of the interdependent networks. This is reinforced by the results of the complementary scenario but the 15% difference between the two scenarios is evidence that the dependence of telecommunications upon electricity infrastructure has significant repercussions for the water supply.

The independent effect of telecommunications network failures is small but it is incorrect to argue that this sector is insignificant. Firstly, it has previously been shown that telecommunications failures infrequently affects water supply but the impact is often large. The nature of the regulatory penalties, with deadbands around performance commitments, means that small events could be inconsequential. In contrast, a large failure affecting thousands of properties could make it impossible to remain within the deadband and therefore trigger a large regulatory penalty.

Secondly, when this independent effect is combined with the cascading effects of power loss on telephone exchanges the combination accounts for 25% of the overall risk. This has important implications for how water companies manage the risks to their operations. The root cause of the failure is in the electricity network but one of the interventions to reduce its impact will be to increase the water infrastructure’s resilience to telecommunications failures.

Unlike the electricity network, the difference between the complementary telecommunications scenarios is unexpected because the model does not account for the dependence of electricity networks upon telecommunications. Whilst it is only small (2% of the total risk) it represents an anomaly that requires further exploration.

It is also noteworthy that the ideal way to show the results would be a diagram which shows how much of the total belongs to a particular subset more intuitively than Figure 5.39. Tree Diagrams, as used in Figure 5.29, and Euler Diagrams, as used in Figure 5.30, were considered but these rely upon the sum of the subsets being smaller than the total (i.e. the risk in a scenario where one or more sectors is made invulnerable must be less than the baseline scenario where all sectors are vulnerable). Figure 5.40 shows that this is not the case and the removal of sectors occasionally increases the frequency of failure.

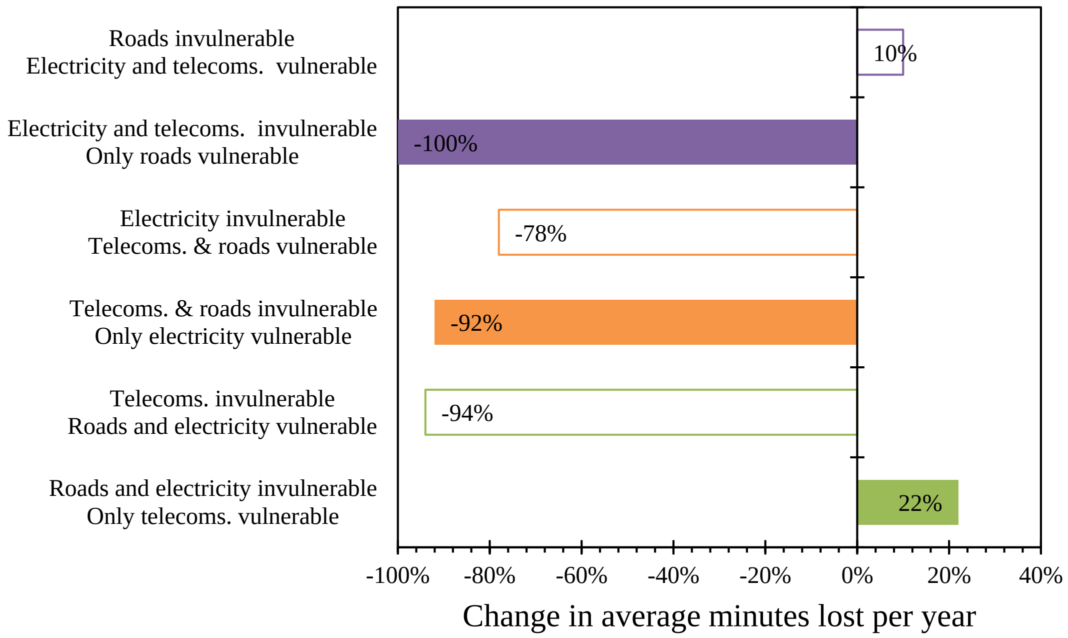


Figure 5.40 Changes in the frequency of failure at Node 37 when different combinations of infrastructure sectors are made invulnerable to hazards. Note how the risk in some scenarios rises.

This counter-intuitive behaviour occurs for two reasons:

i. The operation of pumps to supply a higher area when the supply to the lower area is jeopardised can cause the pressure in this downstream zone to drop rapidly (as was the case in Figure 5.27). This cannot happen if failures in another sector disable the pumps so the lower customer’s service is not affected.

ii. The hydraulic model runs through events in series so is path dependent and removing a failure can shift the course of events onto a different path. This principally affects service reservoirs which fill and empty in cycles. If the timing of the cycles is different, then the reservoir level may be lower at the next failure and therefore the system is more vulnerable

The 2% discrepancy between the complementary telecommunications scenarios in Figure 5.39 is also attributed to the model's sensitivity to small changes. Unfortunately it is impossible to determine what proportion of this difference is due to path dependency in the model and what proportion is attributable to the effect of active pumping stations drawing water from vulnerable areas of the network.

Nonetheless, this is strong evidence that the model is capturing the behaviour of the system. Blockley et al. (2012) described how the complex behaviour of large, interconnected systems can arise from what are individually quite simple processes. They state:

> *"It has been discovered that they [complex systems] may be very sensitive to very small differences in the initial conditions and may contain points of instability where paths diverge" (Blockley et al. 2012, p15)*

Creating a model which can identify these patterns is an important step towards understanding how small perturbations can have a significant impact.

In general, this section sought to establish whether the model could identify which infrastructure sectors have the greatest effect on the resilience of the water supply. In many regards it has shown the model is successful; it identifies that the highways network is largely irrelevant and that the electricity network is the primary cause of supply interruptions. It also shows that the telecommunications network is a significant source of disruption, and 60% of this risk is due to the network's dependence on the electricity network. Finally it shows that the structure of the water network affects the relative importance of the different external sectors. The challenge is extracting this understanding from the model outputs; the results reflect the complexity of the real-world systems and it is difficult to separate the meaningful patterns from the random behaviour of a stochastic and path-dependent model.

5.3 Discussion

"Models are built to answer specific questions; they must be as simple as possible but as complex as required." (Haimes 2012, p334)

The goal of this thesis is to develop risk assessment methods which are useful to these infrastructure providers. Chapter 2 established that infrastructure providers require models which are precise enough to identify effective investment options and accurate enough to justify these decisions to the regulators. In addition, the usefulness of the model, and hence its value, is determined by a balance between the uncertainty of the results and how difficult it is to obtain these results. This section addresses these latter two points in turn.

5.3.1 How accurate and precise is the risk assessment?

Chapter 3 discussed how the usefulness of the existing models of infrastructure interdependency are limited by their lack of realism. The omission of crucial factors such as flow in the networks, capacity constraints and the effects of storage mean that they only deliver generic information which cannot be applied to specific networks.

The framework applied in this model offers substantial advances in this area. The previous section showed that it is capable of assessing the relative importance of different hazards and different infrastructure sectors. It also showed that the structure of the water network itself has a defining role in its resilience. Most importantly, by perceiving which customers are most vulnerable and why they are at risk, the model can identify where investment should be directed.

However every model is, by definition, a simplification of a real-world system and therefore cannot be completely realistic. The model is effective at discerning the relationships between the different hazards and infrastructure sectors but it is impossible to validate the outputs. Chapter 5.2.1 compared the model outputs with water companies' AMP6 performance commitments and identified a number of uncertainties. Sanders (2005) argues that the chaotic nature of complex systems exposed to extreme events often results in some form of decision making stalemate. To move forward it is necessary to understand the processes in action and the uncertainty which surrounds them.

Uncertainty propagation is a problem wherever models are formed from cascading components (Kay et al. 2008, Beven & Lamb 2014), but Sampson et al. (2014) argue it is particularly important in the context of catastrophe modelling due to the focus on extreme events. They show that uncertainties surrounding data can have a dramatic effect on the total loss predicted by models.

It is important to be able to communicate the effects of uncertainty to the decision maker.

> *"The challenge for users of these models is to understand the nature of the uncertainties involved, and the fact that the models are meant to provide credible rather than highly accurate predictions of losses."* (Pita et al. 2013, p101)

Knowledge about the sources of uncertainty not only supports better informed decision making but also means that future studies can address the most potent sources (Bosshard et al. 2013). The following paragraphs identify the key sources of uncertainty in the model.

Importantly, the model shows that a large proportion of the data required for modelling the vulnerability of infrastructure to hazards is available. For example, it has produced a suite of fragility curves which describe the vulnerability of key UK infrastructure sectors to the principal hazards they face (Figure 5.41). Table 5.4 shows, however, that there remain a number of areas which rely on relatively weak assumptions or questionable data.

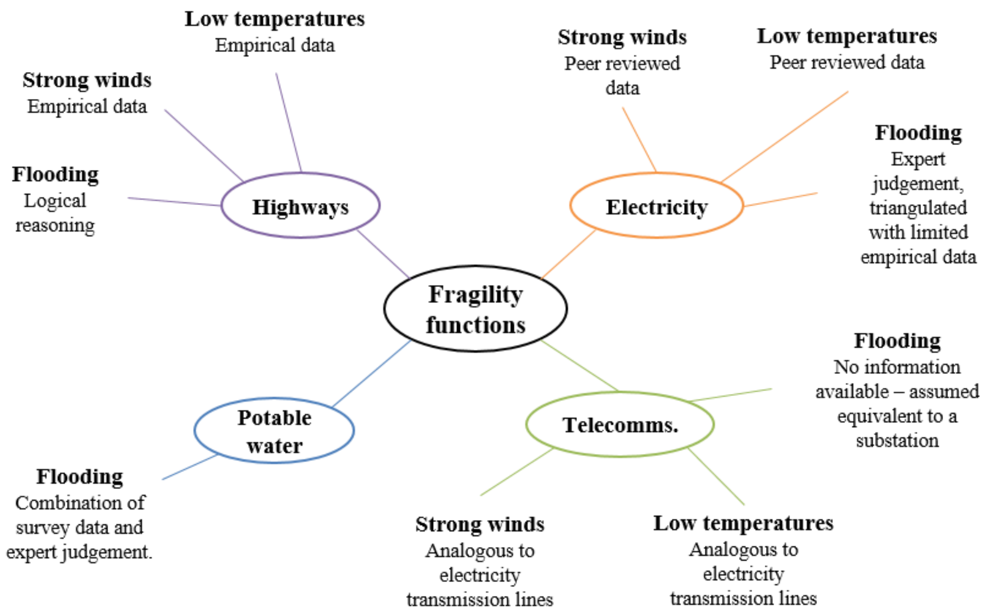


Figure 5.41 Provenance of the fragility curves used in the model

Table 5.4 Assessment of the confidence in each model input and comments upon the associated uncertainty

Model component			**Comments**
UKCP09 weather generator			Peer reviewed and widespread use.
ARMA wind model			Solid method but concerns over extreme values being too high.
Flood risk assessment			Makes a number of simplifications but the frequency of events is accurate.
Fragility curves	Flooding	Highways	Based upon clear logic, triangulated with a number of sources.
		Electricity	Curves drawn using expert opinion, validated with a small set of historical failures and near misses.
		Telecoms.	Assumed to equivalent to electricity substation. Very limited supporting empirical evidence.
		Water	Solid method, but no supporting empirical evidence.
	Excessive cold	Highways	Based on good empirical evidence but could be improved with a longer record (currently 8 years) and more information on local roads.
	Strong winds	Highways	
		Electricity	Peer reviewed data.
		Telecoms.	Based upon the electricity network data, combined with two empirical records for telecoms. networks.
Recovery times	Highways		Based upon good empirical evidence.
	Electricity		Based upon peer reviewed studies of past events but there is limited consensus.
	Telecoms.		Very limited supporting evidence – only two data points which do not align.
	Water		Expert opinion of experienced water company employees.
Alternative power supply reliability			Peer reviewed data, but the values seem inconsistent with industry experience.

Some gaps, particularly regarding the fragility of facilities, arise simply because the information does not exist (e.g. fragility curves for pumping stations). This can be partly ascribed to the differences between the insurance industry, where catastrophe modelling originated, and infrastructure sectors. The insurance industry has a clear commercial interest in assessing damage after an event because it determines how much is paid to claimants. In contrast, infrastructure providers rarely collect the data themselves because their primary focus during an incident is restoring services to customers. Moreover, the insurance companies capture little information on infrastructure because infrastructure owners and operators often chose to self-insure against operational risks (Willis 2006, Marsh 2013). This is an area which the project sponsors might wish to address.

A second issue is where information which may exist relates to third party infrastructure and is not publicly available (e.g. the vulnerability of telephone exchanges to flooding). Yusta et al. (2011) discuss critical infrastructure information sharing in some depth. They argue that sharing information enhances owners and operators ability to assess risks and take actions to protect their infrastructure. They also reference obstacles such as commercial sensitivity, the proprietary nature of some information and security concerns. However, the experience of this case study is that (if the right person is asked the right question) third party infrastructure providers are generally willing to share information. The terms of reference for Local Resilience Forums, set up under the 2004 Civil Contingencies Act, includes provisions for sharing information:

> *"Category 1 and 2 responders are empowered to request information from another responder in connection with a duty under Section 2(1) or 4(1) of the CCA [Civil Contingencies Act] or another function which relates to an emergency" (Cabinet Office 2013, p29)*

The challenge is storing this information in a way which makes easy to understand what is available and easily accessible.

The final input of concern is the ARMA model used to generate a synthetic time series of gust wind speeds. It has been noted that this method produces a small number of very high wind speeds and this may be a contributory factor in the overestimation of the risk. Modelling extreme wind speeds is an active area of research (Vickery et al. 2009, Pita et al. 2013) and the broad scope of this project has prevented this topic from being explored in greater depth. This is a strong candidate for further work.

In addition to uncertainties attached to the impacts of hazards on infrastructure, there are also uncertainties related to the models of how infrastructure networks respond to failed facilities.

Some are epistemic and relate to the limited information about some of the infrastructure sectors. The highways and water networks used in the model are accurate (they are based upon up to date information from the Ordnance Survey and project sponsor respectively) but the electricity and telecommunications networks rely on a number of assumptions. The structure of the electricity network is available through the Distribution Network Operator's Long Term Development Statement, but there is less information on the capacity and configuration of the network. More conspicuously, no data was found describing the telecommunications network so the model relies on knowledge of the location of exchanges and the generic structure of the UK public switched telephone network.

Like data on the fragility of infrastructure components, this gap can be addressed through information sharing between infrastructure sectors. However, it is likely to be more problematic because information on the structure and capabilities of infrastructure is more valuable to anyone seeking to cause intentional harm. By contrast, information on the vulnerability of facilities to natural hazards is relatively inert.

There is also aleatory uncertainty related to the unpredictable behaviour of humans, both customers and operators, interacting with the infrastructure systems. These interactions were excluded from the model scope because they are too unpredictable to represent with precision and a tolerable level of complexity. However, Haimes (2012) argues that since systems interact with humans it is important to account for their behaviour.

The human components of complex networks are both the most likely point of failure and the most adaptable and resourceful components of a response to failures (Stapelberg 2008). On one hand, errors are more likely during an incident because operational staff are working under pressure with only limited information. For example, one area may be accidently isolated whilst reconfiguring the wider network, or changing the flow through a main may cause discolouration.

The resourcefulness of operators in response to incidents is also an important omission from the model. Referring back to the Cabinet Office's four-box model of resilience (Chapter 3), the ability of staff to rezone customers on to different supplies is an important example of response and recovery enabling redundancy. It is therefore a vital component of the system's resilience and likely to be the key contributor in the overestimation of the risk which was identified in Chapter 5.2.1.

However, this aspect of resilience remains very difficult to incorporate into a model because it is impossible to incorporate every potential action of the operator. A model of how infrastructure operators respond to incidents, drawing on the fields of accident theory and risk management (e.g. Hollnagel 2004, Hollnagel et al. 2006), would make an interesting area for research but is far outside the scope of this project.

The previous paragraphs have outlined the principle sources of uncertainty in the model. They have also, in most cases, identified ways of gathering more data to reduce the uncertainty. A significant omission, however, is the quantification of this uncertainty; Juston et al. (2013) argue that the feasibility of reducing uncertainty can only be judged when it is quantified. However, this requires multiple simulations and is not feasible with a model, such as this, which takes a number of hours to run a single realisation. Therefore the sensitivity of models of infrastructure dependency is explored using the second model described in Chapter 6.

5.3.2 How hard is the risk assessment to complete?

The model successfully produces a more realistic representation of infrastructure interdependency. A more realistic model, however, almost inevitably means a more complex model, and the model's usefulness is equally dependent upon the tractability of the model and its outputs.

The challenge of interpreting the model outputs is apparent in the previous chapter's attribution of risk to different infrastructure sectors. Figure 5.37 is an intuitive presentation of the water infrastructure's dependencies but does not identify the precise root cause. Conversely, Figure 5.39 is more precise but produces a complex set of combinations and anomalies.

The anomalies and counter-intuitive outputs are evidence that the model is beneficial. They reveal complex behaviour and provide insights into the resilience of the systems that are unlikely to have been foreseen by the existing risk assessment methods. For example, Figure 5.26 shows that the impact on customers of one asset failure can be reduced if another asset fails at the same time. Equally, some of the results question preconceptions such as that disruption to the highways network can exacerbate incidents by delaying the recovery of facilities. Figure 5.39, albeit with only the support of one case study, indicates that this impact is negligible.

Nonetheless, this insight must be balanced against the ability of the decision maker to understand the model. Modelling develops our appreciation of how the subject system operates and where our knowledge is limited (Gilbert & Troitszch 2005, Juston et al. 2013). A model which is too complicated loses this advantage and is less valuable because understanding the processes operating in systems is key to good decision making (Sanders 2005, Brown & Elms 2015),.

Blockley et al. note that ‘if a situation is considered too complicated there is a danger that organisations may not react at all’ (2013, p15) and there remains an open question over whether the effort required to run the model and interpret the results for every system is within the sponsor’s capabilities and appetite.

On one hand, the water companies have the capabilities to undertake complex analyses and manage decision making processes which involve large uncertainties. This is evident in the water resources planning processes. Furthermore, a concerted effort to collect missing data could address many of the weaknesses discussed in the previous section relatively quickly. If vulnerability to third party infrastructure system failures became a critical issue for water companies, for example if it was placed in the political and media spotlight by a major incident, this model offers a credible solution.

On the other hand, the current level of concern does not match the effort required to follow such a detailed and time consuming approach. Nonetheless, this does not remove the requirement for a risk assessment method which was identified in the Chapter 2.

There are clear ways in which this model could be improved. Firstly, it could be reconstructed to produce results more quickly. It currently runs in a combination of Microsoft Excel and EPANET and a scenario runs in approximately 36 hours on a typical office laptop. The running time could be reduced by replicating it in a more powerful language and employing a more powerful computer. Secondly, the user interface could be improved to allow the decision maker to understand the process more clearly and interpret the outputs more easily. Nonetheless, a less complicated model may be better suited to providing water companies with the breadth of information that they require.

5.4 Summary

Chapter 4 developed a catastrophe modelling / PBD approach for modelling the water sector's dependence upon electricity, telecommunications and road networks, and understanding how the impacts of low temperatures, heavy rain and strong winds on these networks could have cascading consequences in the water sector.

This chapter has applied this model to a water network serving approximately 175 000 people and calculated the effects of a synthetic 1 020 year time series of hazards. It estimates that dependency on other sectors will, on average, cause customers in the area to lose their water supply for ten and a half minutes a year. Comparisons with UK water companies' performance commitments (Figure 2.10) indicate this is a marginal overestimate and four potential sources of error are identified: ii) the wind model produces high wind speeds; ii) EPANET may overestimate the risk because it is not designed to operate under pressure-deficient conditions; iii) the model does not include the ability to rezone customers onto different supplies; and iv) there is uncertainty over the parameters of the fragility and recovery curves.

The model's particular strength lies in identifying the sources of risk. It attributes 75% of this network's risk through interdependency to strong winds; the threat of flooding is more localised and therefore smaller (Figure 5.32). Equally, 90% of the risk is due to failures in the electricity network but a proportion of this risk is due to failures cascading through the telecommunications infrastructure (Figure 5.39). The model also indicates the how the structure of the water network determines its vulnerability. Nodes fed directly from pumps depend upon electricity whereas those supplied from service reservoirs are vulnerable to failures in the telecommunications network (Figure 5.37). Crucially, the model identifies complex system behaviour that is unlikely to be identified by conventional risk analysis (Figure 5.40). For example, it shows that deactivation of pumps due to a failure can reduce the impact of an incident because it protects the upstream network. Counter-intuitively, making these pumps more resilient increases risk.

The main weakness of the model is its complicated nature. It delivers a risk assessment enabling the identification and prioritisation of threats but a significant investment of time is required to implement the model and interpret the results. The computational cost also limits the exploration of alternative scenarios and sensitivity analysis. It is therefore best used to assess specific risks rather than for broad explorations of potential vulnerabilities.

Chapter 6. Model 2: Development & Case Study

This chapter develops an alternative, less complicated model of the water sector's dependence upon third party infrastructure which will support a broader exploration of the system's potential vulnerabilities. The focus moves from estimating the expected impact over a given timescale to identifying the potential for low probability, high impact events.

The hazard model and fragility curves from Model 1 are replaced with the 'reasonable worst case scenarios' published by the Cabinet Office (2011a) and a stocks and flows model is developed in the place of the full hydraulic model. The aim is to produce a model that it is computationally less expensive, easier to interpret, and more straightforward to transfer to other areas.

This model is also applied to a real-world case study, though a different area is used to reflect the contributions of the multiple project sponsors. Two scenarios (inland flooding and hot / dry weather) are used to assess the model's ability to identify the range of potential impacts, which factors are significant in causing these and whether there are tipping points. The model is also used to explore the sensitivity of impacts to changes in model parameters and assumptions about the interfaces between networks.

The first model created a realistic representation of the risks to real-world water supply networks due to dependency on other infrastructure sectors. It was successful in many regards but, as the previous chapter discussed, also has limitations. The outputs are difficult to interpret due to the model's complexity and the time taken to run a scenario reduces the ability to explore alternative scenarios or perform sensitivity analyses.

Further discussions with the project sponsors established that their principal anxiety is understanding the nature of their dependencies on other sectors and the size of the impacts arising from failures in these other networks. Identifying the potential for 'surprises' - threats that emerge from interactions between system components – is critical to managing infrastructure's vulnerability to 'low probability, high impact' events (Blockley et al. 2012). These events are informative because they reveal the inherent vulnerabilities in complex systems; in lesser events the latent weaknesses in the system are more likely to remain concealed (Rogers 2012). The challenge of low probability, high impact events is that precise quantifications of likelihood and consequence are unreliable (Bristow et al. 2012).

This is reflected in the UK Government's guidance on improving the infrastructure resilience. Their *Keeping the County Running* guide (Cabinet Office 2011a) established eight 'reasonable worst case scenarios' which detail the plausible intensity, duration and spatial scale of the natural hazards which they judge are most likely to affect UK infrastructure within a five year horizon.

> *"These reasonable worst case scenarios represent an upper limit on the risks for which the Government plans and against which infrastructure owners and operators can reasonably be expected to build resilience" (Cabinet Office 2011a, p23)*

It is therefore important that infrastructure providers can assess their resilience against these scenarios, including their potential effects on third party infrastructure systems upon, even if they have insufficient data to perform quantitative risk assessment. The primary goal of this chapter is to support this process by developing a model which can explore the plausible range of impacts arising from scenarios and identify how these impacts can be reduced. The first section of this chapter describes the development of this model and the second section applies it to two 'reasonable worst case scenarios'.

A secondary goal of this chapter is to use this model to analyse the sensitivity of event impacts to the parameters and assumptions used in modelling interdependent infrastructure systems. Understanding this sensitivity is important to assess the uncertainty attached to the results from models of interdependent infrastructure systems and to guide future work. This is described in the third section of the chapter.

6.1 Approach

6.1.1 Application of the 'reasonable worst case scenarios'

Each of the Cabinet Office scenarios outlines the characteristics of the scenario (e.g. "major fluvial flooding affecting a large, single urban area" Cabinet Office 2011a, p62) and the potential impacts on infrastructure (e.g. loss of primary transport routes, loss of power supplies etc.). This information can replace the hazard model and fragility curves in Model 1 by setting a plausible range against each of the impacts. This will achieve the aim of understanding what influences the consequences in a given scenario.

Applying the reasonable worst case scenarios in the place of a hazard model has the additional benefit of reducing the overall model's complexity. Moving away from continuous sampling towards multiple realisations of scenarios reduces the challenges associated with extracting critical events from the lengthy record and unravelling any non-intuitive behaviour. This will allow more accessible information to be presented to the decision maker and therefore provides additional value to that of Model 1.

6.1.2 Choice of system dynamics modelling

To model the scenarios it is proposed to move away from bespoke network models towards a system dynamics (SD) framework. The applicability of the approach to interdependent infrastructure has been recognised in the reviews of potential methods (Eusgeld et al. 2008, Yusta et al. 2011, Ouyang 2014) though the literature contains few examples of its application.

The Australian 'Critical Infrastructure Protection Modelling and Analysis Program' (CIPMA) has gathered data from infrastructure providers and created a set of SD models to examine the knock-on effects of failure in the Australian infrastructure (Stapelberg 2008, Australian Government 2010). These models can either be run as individual sectors or combined to assess interdependencies (Buxton 2013).

Min et al. (2007), working at Sandia National Laboratories, demonstrate that a large system dynamics model of interdependent infrastructure, comprised of over 5 000 variables, can be optimized to minimize the economic impact of a disruptive events.

CIPDSS was developed by a collaboration between Sandia, Los Alamos and Argonne National Laboratories at around the same time. It created a decision support system to help government and industry explore the impact of disruptions on critical infrastructures and has been applied to a range of scenarios including agricultural pathogens and telecommunications outages (Bush et al. 2005), power outages (Conrad et al. 2006), influenza outbreaks (Fair et al. 2007, Le Claire et al. 2007) and transport disruption (Santella et al. 2009).

The structure of an SD model is well suited to infrastructure and interdependency. Firstly, they are composed of a set of inter-related variables mirroring infrastructure as a set of inter-related facilities. The initial step of constructing a model is to understand how the elements of a system interact. This can be summarized by a causal link diagram (e.g. Figure 6.1) which shows whether variables have a positive or negative effect on each other.

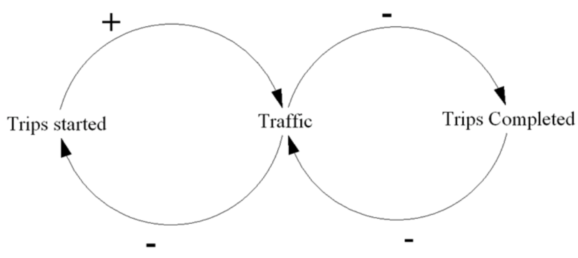


Figure 6.1 Example of a simple causal link diagram

The dynamics of the system arise from the feedback loops that these relationships create; either positive where the behaviour of the system accelerates, or negative when the influences counteract each other and the system remains stable (Sterman 2001). The left hand loop in Figure 6.1 is a negative feedback cycle; new trips add traffic to the system but as the congestion increases fewer vehicles start their journeys. In contrast, the right hand loop is a positive feedback cycle; completed journeys remove vehicles from the traffic, but a congested network reduces the rate at which they reach their destination. These relationships do not have to be physically based; SD modelling is often chosen because the physical processes are too complex to model and therefore empirical relationships between cause and effect are established instead.

The second similarity between infrastructure networks and SD modelling is the concept of stocks and flows. The purpose of infrastructure networks is to transmit goods, whether they are information, energy or tangible products, from a point where they are plentiful to where they are needed. Therefore stocks of goods, and their movement, must be central to a model of infrastructure.

This is reflected by the development of a causal loop diagram into a stocks and flows diagram capturing the movement of commodities through the system. Figure 6.2 shows an example from the CIPDSS project which had previously been interpreted as a causal loop diagram in Figure 6.1.

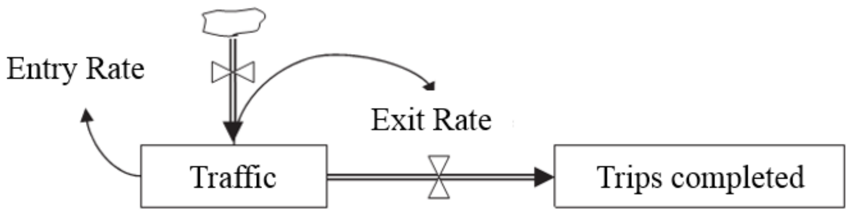


Figure 6.2 Simplified example of the model used to represent road traffic in CIPDSS (Santella et al. 2009). This simple model contains two stocks – the number of vehicles in the network and the number of completed journeys – and two flows – the number of vehicles entering the network and the number leaving. The rate of both of these flows is influenced by the number of vehicles in the network.

A quantitative SD model imitates a system of differential equations but time is measured in discrete time steps rather than continuously which enables a wider range of functions to be used (Gilbert & Troitszch 2006). This is useful in the context of infrastructure resilience because it allows system dynamics to be merged with event based simulation; events leading up to disruption are typically continuous (e.g. a flow of resources to a consumer, the storage level in a reservoir etc.) but the onset of disruption is normally a discrete event (e.g. power is lost, the reservoir empties etc.). A framework based upon discrete time steps can include these events and their impacts, whether they are instantaneous or subject to a delay.

The model's sensitivities, assumptions and uncertainties are important to decision makers (Sanders 2005) but can be obscured if a model is difficult to use or the results are difficult to interpret. A criticism of the previous model was that it was difficult to communicate the complex system behaviour to the user. By contrast, many SD models have been designed to engage with users and decision makers (Voinov & Bousquet 2010).

Ouyang (2014) identifies four weaknesses of SD modelling:

i. The causal loop diagram describing the relationships between variables relies upon the modeller's knowledge and interpretation.

ii. Large amounts of data are required for calibration and this data is often inaccessible.

iii. It only analyses the system level behaviour and does not address the interactions between components.

iv. The lack of data limits validation efforts.

The first and third weaknesses are not a substantive concern for this work because the causal relationships at a facility level are physically based, albeit at a simplified level (i.e. stocks and flows models conserve mass but not energy like hydraulic model such as EPANET).

The most significant concern therefore is calibration and validation of the model outputs. The focus on plausible consequences and understanding the relationships between variables means that this is a less pressing concern than in the previous study.

6.2 Method

The structure of this model reflects the concept of infrastructure as a system-of-systems (Hall et al. 2013, Agarwal et al. 2014) and has two distinct layers.

i. The lower level is composed of a set of standard system dynamics models for each type of water facility (e.g. service reservoir, pumping station etc.) which can be duplicated for individual facilities. Each input variable on these standard models correspond to fields in the sponsor's asset inventory allowing data to be imported quickly and making it easier to replicate the model across an infrastructure provider's organisation. The templates for these models are described in the following section.

ii. The higher level connects the completed templates for each of the facilities together to form the wider infrastructure system. This higher level model includes the interdependencies between water facilities and their dependence upon the third party networks. This is discussed in the subsequent section.

6.2.1 Templates for water facility models

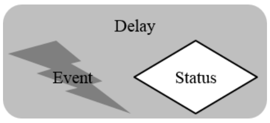
This sub-section outlines the three templates used to model facilities in the water network. In many regards they are similar to a conventional flow chart but the feedback loops and interdependencies between variables mean that conventional flowcharts quickly become unwieldy. The templates contain the four types of variables shown in Table 6.1. In addition, to aid interpretation, the diagrams on the following pages classify the links between variables into five types according to their effect on the affected variable. These are shown in Table 6.2.

The numbers used in the following descriptions correspond to the red numbered labels in each of the diagrams. SIPOC tables, like those provided for the first model in Chapter 4, in Appendix D provide detailed information on the exact rules followed by each component.

Table 6.1 The types of variables in the model

Variable	Description
Input data	Fixed numerical or categorical data which describe the specific characteristics of the facility, e.g. capacity or automatic versus manually controlled.
Stock or flow	A measurable quantity or flow e.g. the level in a reservoir or output a pumping station is programmed to produce. Blue variables only interact with variables within the same template. Yellow variables denote a dependency on another facility in the wider infrastructure system e.g. the water available from an upstream reservoir or the demand for water.
Status	Binary information about a state of operation or knowledge e.g. Does the facility have power? Are staff aware of the situation on this site? Again, blue variables are internal to the template and yellow variables connect to external factors.
Event	An instantaneous occurrence which triggers a change in another variable but can be subject to a delay e.g. the loss of telemetry means that staff need to visit the site but the change in status is delayed by their travelling time.

Table 6.2 The links between variables in the model

Causal link	Description
	Informs / controls
	Enables
	Triggers
	Flow of water
	Delay

Emergency storage reservoir / Contact water tank / Service reservoir / Critical reservoir

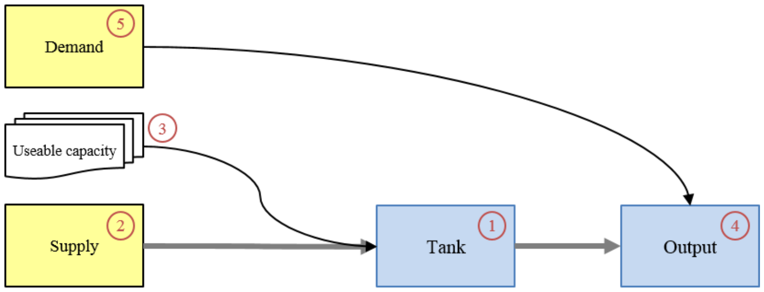


Figure 6.3 Template for emergency storage reservoirs, contact tanks and service reservoirs.

Reservoirs are modelled very simply and consist of a stock (1) whose level is influenced by three variables:

a. The supply from upstream (2).

b. The capacity of the tank which limits how much can be stored (3).

c. The outflow (4) which, in turn, is dictated by the demand of downstream customers (5).

Raw Water / Booster Pumping Station / Water Treatment Works

Raw water pumps and booster pumping stations in the treated water distribution network fulfil identical functions and therefore fit the same template. The use of the same template for water treatment works is less intuitive but their dependencies on third party infrastructure are equivalent: they require power to operate; they are generally controlled by telemetry (this company has invested in automation and remote control to reduce the need for sites to be staffed) and staff require access to repair equipment.

One difference is the treatment works' additional dependency on the physical delivery of the chemicals required to treat the water. However, like the first model, this is outside the scope because there are too many uncertain factors such as the stockpile held on site and the rate of consumption.

These facilities are the parts of the network which are vulnerable to interdependency. These dependencies, coupled with the controls in place to manage these dependencies means that this template (shown in Figure 6.4 overleaf) is more complicated.

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The output of the facility (1) is zero if there is no power to the facility (2). Otherwise, the output is the lesser of the flow it is set to produce (3) and the available resource (4) (i.e. the volume held in the upstream reservoir).

There are two types of setting in the model (5):

- Flow controlled facilities are set to achieve a particular flow which matches either an operational plan or the demand of a particular area (6). The setting cannot exceed the facility's capacity (7).
- Level controlled facilities operate to maintain the level in a reservoir (8). If this drops below the lower threshold (9) then the setting equals the facility capacity (7). The setting returns to zero if the level reaches the upper set point (10).

Regardless of these intended outputs, the setting is only changed if there are the means to do so (11). Settings can be changed remotely if there is the technology to do so (12) and a telemetry connection to relay the instruction (13). Alternatively, all settings can be changed manually if staff are on site to make the adjustment (14).

Staff are triggered to make their way to a site if either telemetry (13) or grid power (15) are lost; these would be recognised by alarms in the central control centre. The delay between the power or telemetry being lost and the staff arriving is determined by the time it takes to reach the site (16).

The loss of grid power will also trigger a requirement for an emergency mobile generator (17) providing that:

a. A permanent generator is not already available (18).
b. There are the provisions to connect and run the mobile generator safely (19).
c. The telemetry system is operating or staff are on site to recognise the requirement for the generator (20).

The generator becoming available is delayed by the time it takes to reach the site (16).

The final part of the jigsaw is the availability of power to the site (2). This is the case if there is either mains power, a fixed generator or a mobile generator on the site. It is assumed that all generators start reliably to prevent increasing the model's complexity by introducing a stochastic variable.

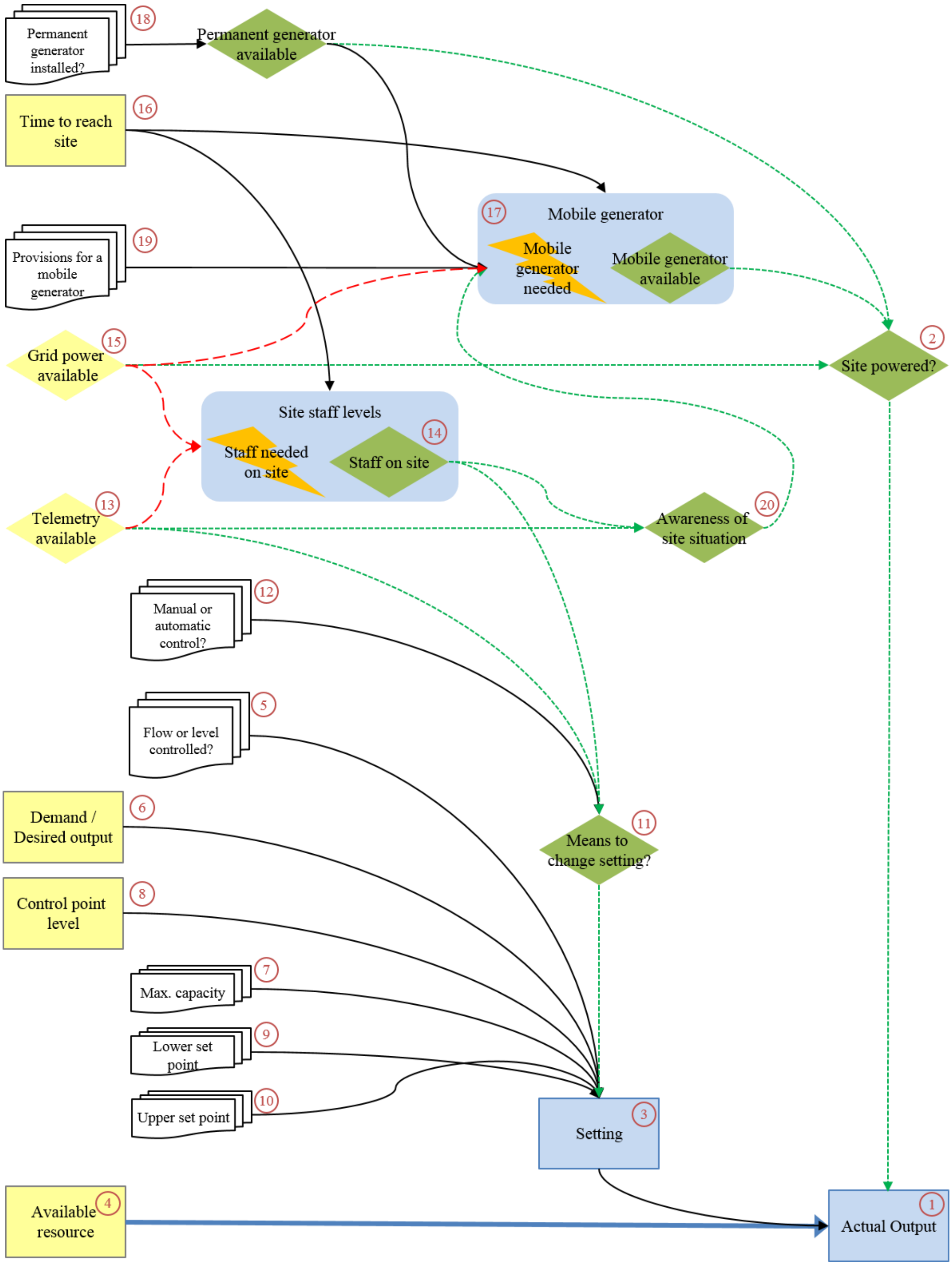


Figure 6.4 Template for raw water pumping stations, booster pumping stations and water treatment works

Demand Zone

A demand zone is formed of a group of District Metered Areas (DMAs) which share the same connection to the trunk main network. The total demand in each zone (1) is calculated by multiplying the number of properties in the zone (2) by the demand per property in the correct time step (3). This demand is compared against the volume which can be supplied (4) and the model establishes whether the zone is in deficit (5).

If the demand exceeds the available supply then the service to customers is interrupted and the model begins to count the length of the interruption (6). If the situation changes and the demand can be met this triggers an event (7) which stops the duration accumulating and resets it to zero ready for any further interruptions. This allows the model to detect multiple short interruptions such as those caused by the diurnal fluctuations in demand. If the interruption duration exceeds a set of thresholds (3, 6, 12 and 24 hours) the number of properties affected is recorded against the relevant length of event (8). The total number of property hours lost in a realisation can be calculated by taking the sum of these totals, weighting each one according to its duration.

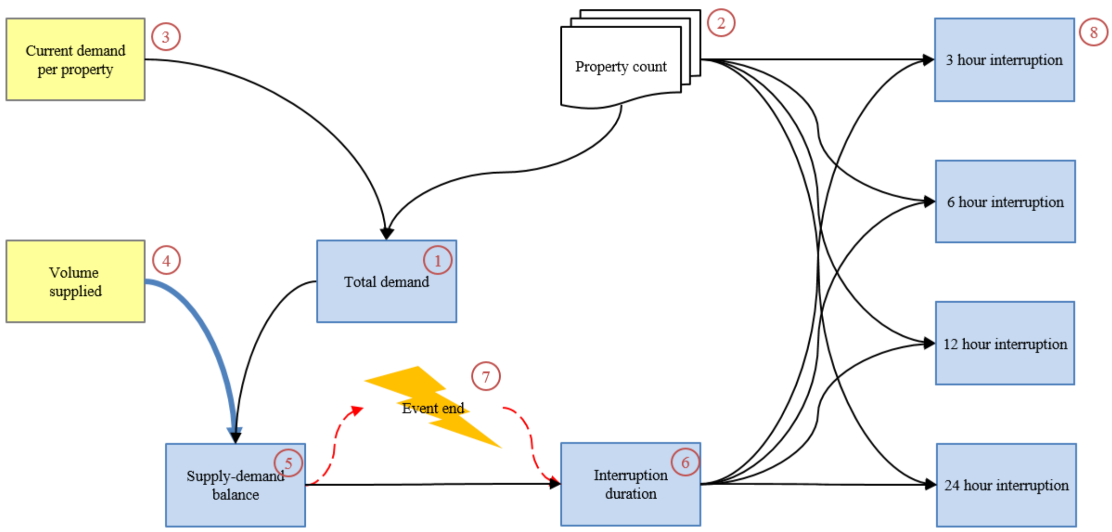


Figure 6.5 Template for demand zones

6.2.2 Infrastructure networks

Each template populated for a specific water facility creates a small system dynamics model of that facility. The external variables inform this model about the state the other infrastructure facilities, within and outside the water network, on which this facility is dependent. Equally, the status of variables within the template influences the behaviour of other facilities in the wider network. This section outlines the high level model which connects these components into an infrastructure system.

Water network

Comprehensive information on the structure and operation of the water distribution network is available through the project sponsors.

One of the simplifications made in this model is to remove the full hydraulic network model used in the first model. The hydraulic model in EPANET had a number of advantages but including a separate piece of software complicated running the analysis. The model running times were greater due the calculation of the flows around the network and movement of data between the different pieces of software. More importantly, it was more difficult to analyse and understand the results because they were spread across two different platforms.

The hydraulic model is replaced by calculating the flows between the different stocks in the system dynamics model. This retains the flows and capacity limits which the realistic representation of resilience requires (Chapter 3) but reduces the complexity of the model. It also resolves concerns over the use of a demand-driven model to simulate pressure deficient conditions because this model only considers water availability rather than pressure.

The flows in the network are calibrated using the operational plans sent to regional and local managers each week detailing pumping station and treatment works outputs that are required. Demand is initially estimated as 500 litres per property per day across the whole model based upon the empirical relationship established in Chapter 4.6. The consumption per property in each demand zone and the allocation of demand to different sources are adjusted until the flows through links in the model closely match the flows detailed in the operational plan.

The choice of case study for the first study was influenced by a preference for a system with few imports and exports. Isolated networks are rare so this model accounts for cross-connections with neighbouring systems. The planned exports are detailed in the operational plans and the model fulfils these providing the levels in the critical service reservoirs exceed 50% of the maximum useable capacity. If the levels drop below this threshold it is assumed that the cross connections which export water will be closed and the relevant valves opened to import water where possible to support the network. The capacity of these imports is hydraulically limited but the model does not consider the supply demand balance in the neighbouring zones. It is recognised that there is geographic interdependence between adjacent zones but this is a necessary boundary condition for the model.

The water components have multiple interactions with the three third party infrastructure networks included in this research.

Roads

The first model concluded that the dependency of other sectors upon the road network was only a small component of the overall risk. The high level of redundancy in networks, particularly in urban areas, means that disruption is only likely when hazards such as snowfall or heavy rain affect many or all routes simultaneously.

Therefore assessing the impact of specific road closures adds little value and it is more efficient to model disruption uniformly across the network. The time taken to reach each facility in normal conditions is multiplied by a factor representing the level of disruption. The normal journey times to each water site from the respective depots can be measured using the Google Maps route planner.

Electricity

The structure of the electricity network is taken from the regional Distribution Network Operator's Long Term Distribution Statement (LDTS) which details the connections between substations. In parallel with the first study, it is assumed that there are no capacity constraints on networks operating at 33kv or higher (i.e. primary substation or above) and a substation can be supplied by any higher order substation to which it is connected.

Each electricity substation is modelled as a simple model variable which has the value of 'true' if it is operational and 'false' if it has failed. The value is changed to false if either: i) the substation fails as part of the scenario, or ii) all the other substations which could feed this substation fail. The failure of transmission lines is implicit in the failure of the substation.

It was noted previously that the intention of this model is that it is compatible with one of the project sponsors' new business risk model. However the LTDS produced by the Distribution Network Operator in their region does not provide information about the 11/6.6kv network. The analysis of the 6.6/11kv network in the first study estimated that the most common arrangement was for water facilities to be connected to two different primary substations (Chapter 4.5). This model therefore assumes that, unless it has its own primary substation, each water facility is connected to the two nearest primary substations. The sensitivity analysis in Chapter 6.5 explores the impact of this assumption.

Telecommunications

The locations of telephone exchanges are taken from the SamsKnows telephone exchange service (https://www.samknows.com/broadband/exchange_search), cross checked against telephone exchanges marked on the Ordnance Survey Mastermap® series and BT Openreach's database of exchanges (http://www.superfast-openreach.co.uk/where-and-when/). Each water facility is assigned to the nearest exchange.

The dependence of telephone exchanges upon electricity is represented by assigning each to the two nearest primary substations.

6.3 Case Study

This model is applied to one of the sponsor's networks to assess whether it can identify the plausible impacts of Cabinet Office's 'reasonable worst case scenarios' and provide insight into which factors exert the strongest influences on these impacts.

There is also a potential opportunity for this model to be incorporated into the new business risk model being developed by one of the project sponsors. They proposed a network serving approximately 153 000 properties and 360 000 customers in a large metropolitan area as a suitably complex system to test the capability of the approach.

The model of the water infrastructure is created using data from four sources:

i. The locations of the facilities shown in Figure 6.6 are extracted from the sponsoring company's GIS system.

ii. The data to populate the inputs for each infrastructure facility is taken from the relevant fields in the company's asset inventory.

iii. The company's network schematics are used to construct the high level model of the water network shown in Figure 6.7.

iv. The flows in the model are calibrated to match the values detailed in the company's production plan for the week commencing 27 February 2014. This is a typical week with normal levels of demand and no asset outages affecting the configuration of the system.

A number of network characteristics can be identified immediately in Figure 6.6 and Figure 6.7. The Central and East zones are fed by gravity from the complex of service reservoirs in the centre of the network; the results of the first study suggest that these supplies are likely to be resilient. In contrast, the North and West zones include pumped systems which are expected to be more vulnerable.

There are a number of significant imports from the surrounding zones. One, feeding the West zone, flows under gravity but two others relying on pumping at WPS Q and WPS R. Therefore, whilst they create resilience, they are also dependent upon power and telemetry to operate.

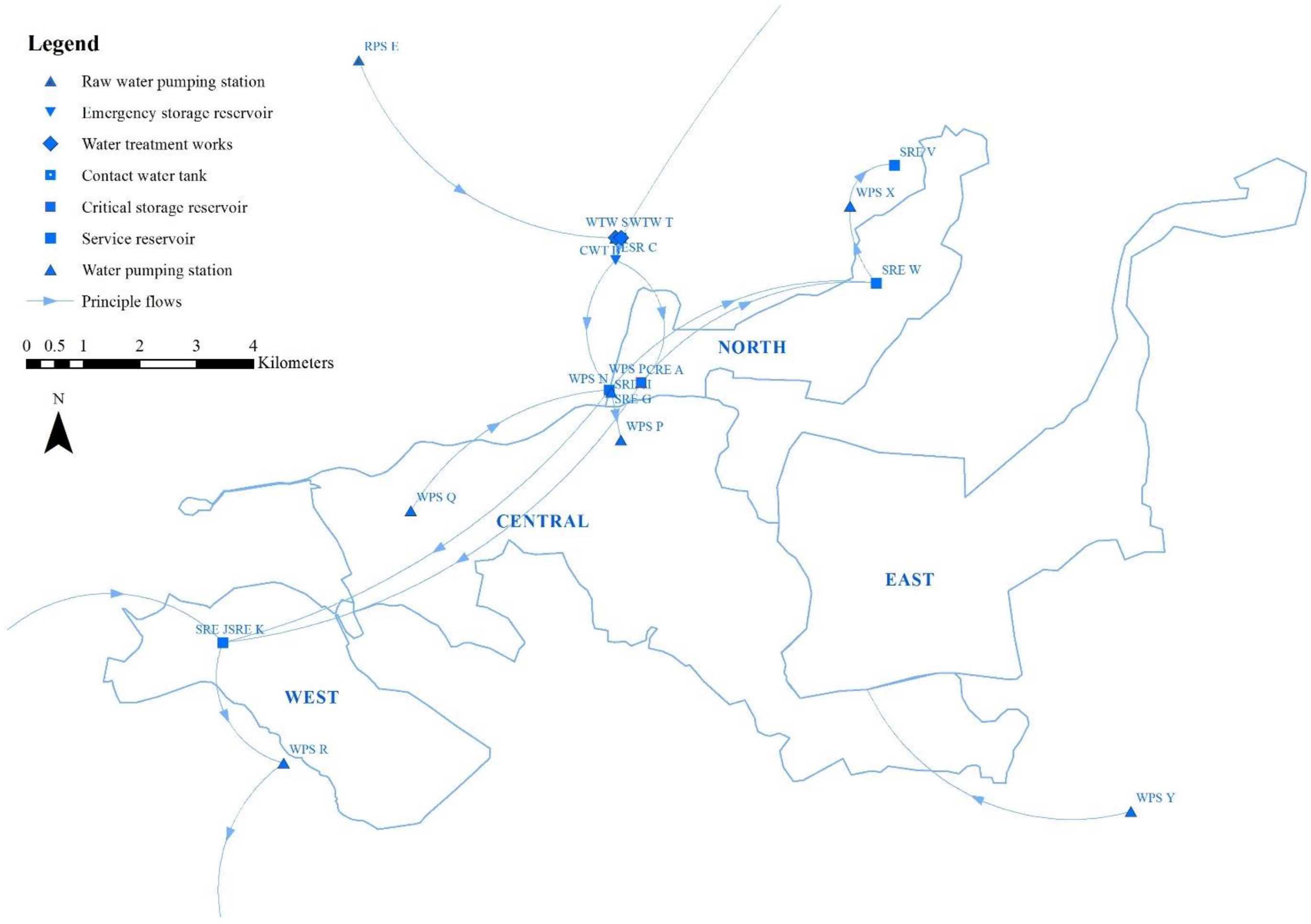


Figure 6.6 Water facilities in the case study area. A further abstraction point and emergency storage reservoir approximately 25 kilometres to the north east are not shown.

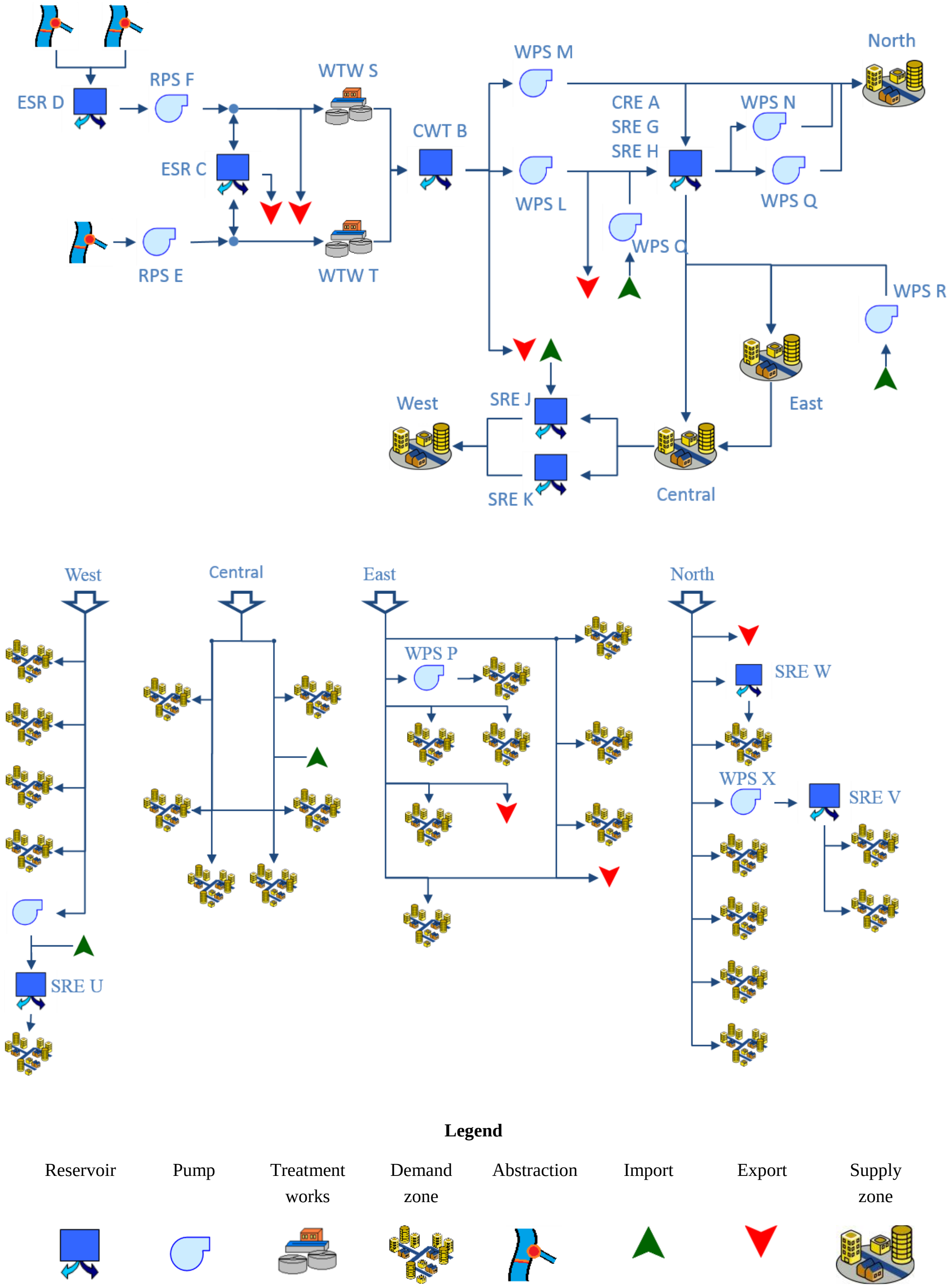


Figure 6.7 Schematic representation of the water network. Each reservoir, pump, treatment works and demand zone represents one of the templates described in the previous section. The other symbols represent the system's inputs and outputs.

These pumping stations providing imports into the network and WPS R in the south west are separate from the rest of the network but most of the other assets are concentrated in two clusters in the centre of the area. This geographic interdependence may have consequences for the resilience of the network because these facilities are likely to depend upon the same electricity substations and the same telephone exchanges.

The third party infrastructure networks and the dependencies between networks are shown in Figure 6.8. The network of telephone exchanges is dense, reflecting the area's urban nature, but the clustering of water facilities means that their relevance to the water system varies.

The electricity network also appear to have a high level of redundancy. Most primary (33kv) substations are connected to two bulk supply points and almost all of these bulk supply points (132kv) are connected to two different grid supply points (400kv). Therefore the high voltage electricity network in the area is likely to be resilient. Equally, despite the apparent clustering of water facilities, the connections from the sponsor's facilities to the two nearest primary substations frequently diverge and connect to different parts of the electricity network. This is likely increase the resilience of the water network to natural hazards.

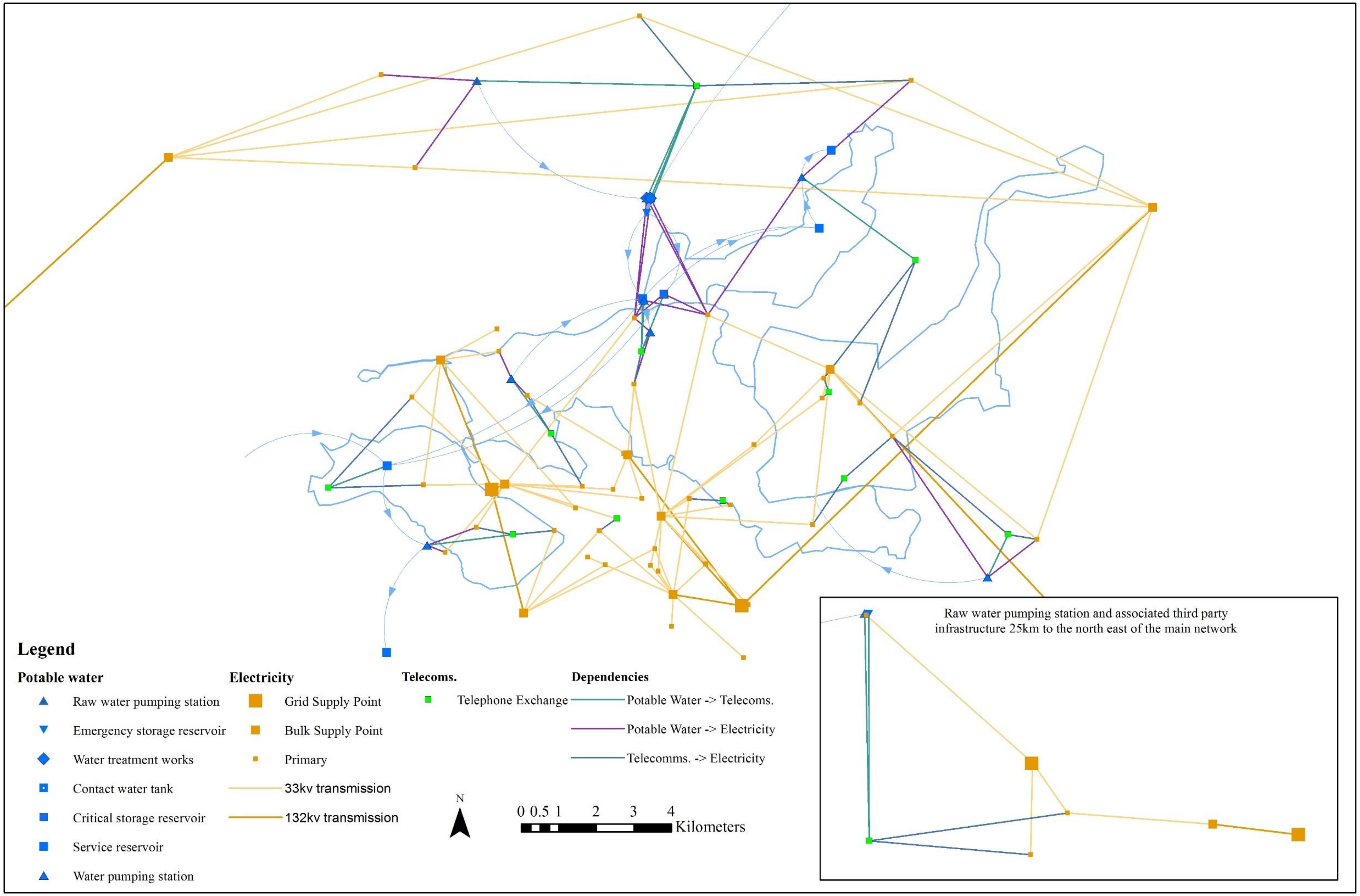


Figure 6.8 Third party infrastructure and dependencies between sectors. The infrastructure supporting the abstraction point to the north east of the area is shown in the inset panel.

6.4 Analysis of 'Reasonable Worst Case Scenarios'

The following section demonstrates the application of the model to two of the 'reasonable worst case scenarios' published by the UK Cabinet Office: inland flooding and a prolonged period of hot and dry weather.

6.4.1 *Inland flooding*

<u>Potential impacts on infrastructure</u>

Figure 6.9 shows that the scenario identifies nine potential impacts of inland flooding on infrastructure. Three of these impacts (closure of local businesses, increased demand for health and emergency services, and loss of emergency services' assets) are outside the scope of this research (see Chapter 3). A shortage of staff or emergency generators are also omitted. They are closely related to the response and recovery aspect of resilience but require the modelling of a central pool of resources which can be shared between facilities. This is beyond the scope of this research but is an obvious option for exploration in further work.

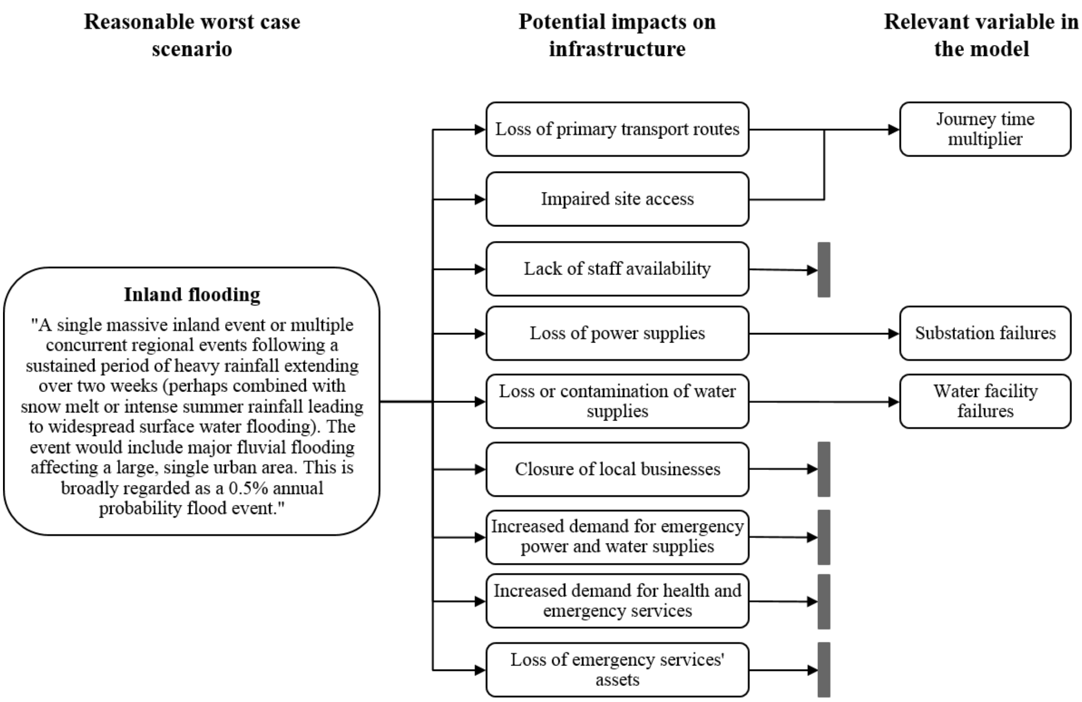


Figure 6.9 Potential impacts of inland flooding detailed in the Cabinet Office 'reasonable worst case scenario' (2011a) and relevant model variables

Loss of primary transport routes and impaired site access can be combined and represented by adjusting the time it takes to reach each facility (Table 6.3).

Table 6.3 Potential impacts on infrastructure due to inland flooding represented by simple uniform distributions

Potential impact on infrastructure	Model variable	Plausible range of values explored
Loss of primary transport routes Impaired site access }	Multiple of normal time taken to reach site	1 to 300

In each realisation of the scenario a random sample is taken from a uniform distribution covering the plausible range of values based on the impact of past events. Some of the sites isolated by the 2005 Cumbrian floods were inaccessible for up to 72 hours (Horsfall et al. 2005) and the Mythe water treatment works affected by the 2007 floods was similarly inaccessible for three days (Severn Trent Water 2007). The average time to reach each facility in the model is approximately 15 minutes so a multiple of 300 was calculated by dividing 72 hours by 15 minutes.

The loss of power supplies and loss or contamination of water supplies reflect the discrete failures of individual sites so must be modelled differently. Bernoulli trials are used with a failure probability selected to ensure that the realisations include a full range of different failure patterns.

The exposure of the water and electricity facilities to flooding is not uniform across the area so it is important to identify which facilities could plausibly be affected by flooding. Table 6.4 outlines the four different levels of flood likelihood captured on the fluvial and coastal flood maps produced by the Environment Agency (2014e). The Cabinet Office state that the worst case scenario has a return period of approximately 200 years so facilities within the high or medium risk zones are identified as exposed to flooding

Table 6.4 Environment Agency flood risk categories

Category	Annual probability of fluvial or coastal flooding
Very low	Less than 1 in 1 000
Low	Between 1 in 1 000 and 1 in 100
Medium	Between 1 in 100 and 1 in 30
High	Greater than 1 in 30

There is a disparity between the 200 year return period of scenario and only identifying substations vulnerable to a 100 year return period flood. However including substations with a low flood risk would extend the group of vulnerable substations to those which were exposed to a 1 000 year return period event and would be contrary to the Cabinet Office guide's emphasises on proportionality (see Chapter 2.3). In reality, the difference in this specific case study is negligible as only two further sites are within the low risk zone. Both are redundant feeds to telephone exchanges so their impact is unlikely to be insignificant.

There are seven electricity substations and one raw water pumping station within the medium or high risk zones (Figure 6.10). It is interesting to note that four of the seven substations in the high and medium risk zones are 132kv bulk supply points (BSPs) and therefore their failure is expected to have a large impact. The presence of so many important assets in flood prone areas, and relatively lower number of less critical assets, is initially surprising. However, it may be explained by the history of localised power generation and the location of power stations close to water sources. Power generation has become more centralised but these sites remain hubs for the local distribution infrastructure. This is the case for the BSP G which is discussed in detail below.

Conversely, the vulnerability of water facilities to flooding is remarkably low. With the one exception all sites are on higher ground, including the second river abstraction point which is over 100 metres away from the river bank and falls within the very low risk category (the annual probability of flooding is less than 1 in 1 000).

Notwithstanding, both abstraction points can fail due to the effect of flooding on raw water quality. High discharges in rivers often increase the turbidity of raw water which impedes the treatment processes and consequently reduces the effectiveness of disinfection (DWI 2014). During a flood event it may be necessary to restrict or stop abstraction to ensure that the drinking water provided to customers is safe.

These potential failures are incorporated into the model as Booolean trials. A uniformly distributed random variable is created for each of the flood exposed substations and the two abstraction points. These are sampled at the start of each realisation and compared with failure probabilities of 10% for substations and 15% for abstraction points (these values were chosen to ensure the realisations contained a full set of the plausible combinations). Failed facilities were removed from the model for that realisation.

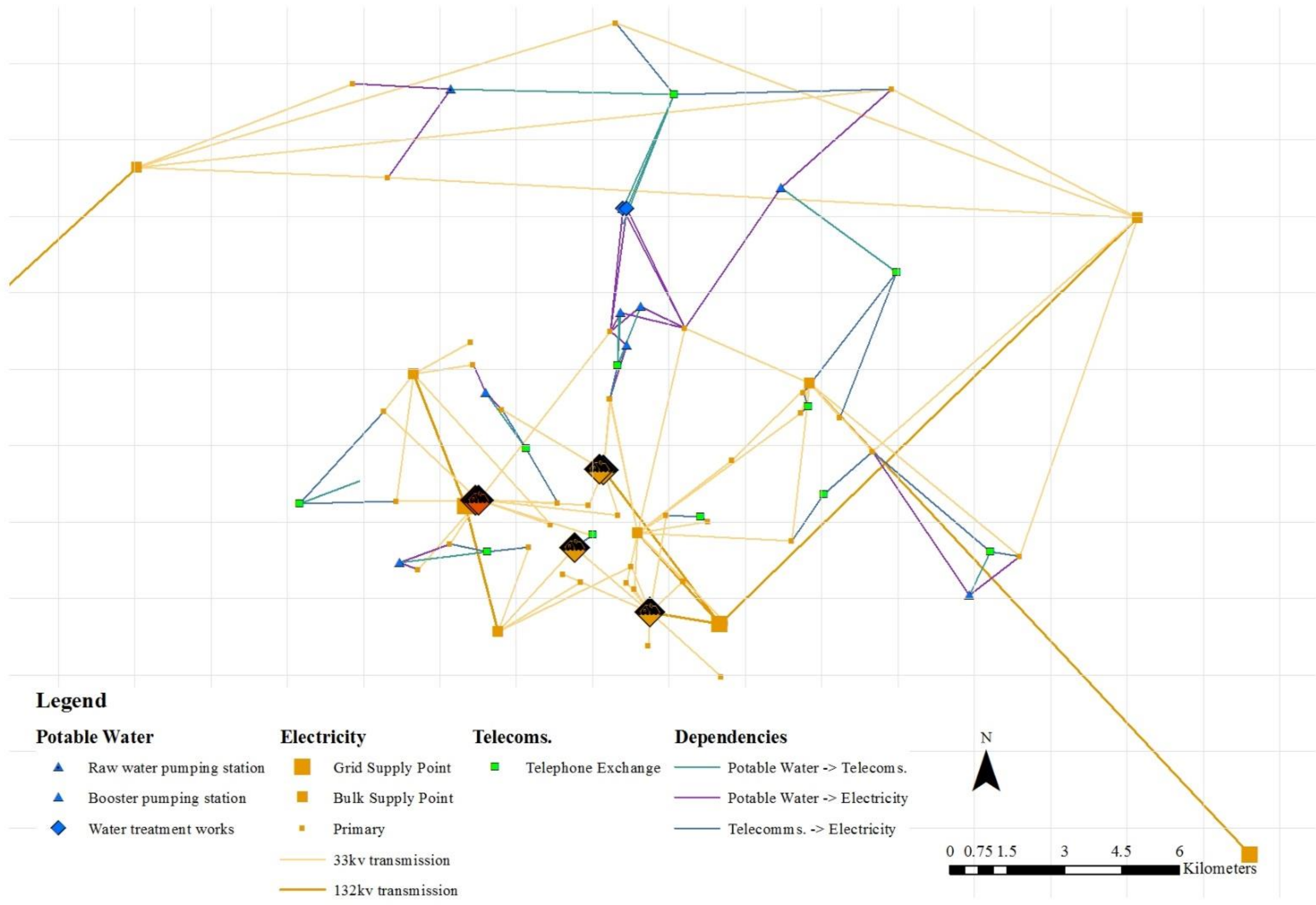


Figure 6.10 Substations within the medium and high flood risk zones. Six of substations are shown though the juxtaposition of two pairs of substations results in overlapping symbols. The seventh substation feeds the raw water pumping station 25 kilometres to the north east of the main network.

Scenario results

Figure 6.11 shows that the distribution of the impacts across 20 000 realizations of the scenario is bimodal. There is clearly an important tipping point where a particular failure or combination of failures has a significant impact on the water supply. Identifying these contributory circumstances is likely to pinpoint ways of increasing resilience.

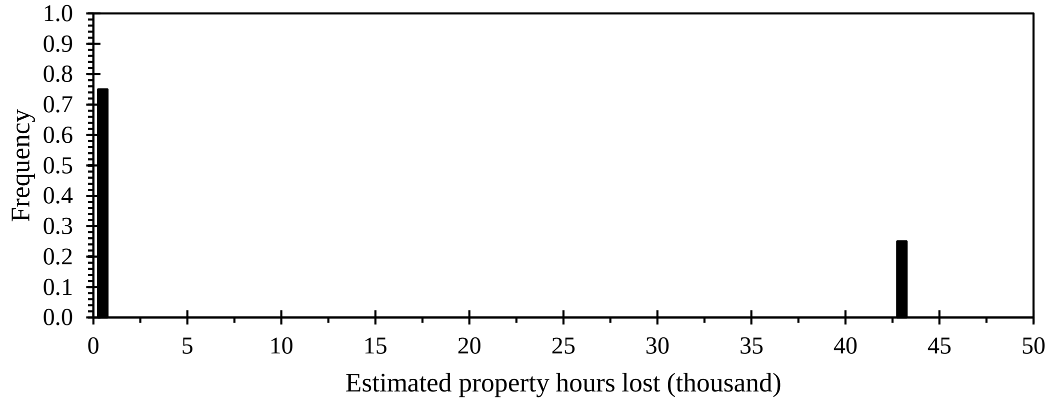


Figure 6.11 The distribution of the impact in 20 000 realisations of the inland flooding 'reasonable worst case scenario'. In 75% of realisations the flooding has no impact, but the remaining 25% each cause 43 000 property hours to be lost.

Reinforcing the results of the first study, Figure 6.14 shows that there is no correlation between the increase in journey time and the impact (the Spearman rank order correlation coefficient is -0.004 with an associated p-value of 0.574). It is important to note that this model, like the first, does not include the dependence of treatment works on chemical supplies but it does include the need to deliver mobile generators.

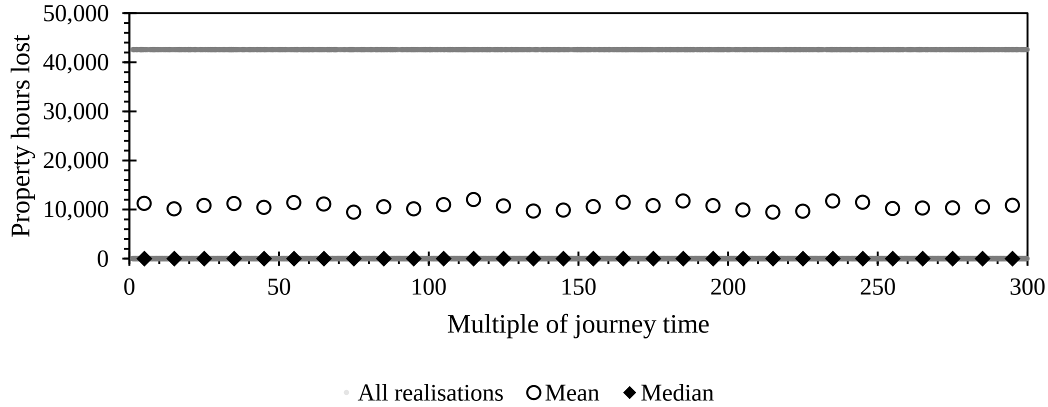


Figure 6.12 There is no correlation between the journey time and the impact of a realisation. The results for individual realisations are split between zero and 43 000 (in line with the distribution shown in Figure 6.11 whilst the mean and median values do not change.

The difference between the model results and the accepted view that disruption to highways exacerbates the impacts of events could be attributed to two factors. Firstly, these results represent only one, specific case study and another infrastructure system may respond differently. For example, a more rural location would increase journey times and a greater number of smaller sites may mean that fewer sites have their own generators already installed. Secondly, as noted in Chapter 5.2, accounts of past events may misrepresent the root causes of disruption as difficulties reaching sites are prominent in the recollections of staff.

Similarly, there was no correlation between the loss of abstraction points and the total impact. Across the 20 000 realisations the mean impact when both sites were operating or both unavailable was 18 175 and 18 097 property hours lost respectively and a two-sample t-test indicates there is no significant difference to a 95% confidence level. This outcome is explained by the large emergency storage reservoir upstream of the treatment works which can provide water if supplies from the abstraction points are lost.

In contrast, the linear relationship between substation failures and impact in the water sector shown in Figure 6.13, combined with the tipping point identified in Figure 6.11, indicates there is a single, critical substation at risk. An increase in the number of failed substations creates a proportional increase in the probability that this critical substation is one of the failed facilities.

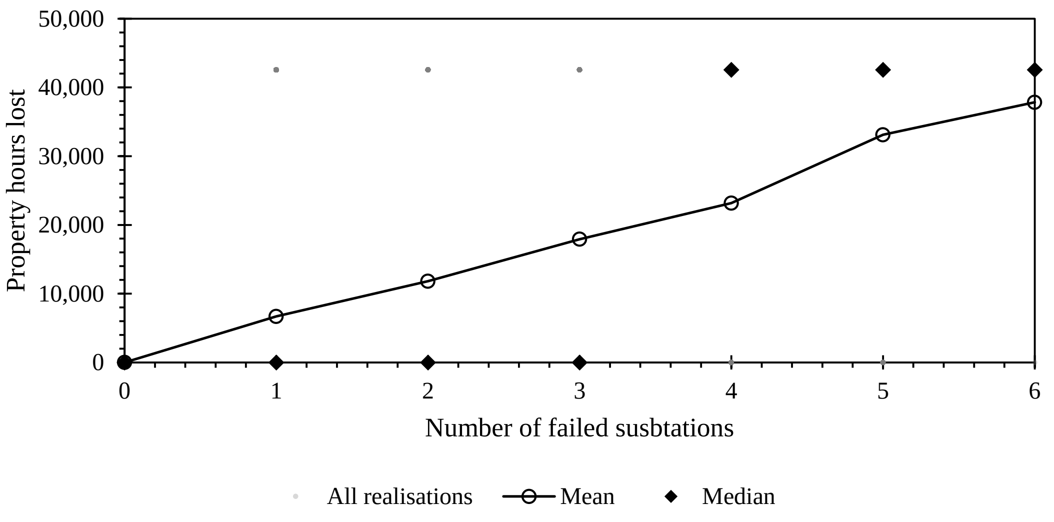


Figure 6.13 The mean impact increases steadily with an increasing number of substations failures. The results of individual realisations are still split between zero and 43 000 property hours lost but the frequency of the latter increases until above four failures the median result switches to 43 000 hours lost.

This is confirmed by Figure 6.14 which shows that the mean impact is the same irrespective of whether six of the seven substations have failed. For the seventh, BSP G, the mean impact is zero in realisations where the substation is operating and 72 000 property hours lost when it fails. The importance of this substation could be attributed to its elevated position in the hierarchy of the electricity network but three of the other six substations which are exposed to flooding are also bulk supply. Therefore the configuration of the electricity and water networks must be significant.

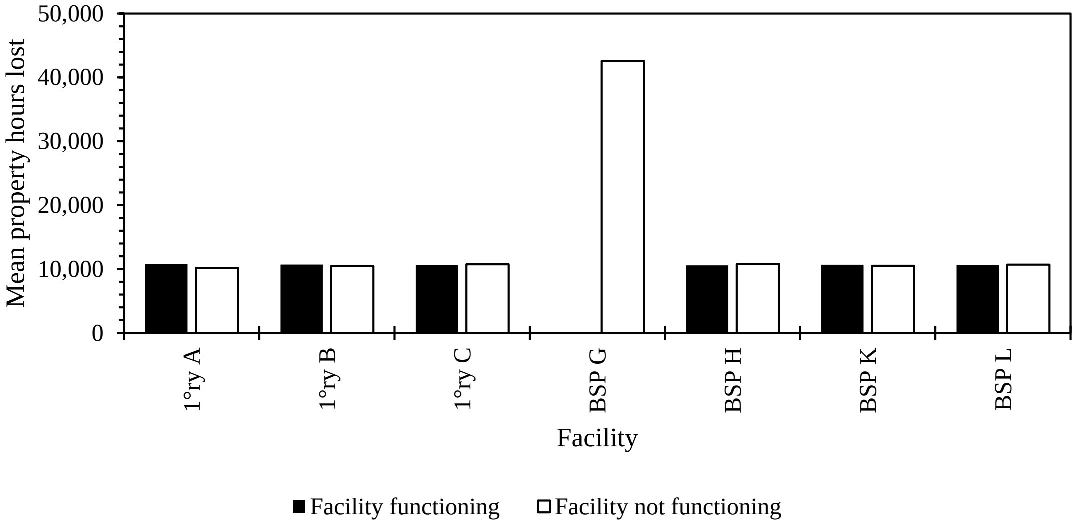


Figure 6.14 The mean impact when each of seven flood exposed substations is either operational or has failed. Note how for six of the seven substations the mean impact is the same regardless of whether the substation has failed. In contrast, the average impact is zero in realisations where BSP G does not fail and 43 000 property hours lost in realisations where it does fail.

It is noteworthy that BSP G has an immediate neighbour (BSP H). Their juxtaposition and common exposure to flooding suggests that their geographical interdependence may negate the redundancy created by primary substations connecting to multiple supply points. However, this impact is not apparent in Figure 6.14 and BSP H appears to have no effect. This is explained by further study of Figure 6.8 which shows that no primary substations connect to only these two bulk supply points; all have connections to other supply points which are not vulnerable to flooding.

Furthermore, Figure 6.8 also shows that almost every potable water facility in the region through its connection to two primary substations can receive power from two entirely different parts of the electricity network. The key exception is WPS R; the two primary substations which feed this pumping station have a common dependency on BSP G and therefore the pumping station is vulnerable to the flood scenario.

The failure of WPS R is significant because, with the exception of a limited import from the neighbouring zone, it is the only supply to Service Reservoir U and two DMAs containing 1 400 properties (Figure 6.15).

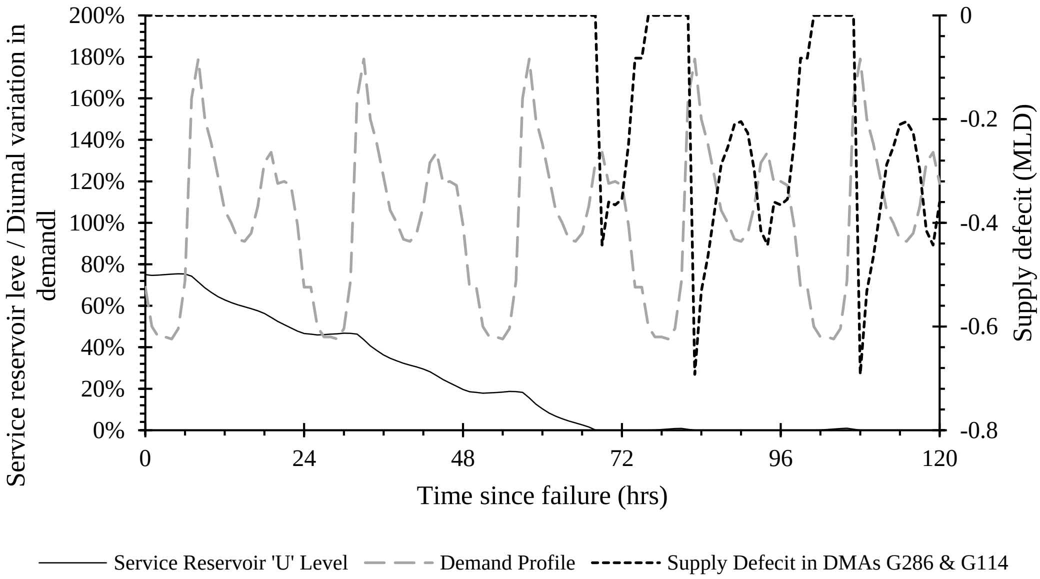


Figure 6.15 The response of Reservoir U to the failure of WPS R and the consequential effect on supplies to customers in two DMAs. The pumping station failure causes the reservoir to empty over a number of days until customers begin to experience supply interruptions. Notably, the import from the neighbouring zone is capable of meeting the low level of demand overnight. Therefore the interruption is only intermittent and the reservoir fills slightly overnight before emptying again early in the morning. Figure 5.26 shows similar behaviour in Model 1.

The slow decline in the service reservoir level in Figure 6.15 highlights the effect of not including the recovery of failed facilities in the model. The five day time period used in the model is reasonable given that the Cabinet Office scenario indicates that the flood event may last up to two weeks. However, this component of resilience should be considered when assessing the benefits of any measures to improve resilience.

The concentration of vulnerability in one dependency is highly significant for an infrastructure provider looking to increase their resilience. Figure 6.16 shows that installing a mobile generator connection at this specific site - a low cost intervention – could have a dramatic effect on resilience of customer’s water supply. Across the 10 000 realisations of this scenario the mean impact of realisations where BSP G fails is 82% lower than the original scenario.

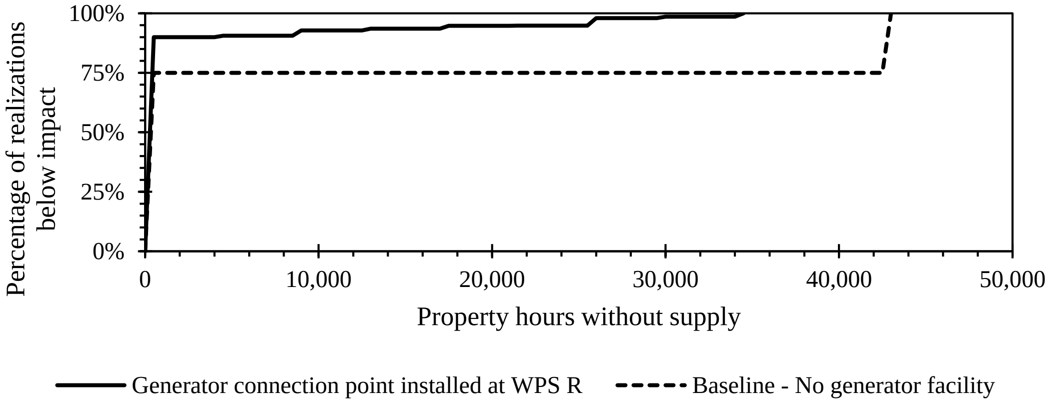


Figure 6.16 A comparison of the impacts in the baseline inland flooding scenario and an alternative scenario where a mobile generator connection point has been installed at WPS R. 90% of realisations have an impact of less than 1 000 property hours lost and there is no longer the tipping point effect, instead the impact rises steadily thoroughly the remaining 10% of realisations.

Importantly, the intervention also changes the pattern of the water sector's dependencies. Figure 6.17 shows that, whilst the generator reduces the dependence upon power, it also introduces a new dependency upon the road network. The likelihood of access being prevented for four days is small. Nonetheless, the application of the model to the reasonable worst case scenario has provided the decision maker with two valuable pieces of information. Firstly, a significant threat due to dependence on one sector can be significantly reduced by a single, low cost intervention. Secondly, this intervention does not eliminate the threat because it, in turn, is dependent upon a different sector.

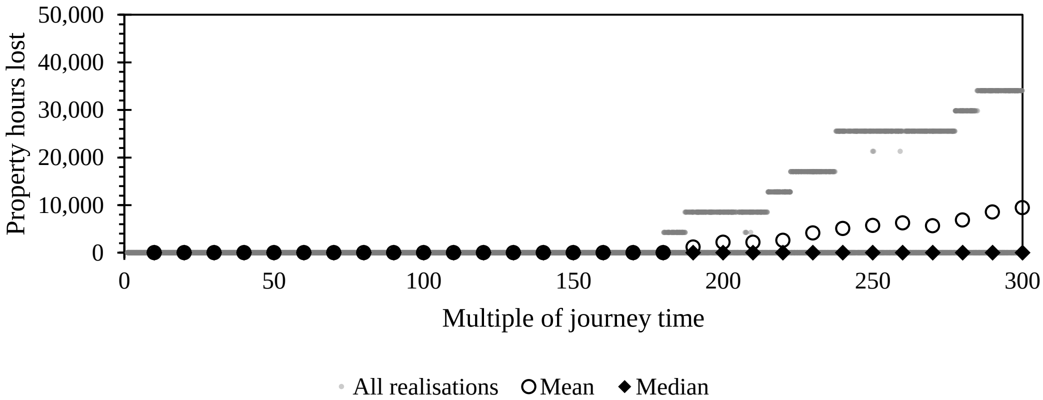


Figure 6.17 The installation of a mobile generator connection at WPS R introduces a dependency upon the road network. If the journey time to reach the site increases by a factor of more than 180, for this site equivalent to approximately 72 hours, then the mean impact begins to rise. At 72 hours the service reservoir empties but the drop in demand overnight means the interruption is brief. However, if the generator cannot be installed by the following morning when demand increases the interruption is longer lasting and therefore has a greater impact.

6.4.2 Prolonged period of hot/dry weather

<u>Potential impacts on infrastructure</u>

The second example of the model's application assesses the potential impacts of the Cabinet Office's scenario for prolonged hot / dry weather. They identify the nine potential impacts on UK infrastructure shown in Figure 6.18.

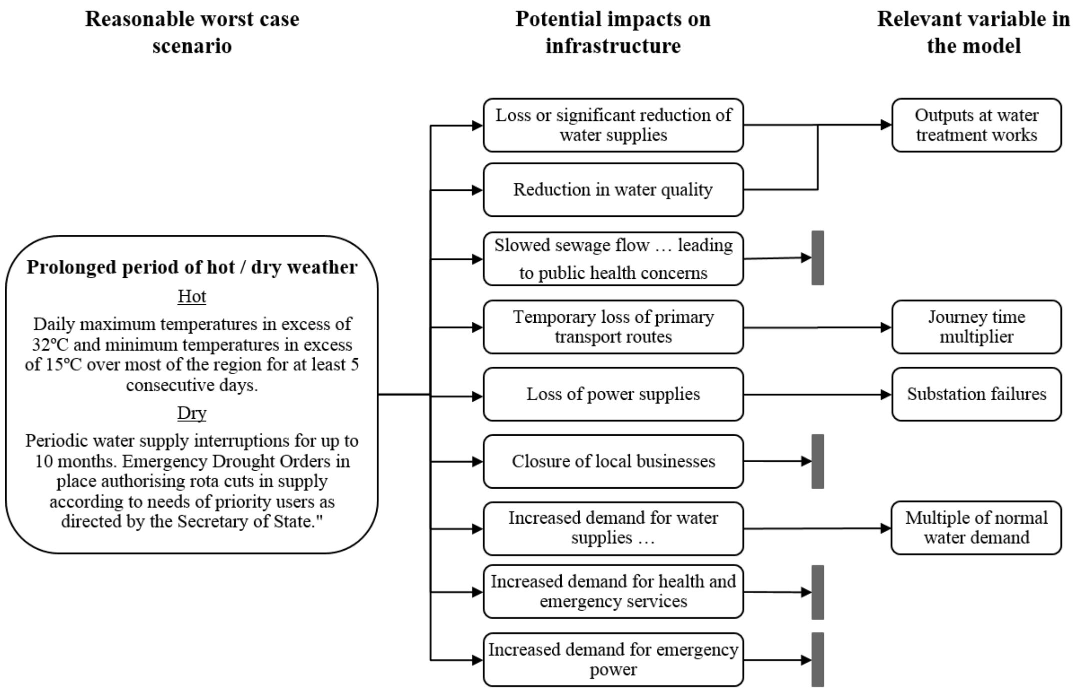


Figure 6.18 Potential impacts of a prolonged period of hot/dry weather detailed in the Cabinet Office 'reasonable worst case scenario' (2011a) and relevant model variables

The potential impacts which were identified as outside the scope in the inland flooding scenario are similarly omitted from this scenario. To maintain consistency the plausible range for the multiple of the normal journey time representing disruption to travel is also identical to the previous scenario. There also three additional potential impacts which reflect the direct effects on the water network (Table 6.5)

Loss of water supplies and poor water quality have the same effect of reducing the water which is available to abstract, treat and deliver through the potable water network. Therefore they are combined and modelled as a reduced output from water treatment works. The upper bound for each of the two works is dictated by their maximum operational capacity whilst the lower bound reflects complete closure.

Table 6.5 Potential impacts of prolonged hot and dry weather on infrastructure represented by simple uniform distributions

Potential impact on infrastructure	Model variable	Plausible range of values explored
Loss of primary transport routes	Multiple of normal time taken to reach site	1 to 300
Impaired site access		
Loss or significant reduction of water supplies	Output at WTW	0 to 60
Reduction in water quality		0 to 60
Increased demand for water supplies	Multiple of normal water demand	1 to 2

Two sources of information are available to guide the plausible range for increases in demand. Firstly, United Utilities use a peak factor of 1.5 to 1.6 as part of their plans for a new water supply system in West Cumbria[1] (United Utilities 2014b). Secondly, Figure 3.5 showed that the water demand approximately doubled in response to the flooding of Mythe water treatment works in 2007.

Hot, dry weather affects the electricity network in two ways. Firstly the demand for power for air conditioning and other cooling increases the pressure on the network. This can be compounded by the reduction in network capacity caused by maintenance work planned for the summer when demands have historically been lower (ENA 2011). Secondly, most network components cool to the atmosphere (Electricity North West 2011). If the ambient temperature is higher they become more likely to overheat and their capacity is reduced (National Grid 2010).

In the inland flooding scenario only a subset of substations were exposed to the hazard but hot and dry weather affects all facilities. There are 56 substations in the case study and therefore $7x10^{16}$ different combinations of failures. It is not possible to consider every combination but a large sample will identify the key patterns. Therefore the failure probability of each substations is set to 0.95 and the number of realizations doubled to 40 000.

[1] This is an unusual case because short periods of peak demand (e.g. due to a heatwave) are not normally considered in water resources plans. However, this new system will be the sole supply to customers and therefore must meet peak demand.

Scenario results

Figure 6.19 shows that the results from this prolonged hot and dry weather scenario is markedly different from the flooding scenario. Firstly, the large impact is two orders of magnitude greater, reflecting this scenario's potential to affect the whole network rather than a limited number of locations. However, the curved profile indicates that there is not a single, critical tipping point; instead the impact is a result of multiple failures and factors.

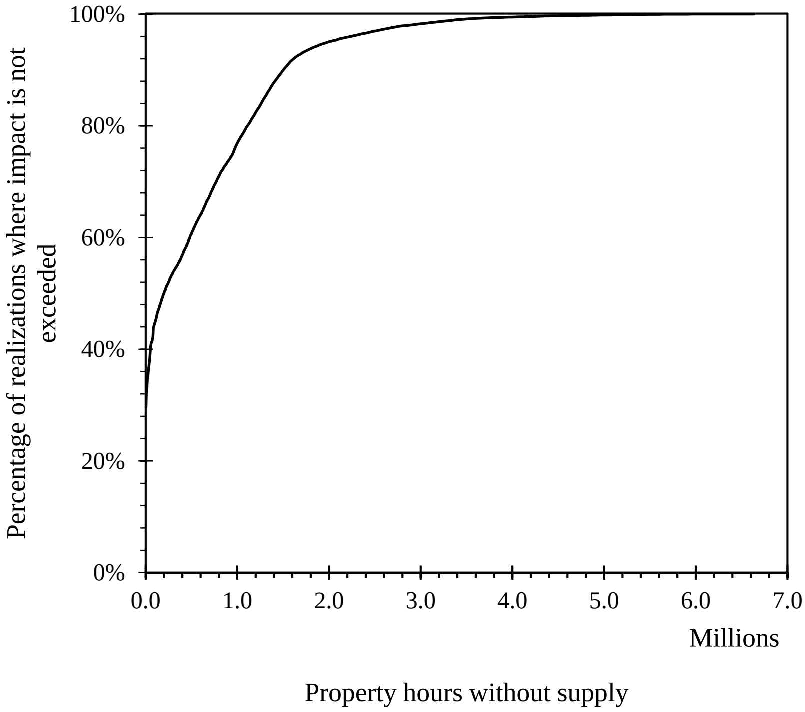


Figure 6.19 The distribution of property hours with out supply in 40 000 realisations of the prolonged hot/dry weather 'reasonable worst case scenario'. There remain a proportion of realisations (30%) with no impact, thereafter there is an almost linear increase in impact until the final 10% of realisation where there is a significant tail of extreme values. Note that the equivalent information for the first scenario was shown as a histogram; in this case the wider range of values makes a cumulative frequency plot more appropriate.

Whilst the distribution of impacts is different, analysis of the importance of the different effects on infrastructure identifies some similar patterns to the first case study; Figure 6.19 shows that disruption to travel is not correlated with the impact of the event (Spearman correlation coefficient: 0.021 , p-value: <0.0005).

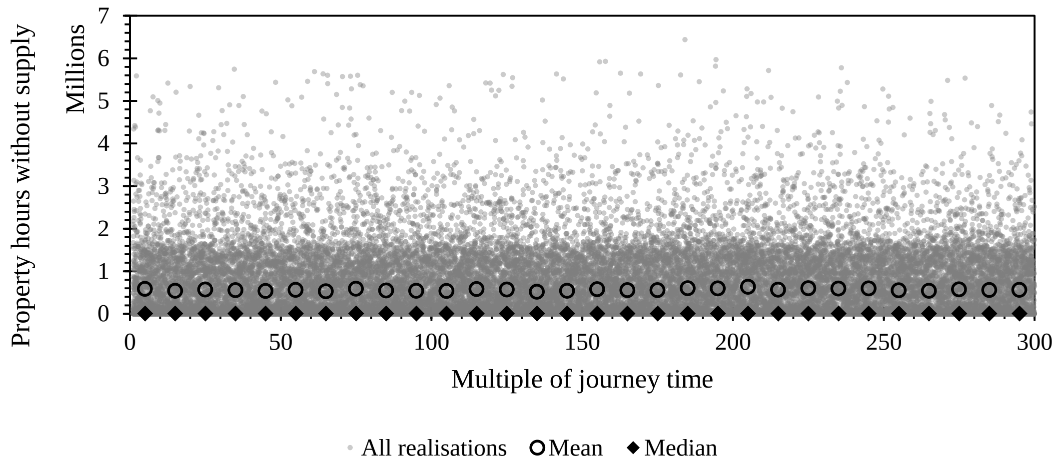


Figure 6.20 Impact and travel disruption are not correlated in the hot dry weather scenario. The values for individual realisations show uniform scatter through the full range whilst the mean and median remain consistent.

The scenario also includes the impacts on water availability and local demand. It is important to note that the terms ‘supply-demand balance’ and ‘supply demand deficit’ are not used in their specialised water resources sense. They simply refer to the net inputs and outputs from the network.

The impact and the supply-demand balance within the water infrastructure appear closely linked with Figure 6.21a showing that the average impact increases as the input into the system falls and Figure 6.21b showing the same relationship with increasing demand. The symmetry between them is expected given they are opposite perspectives on the same problem.

Figure 6.22 expands on this by plotting the impact against the supply-demand balance in the network, minus the effect of any imports or exports. It shows that large failures can occur even when the internal stress on the network is small; there are five events which have an impact greater than 3 million property hours without supply when the supply-demand balance is positive. This indicates that failures in the external networks, most probably the power network, are capable of directly causing failures. These are cascading failures in the typology introduced by Rinaldi et al. (2001) (see Chapter 3)

However, large events also become increasingly common as the supply-demand deficit falls. This implies that the probability of failures in the third party infrastructures having a disproportionate effect increases as the system comes under greater stress. This reflects the concept of escalating failures introduced by Rinaldi et al. (2001).

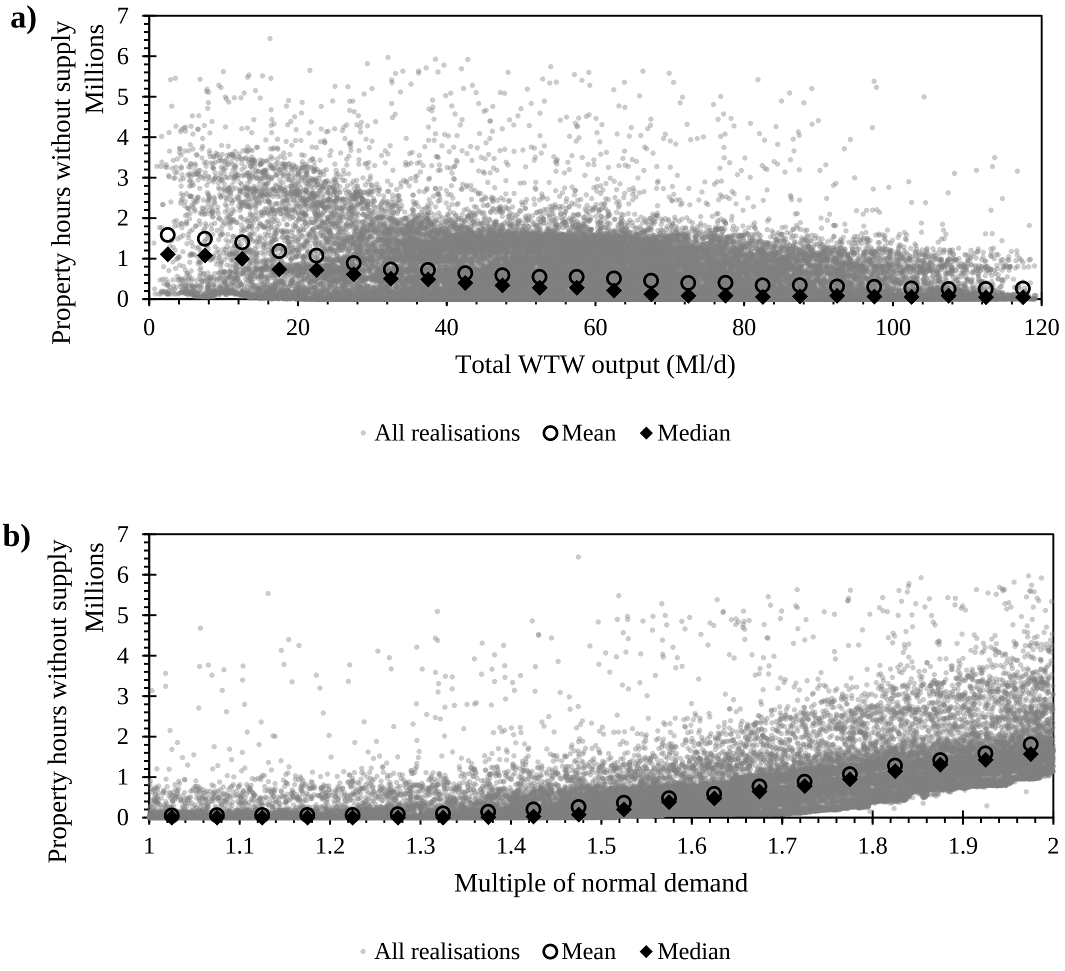


Figure 6.21 The correlation between impact and the components of the supply-demand balance. Figure a) shows average impact increases as the output of the treatment works falls. In the complementary case, Figure b) shows that higher demand is correlated with higher impact.

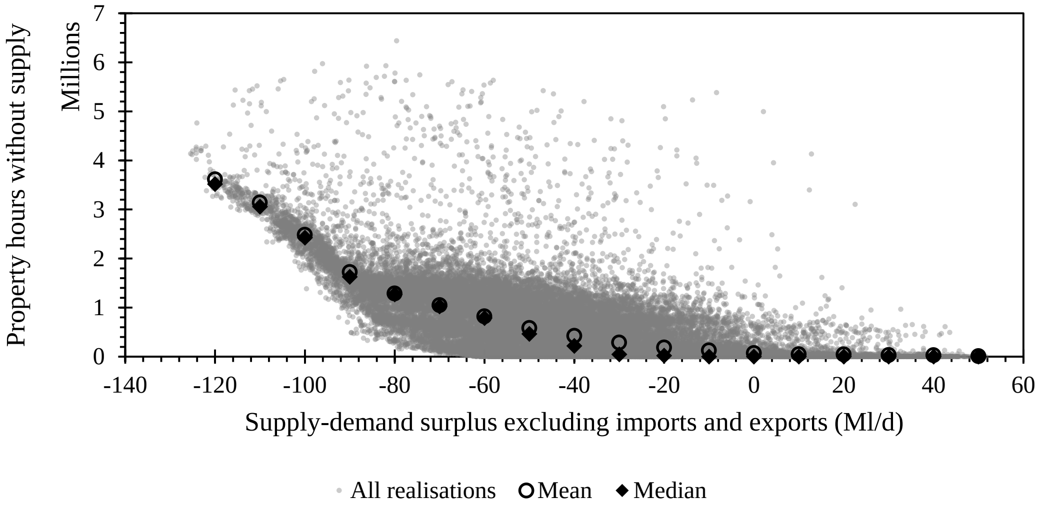


Figure 6.22 The correlation between impact and the supply-demand balance in the network

Figure 6.23 shows the correlation between the impact and the number of substation failures. It is important to note that the shape of the results is influenced by the method of sampling discrete failures; realisations with only two failures occurred most frequently and there are only 42 realisations with nine failures. This, however, does reflect the relative likelihood of these events occurring in reality.

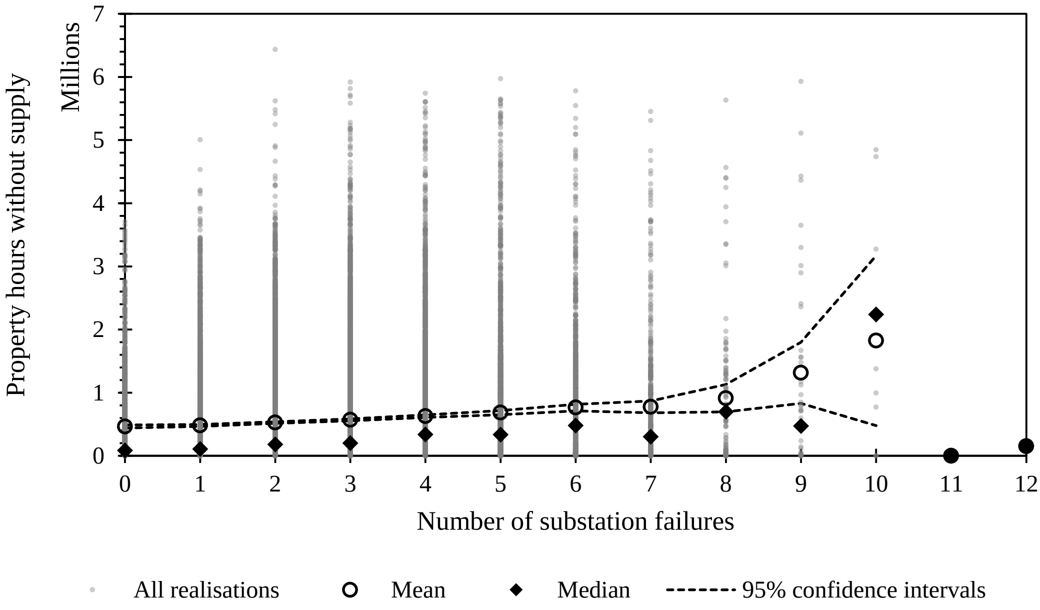


Figure 6.23 The correlation between impact and the number of failed substations. The decreasing sample size above eight failures is represented by the widening confidence intevals; for 11 and 12 failures is only one result.

Unexpectedly, the maximum impact occurs in a realisation where only two substations fail and demonstrates that a small number of failures at critical substations, combined with a supply-demand deficit, can have a major impact. In this case the failure of Grid Supply Point C and a local primary substation causes Pumping Station Q to lose power preventing water from being imported from a neighbouring zone.

There is only one realisation for both 11 and 12 failures so it is impossible to draw any reliable conclusions at this point. However, in the categories where there are more failures the mean impact appears to rise exponentially. This is indicative of redundancy in both of the networks: when there are few failures there is a small probability that electricity supplies will be lost to enough water facilities to affect customers. As the number of failures increases, there is an increasing chance of simultaneous failures affecting both the main source and the redundancy sources. It is interesting to note that when there are 10 substation failures the median exceeds the mean, suggesting that widespread failures are becoming the norm rather than exceptions. However, the sample size is too small to confirm this hypothesis.

It is apparent from this scenario that the potential impacts of hot and dry weather on this network are much greater than the previous inland flooding scenario. This reflects a number of factors. Firstly, the threats of flooding are localised whereas hot and dry weather can cause more widespread failures. Secondly, and perhaps counterintuitively, the potential internal effects of hot and dry weather on the water network are greater. The low exposure of water facilities to flooding and the provision of emergency storage makes the network resilient to the former scenario but there are fewer controls in place for the threats posed by hot and dry weather. The scenario has highlighted how dependency on other sectors can escalate internal pressures, and conversely how internal pressures can exacerbate the impacts of failures due to dependency. These implications are discussed further in Chapter 6.6.

6.5 Sensitivity Analysis for the Electricity Sector

This section addresses the sensitivity of the model in a broader sense and reflects back on some of the uncertainties identified in both of the two case studies developed in this thesis. It focuses upon the electricity sector as the results of both case studies suggest this is the water sector's most important dependency.

Three different aspects of the model's sensitivity are explored:

i) The effect of changes in the probability of failure at substations exposed to flooding.

ii) The effect of changes in the probability of transmission line failure.

iii) Changes in the number of connections between each water facility and primary substations.

6.5.1 Sensitivity to changes in the resistance of substations to flooding

The events of 2005 and 2007 (see Chapter 1) mean there is a high level of concern about the flooding of electricity substations. Therefore it is important to understand how changes in flood depth or the probability of substations failing might affect the impact upon the water sector and its customers.

However Figure 6.24 shows that, in this study, analysis of this sensitivity reveals little. Section 6.4.1 identified the direct connection between the failure of BSP G and the impact of losing WPS R so the response of the mean impact to changes in the probability of a substation failing is directly proportional. The fragility function defined in Chapter 4.3 is also linear, so the relationship between the total impact and changes in flood depth and the fragility function is similarly proportional.

It is important to note that, whilst this study indicates the relationship between substation flooding and the delivery of water to customers is simple, this case study is only representative of one infrastructure system. The limited exposure of facilities to flooding and the one-to-one dependency is unlikely to be universal and repeating the study with a different network may provide a different result.

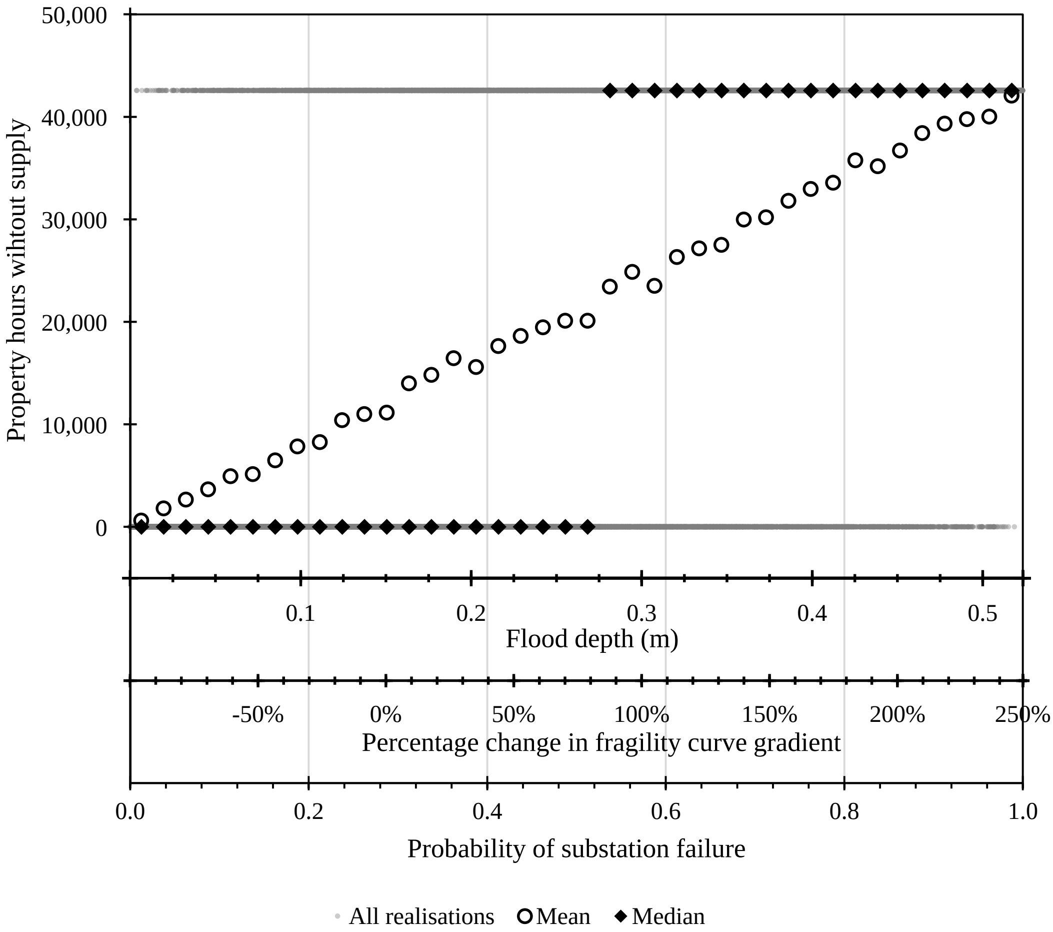


Figure 6.24 The sensitivity of the total impact to changes in the probability of substation failure due to flooding. In common with the inland flooding scenario above the results of realisations are split between zero and 43 000 property hours lost. However the mean impact rises consistently with increasing probability of substation failure.

6.5.2 Sensitivity to changes in the resistance of electricity transmission lines to high wind speeds

Sixty seven percent of the risk in the first case study was attributed to either strong winds, or the combined effect of wind, moisture and low temperatures. Furthermore, the presence of very high wind speeds in the time series of hazard intensities was also highlighted as a concern. Therefore it is important to understand the sensitivity of the impact to changes in the probability of transmission line failure.

To examine this sensitivity three modifications were made to the model:

1. A variable was introduced to randomly sample the failure rate per kilometre of transmission lines from a log-uniform distribution between 1×10^{-18} and 0.15. According to the fragility function fitted in Chapter 4.3 these equate to gust wind speeds of 0.61 and 150 miles per hour respectively and therefore they ensure the full range of plausible values and potential errors are explored. The use of a log-uniform distribution reflects the exponential nature of the fragility curve and increases the number of samples at the more common low values.
2. The length of each link between electricity substations was estimated by measuring the geographical distance between the two substations and increasing it by 42% to reflect the typical difference between the straight-line distance and the route of the transmission line (see Chapter 4.5).
3. The variables identifying the availability of each substation were adjusted to incorporate the failure of the incoming transmission lines.

Figure 6.25 shows the non-linear relationship between the failure rate, and therefore the wind speed and fragility curve parameters, and the total impact. The conversion from failure rate to wind speed (upper axis) and change in fragility curve parameter (middle axis) was made by rearranging the fragility curve for transmission lines operating in temperate conditions which was taken from the work by McColl et al. (2012) (see Chapter 4.3).

$$P(fault|w) = 2.77 \cdot 10^{-17} \cdot w^{7.30} \qquad 6.1$$

Where:

P(fault|w) = the fault rate given wind speed w in normal conditions.

w = three second gust wind speed (mph)

The non-linear relationship is evidence that the redundancy in the network is making it more resilient to small events. When the failure rate is below 0.025 faults per kilometre, equivalently to gusts of approximately 112 mph, the mean impact is small and driven by a number of isolated failures. Above a fault rate of 0.05 faults per kilometre (≈125 mph) the impact accelerates rapidly as there is an increasing frequency of systemic failures which affect the whole of the network including sources of redundancy. Between these two thresholds in an intervening period where small failures occur regularly but widespread failures are rare.

Identifying these thresholds is important to understanding the sensitivity of model outputs. An underestimation of hazard intensity will not recognise the exponential increase in impact but, equally, the increase of 600 000 property hours without supply between wind speeds of 133 and 137 mph is evidence that overestimation of wind speeds could severely increase the estimated impact.

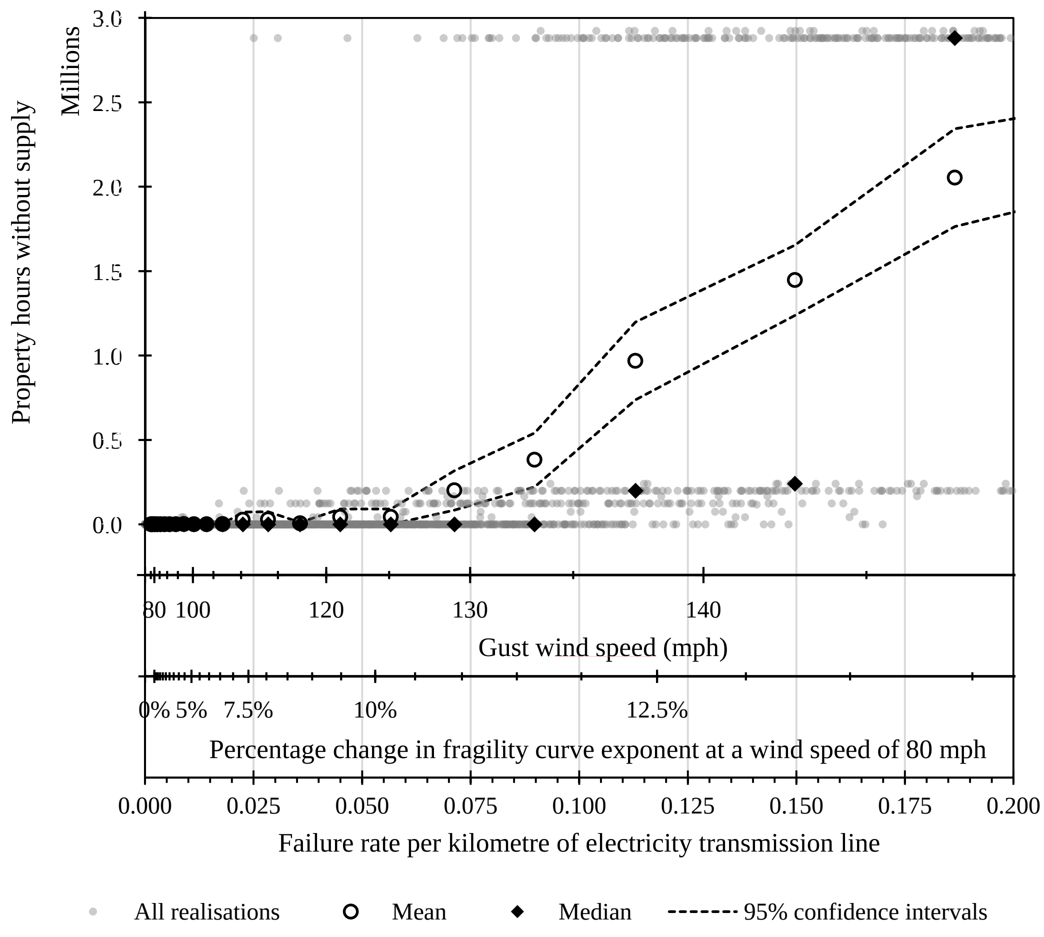


Figure 6.25 The sensitivity of the total impact to changes in wind speed (upper axis), facility curve parameters (middle axis) and the failure rate of electricity transmission lines (lower axis)

Gusts of 125 miles per hour are not inconceivable in the UK. The 1987 storm included gusts of 115 mph and speeds of 127 mph were recorded at the Great Dunn high level weather station during the 2005 Cumbrian storms (Met Office 2005, 2012). Both resulted in widespread loss of power and, as discussed in Chapter 1, the Cumbrian storms also caused many customers to lose their water supply. In this regard, both the models developed in this research are credible.

The remaining concern is the frequency with which these events occur. There are 33 individual hours spread over 16 events in the 1 020 year time series used in the first study indicating a return period of approximately 60 years. If the frequency of events of this magnitude is overestimated then the number of systemic failures which affect the whole network is also likely to be too high. Revisiting the model used to produce the time series of wind speeds in the first study is an important area for further work.

A further consideration is the sensitivity to changes in the parameters of the fragility curve (the middle horizontal axis in Figure 6.25). This sensitivity is more significant with a 10% increase in the exponent of the fragility curve equating to the 125 mph threshold identified in the previous paragraphs. There is considerable scope for variability in this value. It is noted that the exponent for the cold weather fragility curve is 75% greater than for the temperate fragility curve; therefore it could have a large impact on the overall result. These curves represent the best available information but, nonetheless, there remains considerable uncertainty. Further work to reinforce this information would also be beneficial.

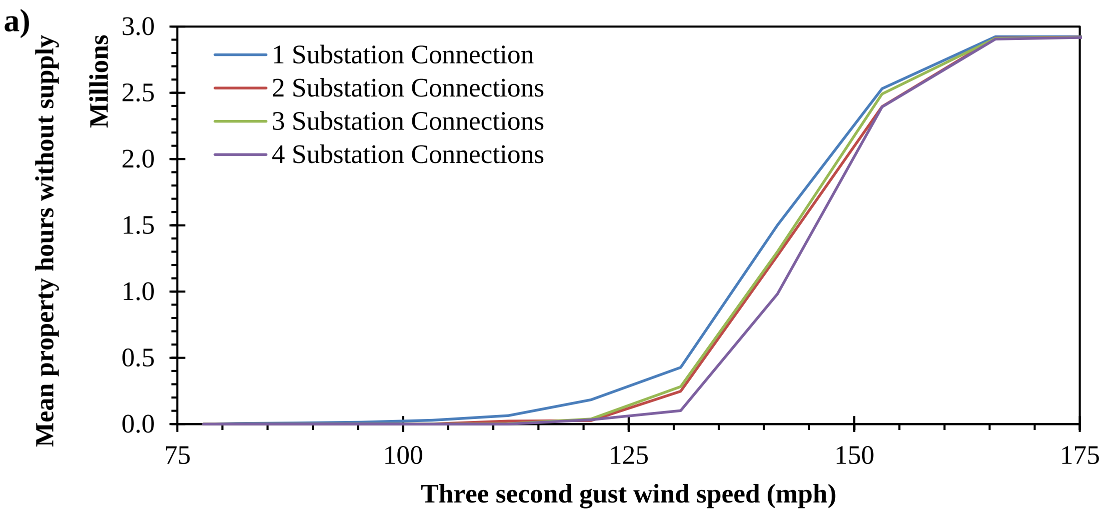
6.5.3 Sensitivity to changes in the number of primary substations which can feed each water facility

Despite the widespread interest in the resilience of interdependent networks, little attention has been paid to the interfaces between the networks and how this affects their vulnerability (Winkler et al. 2011, Ouyang & Dueñas-Osorio 2011). This is an area which concerns the project sponsors. Their critical facilities connect to multiple local substations but they are aware that these substations may depend upon the same BSP or GSP. This introduces a common point of failure and reduces resilience.

This gap is addressed by running three additional scenarios where facilities were connected to only the closest substation, the closest three, and the closest four substations.

These were combined with the previous scenario with two connections to make a continuous set. There is one exception as the raw water pumping station to the north-east (RPS F) has a dedicated primary substation so redundant connections are not relevant.

A comparison of the four scenarios under different failure rates is shown in Figure 6.26. The fragility curve from Equation 6.1 has been used to convert failure rates to wind speeds as these are more intuitive to interpret.



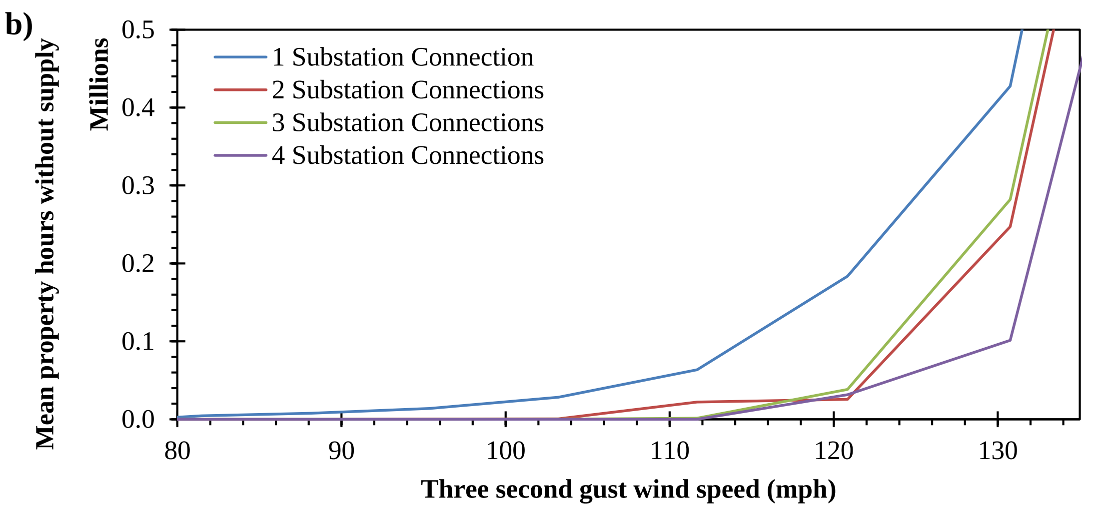


Figure 6.26 The effect of changing the number of substations to which each water facility is connected. a) shows the full range of results and b) adjusts the scales to focus upon the realistic range of wind speeds which is of most interest to infrastructure providers. a) shows that the peak impact in all cases is slightly less than three million property hours lost and suggests that the number of substation connections is not important at extreme wind speeds. However, b) shows that below this level a four connections provide more resilience with the mean impact consistently lower than the other scenarios. Conversely, the scenario with only one connection appears to be consistently outperformed by the other three. Both graphs indicate that there is little difference between two and three connections.

Figure 6.26a suggests that at wind speeds above 150 mph the number of connections is irrelevant; this is intuitive as such extreme events are likely to cause simultaneous failures across the whole network. However Figure 6.26b indicates that at more probable wind speeds the scenario with only one connection is much less resilient than the other scenarios and therefore a risk assessment based on this assumption may overestimate risk.

The similarity between the results from the scenarios where there are two and three connections supports the project sponsor's concern that additional connections may not be delivering value because they simply provide a new route to a common point of failure. Furthermore, the additional resilience created by a fourth connection does not become apparent except in extreme events. On this basis, two connections seems a proportionate level of redundancy.

Figure 6.27 displays the standard deviation for each scenario at different wind speeds and therefore provides insight into how the number of connections affects the spread of impacts. The low standard deviations at low wind speeds show that failures are rare and the spread of impacts is small. The very high standard deviations in the middle range indicate a phase where large values are becoming common but the variation is maintained by the switching between small and systemic events (this bimodal distribution is visible Figure 6.25). The fall in standard deviation at high failure probabilities reaffirms that all four scenarios, and all realisations, converge on the same impact as the redundancy in the system is eliminated and systemic failures dominate.

Figure 6.27 also shows more clearly that increasing the number of connections causes the initial impact to occur at higher wind speeds. The scenario with only one connection again stands out as the first failure occurs at wind speeds over 15 mph slower than the other scenarios. However, the standard deviation rises slowly which is consistent with a system where individual water facilities are vulnerable to individual failures in the electricity network. The gradient increases as the system makes the transition from isolated individual, isolated impacts to multiple failures across the network which either combine to have a large cumulative effect or erode the redundancy in the water network.

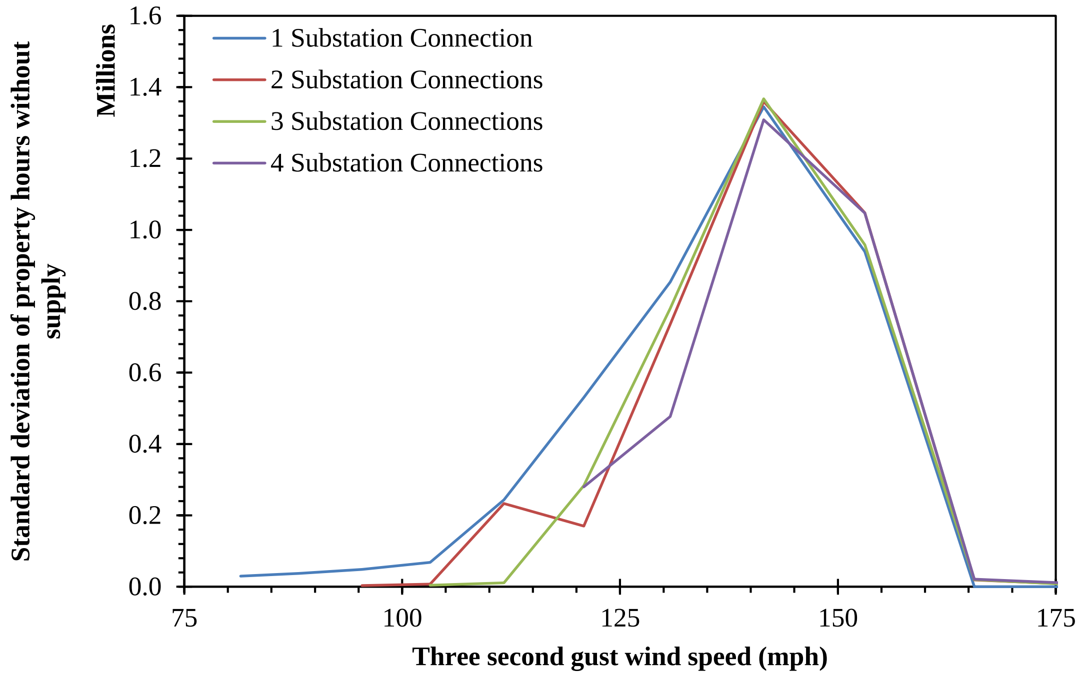


Figure 6.27 The standard deviation of the impacts with different connection densities shows that an increasing number of connections increases the hazard intensity at which the first failures occur. Note that only the standard deviations where the mean is not zero are shown.

It is also noticeable that the standard deviation at the first failure in the scenario with a connection density of four is markedly higher than the other scenarios. This indicates that this scenario individual facility failures are rare and the system moves directly into major systemic failures. Therefore, whilst this scenario is more resilient, it is important to note that the organisation may be unaware of the risk of major failures because they are not experiencing the more frequent smaller failures. This ties into the idea of latent flaws expressed through the Swiss Cheese model (see Chapter 2.3) and the need to identify the potential for low probability, high impact surprises.

These results only represent a single case study, which by virtue of its redundancy, appears to be a very resilient network. The results cannot be assumed to be representative of every network. However, they both highlight the importance of assumptions about the interfaces between networks and demonstrate that the model can provide insight into the behaviour of complex systems. This is discussed further in the following section.

6.6 Discussion

Chapter 1 identified three requirements for a model of dependency on third party systems to be useful to infrastructure providers. This section assesses this model against each.

6.6.1 Do the results identify weaknesses and therefore ways to improve resilience?

The aim of this model is to support infrastructure providers in identifying the plausible consequences of worst case scenarios, and understanding which perturbations could cause disproportionate impacts. This was motivated by a recognition of the difficulties and uncertainties attached to the probabilistic modelling of low probability, high impact events (Government Office of Science 2012), the ability of complex systems such as interdependent infrastructure to produce unexpected outcomes (Popescu & Simion 2012, Blockley et al. 2013) and the need to assess the impacts of the UK Cabinet Office's 'reasonable worst case scenarios'.

The application of the model to two of these scenarios indicates that it achieves this aim. It shows that the case study network is largely resilient to flooding due to the low exposure of infrastructure facilities and the redundancy in both the water and electricity networks. The notable exception is one booster pumping station which relies solely upon a bulk supply point exposed to flooding. The model was therefore used to simulate the effect of creating a mobile generator connection point at this facility which reduced the threat considerably, though it also introduced a new dependency upon the highways network.

The potential impacts of the hot / dry weather scenario are markedly higher since this scenario puts the entire electricity network at risk. It is not possible to compare the scenarios directly because the flooding affects only a small subset of substations and other factors also affect the impact in the hot / dry weather scenario. Notwithstanding, Figure 6.28 shows some key themes.

The inland flooding scenario is the very simplest of cases where the sole supply to a group of customers has a one-to-one dependency. Therefore the system has no redundancy and, as Figure 6.28a shows, the impact is directly proportional to the number of failures. In contrast, the profile in Figure 6.28b is curved because the wider system has redundancy and the whole system is exposed to the hot and dry weather.

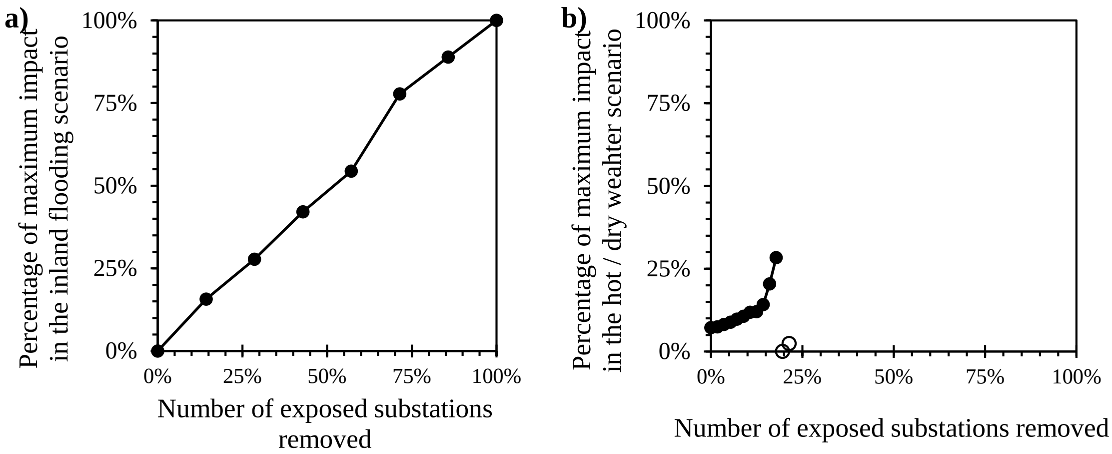


Figure 6.28 The effect of redundancy. The results of the inland flooding scenario (a) where there is a direct one-to-one dependency produces a directly proportional relationship between the number of failures and the impact. The results of the hot/dry weather scenario (b) where there is resilience produce a curved profile. Hollow circles are used to represent the high failure rates where there was only one example of each so the sample is unreliably small, the samples run in this research do not extend beyond the failure of 21% of substations.

Which of the scenarios displays greater resilience is not a simple question. The answer depends on definitions of resilience and vulnerability, and the different perspectives of the two models developed in this research. The inland flooding scenario is the more probable (BSP G is in the high flood risk zone) so would feature highly in a risk analysis such as that conducted in the previous chapter. However, it affects one of the furthest points of the system and the impact is localised. It is questionable, given the low and predictable impact, whether the impacts are disproportionate to the initial perturbation.

On the other hand, the threats identified in the hot and dry weather scenario are quite improbable but unpredictable. At low intensities the redundancy provides resilience but multiple failures at high intensities erode the redundancy. Furthermore, since the whole network is vulnerable to the hazard, failures at critical nodes in the water network can have cascading impacts through the whole network. This explains why the curve in Figure 6.28b ‘overtakes’ the straight line in Figure 6.28a. Increasing the range of results from this study to include complete network failure is an obvious candidate for further work.

The hot and dry weather scenario goes further by demonstrating the interdependency between internal stresses, in this case the supply-demand balance, and the impacts of failures in third party networks. The impact of the latter becomes progressively greater as the internal stresses increase. This is intuitive but the realisation with the largest impact highlights how the combined occurrence of three factors can be potent.

The effect of the third party infrastructure failure in escalating the impact of the low output at the water treatment works echoes Blockley et al.'s (2013) observation that small changes in complex systems can produce very different outcomes. It also reflects Perrow's Normal Accident Theory (1984) and its development into the Swiss Cheese Model by Reason (1990). The supply-demand deficit constitutes the threat to the system and importing water from a neighbouring zone is one of the risk controls. The exposure of this import to failures in the electricity network creates latent flaws in the risk controls which may only be revealed when the events occur concurrently.

Pate-Cornell (2012) discusses these 'perfect-storm' risks where the probability and mechanisms of individual events may be well known but their simultaneous occurrence is not considered.

> *"The key here is that these factors are not anticipated because their conjunctions seem too rare to care about." (Pate-Cornell 2012, p1825)*

The joint probability of low output, high demand and the failure of these specific substations may be small but the common exposure to prolonged hot and dry weather means that it cannot be assumed that they are independent. Given the potential magnitude of the disruption it is important that decisions makers can identify these risks.

6.6.2 Do the results provide reliable evidence to support decision making?

The main advantage of this model over Model 1 is its greater simplicity and the ability to understand its operation. Figure 6.29 shows one of the dashboards allowing the decision-maker to visualise scenarios. They can therefore assess whether the model accurately represents their understanding of how the system would operate under different scenarios.

The ability of experts to visualise the scenarios can also help develop a better understanding of the systems. Expert opinion on complex and low probability, high impact events can be unreliable because threats fall beyond or between the 'comfort zones' of recognised experts (Government Office for Science 2012, Brown and Elms 2015). Blockley et al. (2012) note that even diverse teams can be unwilling to react to complex and improbable threats which therefore remain unmanaged and poorly understood. Engaging experts and decision makers with the model can help synthesise knowledge about the systems into deeper understanding which, Brown and Elms argue, 'can lead to better and more sure-footed decisions' (2015, p66).

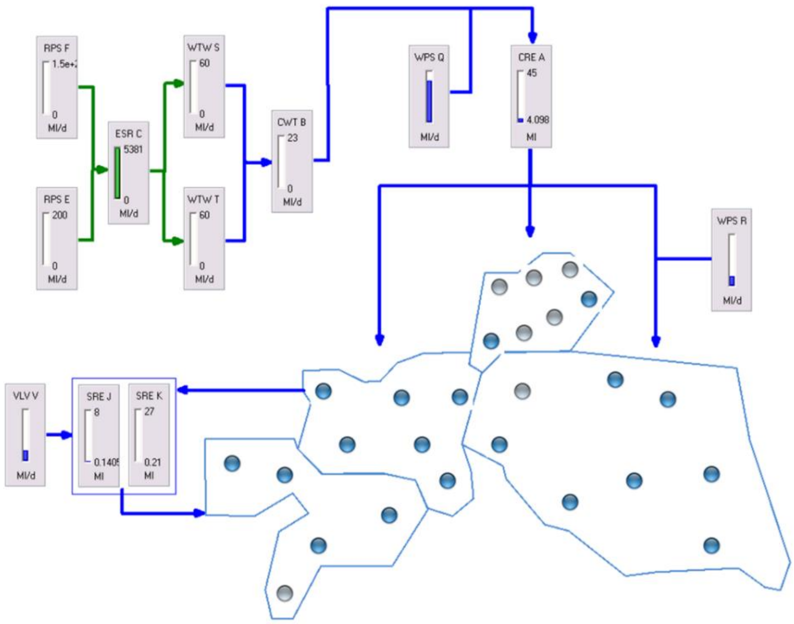


Figure 6.29 Example dashboard from the model. Bars represent facility output and blue / grey circles represent demand nodes with and without supply. In this case a large power cut has affected the northern part of the network. The water treatment works has failed but WPS Q is supporting many of the nodes; those which have failed rely upon local pumping stations.

The model also has weaknesses. Most prominent is the assumption that failed sites remain failed for the full duration of the realisation. This may be realistic in some cases (e.g. the flooding of a major substation or water treatment works) but it is likely to overestimate the impact in other scenarios (e.g. when substations are affected by high demand).

The ability to provide mobile emergency generators and to import water from neighbouring zones makes the model more representative of how infrastructure providers would respond to events. However, this representation is not perfect. In particular the setting for water treatment works and centrally controlled pumps remain constant regardless of the scenario. Equally, whilst the model captures the major imports and exports, there may be opportunities to reconfigure multiple small areas to receive supplies from the neighbouring zones. It is unclear how this aspect of infrastructure resiliency can be modelled with more accuracy, as discussed in Chapter 5.3 it is inherently unpredictable on the larger scale at which infrastructure resilience needs to be considered.

The other significant concern is the lack of information about the ‘last-mile’ connections between primary substations and water facilities. This concern is more acute because the previous section demonstrated that both the average impact of failures and the pattern of failures are sensitive to the number of substations connected to each water facility.

6.6.3 Can the model be applied in an industrial setting?

The main limitation of the first model was its intricacy; the combination of a hazard model, stochastic identification of failures and continuous simulation made interpreting the results challenging. The model provided important insights into where, why and how the system was vulnerable but it is difficult to envisage it being used except for where there are specific concerns.

This chapter has responded by producing a simpler model which is more practical in a number of ways. Firstly, the model runs more quickly due to the combination of specialist software and discrete event simulation. The precise running times depend upon the number of failures but 10 000 realisations of the inland flooding scenario requires under three hours. The widespread impact of the other scenarios and the sensitivity analysis make the model slower with 10 000 realisations taking approximately 20 hours. Secondly, as discussed above, dashboards allow decision makers to verify the model is operating accurately and helps to develop their understanding of the network. Consideration has also been given to the process of replicating the model for other water supply networks including the use of standard templates and fields from the company's asset database.

Importantly the model still incorporates characteristics of the water networks such as storage and capacity constraints to create a realistic model of dependencies. However, there are other costs associated with the simplification. The principal drawback is that the model does not quantify nor explicitly consider event likelihood. This is an equal factor in the expected consequence over a given timescale and therefore, arguably, a vital factor in setting a proportionate resilience strategy.

The Blackett Review notes that the weakness of deterministic methods is that the outputs are not readily comparable (Government Office for Science 2011). This is apparent in the outputs from two scenarios in this case study; identifying which of the two scenarios poses the greater risk is a subjective choice between the more probable, low impact event and a less likely but highly damaging one.

The counter-argument is that all decisions are in some way subjective (Brown & Elms 2015). Providing more complete and probabilistic information simply moves the subjectivity to deciding whether the probabilistic information is sufficiently reliable to support the decision. There is a credible argument, founded in the UK Government's

Blackett Review of High Impact Low Probability Events, that the two models developed in this thesis are complementary. The first model provides a means of obtaining a precise risk assessment for a limited area of particular concern. This model does not provide the same level of detail but allows the ‘stress-testing’ of assumptions, sensitivities and uncertainties. Through this infrastructure owners and operators can understand their systems’ resilience and vulnerability in the wider sense.

6.7 Summary

The chapter has developed an alternative model of the dependency of water infrastructure on electricity, telecommunications and highways networks. It uses the UK Government’s ‘reasonable worst case scenarios’ to explore the potential impacts of natural hazards and identify what factors contribute to or trigger these impacts.

The model identified a number of specific weaknesses in the large water network used as a case study. It indicates that a pumping station, which is the sole supply to approximately 1 400 properties, is wholly dependent upon a substation that is exposed to flooding. Equally, it suggests that a connection point for a mobile generator at this pumping station reduces the mean impact of this substation’s failure by 82% (Figure 6.17).

Elsewhere, the hot / dry weather scenario illustrates the importance of including internal stresses alongside the impacts of failures in third party infrastructure networks. Higher internal pressures increase the likely impacts of external failures and, equally, external failures inhibit the system’s ability to manage internal stresses. For example, the largest impact from 40 000 realisations of the scenario was caused by the combination of high (but not excessive) demand, reductions in WTW output; and – crucially – the loss of power to the emergency pumping station needed to meet these internal pressures.

The Cabinet Office scenarios represent the level of event for which water companies are expected to be prepared. Identifying vulnerabilities across the full range of potential impact, including those such as these which are often hidden by the complex interactions between components, is an essential part of providing this level of resilience.

The model has also been applied to assess how changes in the parameters of fragility curves and assumptions about connections between networks can affect estimates of the network’s vulnerability. The results show that these sensitivities can be substantial and therefore the conclusions of studies must be interpreted carefully. For example, reducing the number of connections from each water facility to primary substations from two to one has the effect of reducing the wind speed at which the first impact occurs by almost 14 mph (Figure 6.26). Equally, and of particular relevance to Model 1, increasing the peak wind speed from 125 mph (the peak experienced in the 2005 Cumbrian Storms) to 135 mph causes the mean impact to rise by 157 000 property hours without supply (Figure 6.25). There is considerable scope for further work to refine these assumptions and produce more accurate and precise assessments of the risk from dependencies.

Model 1 provides a probabilistic assessment of risk due to dependence but its complicated nature makes it less well equipped to explore the full range of potential impacts. This model provides complementary information. It does not provide detailed information on which vulnerability is more likely but detects potentially catastrophic low probability, high impact events. Once identified, these can be incorporated into the water company's risk management processes and appropriate controls put in place.

Chapter 7. Conclusions & Recommendations

This chapter summarises the key findings of this research, their implications for water companies and other studies of infrastructure interdependence. These are cross-referenced against the research questions established in Chapter 1.2. This chapter also identifies ways of improving the models and avenues for wider further research.

The resilience of infrastructure is critically important and water companies must deliver a reliable service to customers. The Government policies which emerged from the 2007 floods encourage infrastructure providers to reduce their vulnerability and regulators can impose strict penalties upon companies who fail to meet targets (Research Question 1a). However, this is counter-balanced with measures to protect customers from excessive costs and Ofwat's Price Review process challenges water companies to demonstrate that their investment plans are proportionate (Research Question 1b). Water companies require reliable and robust information to target the areas where the vulnerability is greatest and to demonstrate this to regulators.

Of particular concern to water companies, and to infrastructure providers more generally, are the risks posed by dependencies between infrastructures. The complexity of interactions between sectors and infrequency of events means empirical data is limited yet the potential impacts are large. Water companies need new ways to assess and understand these risks to produce effective and defensible resilience strategies. In response, the aim of this research was to 'develop methods which can assess the vulnerability of water networks to failures in other interconnected critical infrastructure systems, and to assess whether this information can be used to improve the resilience of the water networks.'

It achieves this by producing two models and applying them to real-world case studies. Model 1 targets the water companies' desire to prioritise risks, both between different dependencies and in comparison to their wider business, and produces a quantitative, probabilistic risk assessment. Model 2 explores the wider space of potential risks to support the identification of potentially catastrophic low probability, high impact events.

7.1 Key findings

7.1.1 Model 1

The first model, outlined in Chapter 4, is based on catastrophe modelling and performance based design methods, and consists of a series of component processes:

i. Chapter 3 limits the scope to meteorological hazards as they pose a significant threat to UK infrastructure and there is sufficient information available to characterise their likelihood and potential impact (Research Question 2a). The UKCP09 Weather Generator was identified a source of synthetic but statistically equivalent time series of rainfall intensities and temperatures. Gust wind speeds were produced using a purpose-built ARMA model (Research Question 2b).

ii. A library of fragility curves has been created describing the effects of these hazards on the functionality of facilities in four UK infrastructure sectors (roads, electricity, telecommunications and potable water) (Research Question 3a). To the author's knowledge, this is the first time that a comprehensive set of such curves focused on functionality has been compiled. The new family of curves based on incident data from the Highways Agency is a good example of how such empirical fragility curves can be developed.

iii. A set of realistic network models have been developed to assess the impact of facility failures, including those in other sectors, on system performance (Research Questions 4a & 4b). This includes a new approach for assessing how capacity constraints in densely connected electricity distribution networks affect redundancy. The metric of average property minutes without supply is used to capture the vulnerability of specific areas and the network as a whole.

This model is novel in assessing the effects of three simultaneous hazards on three external infrastructure networks and the consequential impacts on water network facilities. It is also unusual in its use of flow-based models, including storage, to more accurately assess the impacts of facility loss on service delivery.

The results (Chapter 5) suggest that this multi-faceted approach is essential for developing a full understanding of the network's vulnerability. For example, the electricity network is the source of approximately 90% of the total risk but only a proportion of this amount (approx. 75% of the total risk, see Figure 5.39) results from the direct dependency of water facilities on power. The balance (approx. 15% of the total) arises from the telecommunications facilities' dependence on power and the impacts of their failures on the water network. This information is valuable because it indicates to the decision maker that reducing their dependency on telecommunications could reduce their exposure to faults in the electricity network.

The realistic modelling of the network's structure (i.e. pumps, reservoirs etc.) demonstrates that this fundamentally affects the extent and the nature of the system's dependencies. A large proportion of the total risk is concentrated in a small number of nodes (Figure 5.29). Furthermore, nodes fed directly from pumps depend upon electricity and affect fewer customers but fail frequently. Nodes fed from service reservoirs rely upon telecommunications and fail rarely but affect many (Figure 5.37).

This indicates that parts of the network already have inherent, and previously largely unrecognised, properties which manage the risks from dependencies. Identifying these strengths is important because it allows resilience strategies to target other, more vulnerable, parts of the network. For example, installing a small number of reliable standby generators could resolve the frequent failures at small, directly pumped nodes. It also shows that using topological models to analyse water networks is flawed.

Notwithstanding its strengths, the model also has weaknesses. There is uncertainty attached to the fragility curves and distributions of recovery times, and there are specific concerns about the accuracy of the model used to produce wind speeds and the ability of the water network model to account for the network behaviour under pressure deficient conditions. The complexity of the model also makes it difficult to interpret the results and limits the scope for analysing alternative scenarios or conducting sensitivity analysis.

7.1.2 Model 2

The second model (Chapter 6) focuses on identifying low probability, high impact risks. The strengths of the first model were retained including: the representation of the three external sectors; the ability to consider different hazards; the representation of network components; and calculation of the impact on customer.

Conscious of the complexity of the first model, it also made a number of changes. The UK Cabinet Office's 'reasonable worst case scenarios', which represent the upper limit that UK infrastructure providers are expected to consider, were identified an alternative source of information on hazards and their potential impacts on UK infrastructure (Research Questions 2b & 3a). They were used in the place of Model 1's hazard model and fragility curves. A stocks and flows model took the place of the hydraulic model to make the model easier to implement and the results easier to interpret (Research Questions 4a & 4b).

The key feature of this model is the ability to realistically represent the behaviour of the complex infrastructure system in a way which is accessible to the decision maker. This is an important step towards closing the gap between theoretical studies of interdependence and the practical requirements of those managing real systems.

In the inland flooding scenario, for example, a tipping point is identified where the flooding of a substation causes a specific group of customers to lose supply. Installing a mobile generator connection point at this facility significantly reduces the threat (the mean impact of 10 000 realisations is reduced by 82%) (Figure 6.16, p.245), though in the process it introduces a new dependence upon the road network (Figure 6.17, p.245)

The model also highlights a vulnerability to the Cabinet Office's prolonged hot and dry weather scenario due to the simultaneous effects on water treatment works output, high demand and electricity faults which may affect emergency pumping stations. The potential magnitude of this event is significant with an estimated impact of 6.4 million property hours without supply. These vulnerabilities which arise from the complex interactions of system components are unlikely to be identified by conventional risk assessment processes.

The less complex model also enables sensitivity analysis of some of the key uncertainties in both models. This research focuses upon the water network's dependency on the electricity network. It shows that below certain thresholds the sensitivity of the results is low but it can accelerate rapidly at higher failure rates. Of particular note is the sensitivity of the total impact to changes in the number of connections between the dependent and external network (Figure 6.26, p.257). Many studies assume a single connection to the closest major substation but the analysis in the first model suggests most sites have multiple connections. The sensitivity analysis indicatess that they are significantly overestimating the risk as a consequence. In contrast additional connections appear to have a less substantial impact.

7.1.3 Usefulness for water companies

The value of the models for infrastructure providers (Research Question 5a) has been assessed against three criteria.

i. *Do they identify where their systems are vulnerable and hence where to direct efforts to reduce risk?*

This is a particular strength of both models; they identify where, why and how specific networks are vulnerable to failures in other sector.

ii. *Do they provide quantitative information which decision makers can use to make evidence based decisions?*

The first model produces a quantitative estimate of the expected annual number of minutes each group of properties is without water supply due to third sector dependencies. This value is a slight overestimate and subject to a number of uncertainties but it provides an important starting point for further analysis. The second model provides a quantitative assessment of the potential magnitude of event but does not quantify likelihood.

The principal benefit of both models is formalising the assessment of risk. From a regulatory perspective this makes it more transparent and auditable but the results will inevitably require sense checking against operational experience.

iii. *Are they practical to implement in an industrial context?*

The complex nature of infrastructure dependencies makes realistic modelling and analysis challenging. The first model could be used successfully for specific risk assessments but, on balance, is too complex to be deployed at a strategic level. However, further work to improve the model components and reduce uncertainty would make the assessment more valuable and therefore improve the cost-benefit ratio of undertaking the analysis.

The second model is more accessible to decision makers. The structure of standard components makes it more straightforward to implement and the clearer presentation of outputs allows more ready interpretation. This is beneficial in two regards. Firstly, it allows the decision maker to validate the outputs against their own experience. Secondly, the process of interpretation can develop a deeper understanding of vulnerabilities in the system and, consequently, the resilience of customer's water supply. It is recommended as an initial step to assessing the risk to these water services due to their dependency on other critical infrastructure networks.

7.2 Recommendations for further work

The purpose of this research was to bridge the gap between the existing theoretical work on interdependent infrastructure and making the study of these dependencies a functional part of water company's risk management processes. This research has narrowed the gap considerably but not closed it entirely and there is ample scope for further work.

7.2.1 Incremental improvements

The breadth of this research has not permitted the detailed exploration which some topics warrant. Opportunities for incremental improvement include:

i. *Improved models of extreme wind speeds.*

This is identified as key source of error in the first model. However, it is an active area of research in its own right so further work is likely to identify or develop better solutions.

ii. *Improved fragility curves and distributions of recovery times for UK infrastructure.*

This research has compiled a library of fragility curves for UK infrastructure but there are limited empirical data to support them so there remains significant uncertainty. Improving these curves will be beneficial not only for the assessment of infrastructure interdependency but also the wider analysis of infrastructure resilience. There is also ample scope for curves to be applied as part of a proactive response to forewarning of hazards.

iii. *A model of the water network which is accurate under pressure deficient conditions.*

A model of hydraulic networks under pressure deficient conditions was not used in Model 1 because it was too computationally intensive and the required adjustment of the source code of EPANET was outside the scope of the project. It is noted that recent work by Sivakumar & Prasad (2014, 2015) offers a potential route to overcome these obstacles.

iv. *The inclusion of recovery times in Model 2 and sensitivity analysis.*

A weakness of the second model is the assumption that failures are permanent when they could be brief, prolonged or even intermittent. The presence of storage in the networks means a rapid recovery can prevent an impact on customers. Recovery times are also an uncertain element of Model 1, and infrastructure modelling in general, so it would be valuable to assess their relationship with the total impact.

v. *A better understanding of the 'last mile' connection.*

Most studies focus on the strategic networks; these are less complicated, have the biggest impact if they fail and generally better data availability. However, when considering interdependence every level of the hierarchy matters because it could feed a vital component in another network. Industry experience suggests that the final connection to the dependent facility (or home) is the most vulnerable and the sensitivity analysis in Chapter 6.5 shows assumptions in this areas have significant implications for estimated impacts. The complexity of local networks mean that it is not feasible to incorporate them into every model. However, a systematic appraisal of the role of the 'last mile' connection will identify patterns which can be generalised into higher level models.

7.2.2 Opportunities for new research

i. *Climate change impact assessment*

The durability of infrastructure means that decision makers need to consider how their networks will perform decades into the future, including the potential impact of forecasted climate change. These models provide a framework for completing such an assessment which includes the risks posed by interdependency.

ii. *Understanding the human component of infrastructure response and recovery*

This research has focused on the interactions between the physical infrastructure systems. The resourceful actions, and occasional errors, of operational staff are inherently unpredictable so have not been included. However, there is wide literature on accident theory and how organisations can maintain high level of reliability with many parallels to the operation of critical infrastructure. This would be an interesting alternative route for further exploration.

Chapter 8. References

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APPENDICES

Appendix A. **Model 1 Schematic**

Appendix B. **Closures of the UK Strategic Road Network between 2006 and 2013 (data provided by the Highways Agency)**

Appendix C. **Model 1 Results**

C.1 1 020 years of raw hazard values
C.2 Condensed hazard time series
C.3 Infrastructure facility failures
C.4 Node pressures
C.5 Hazards, interruption durations and time to impacts
C.6 Property hours lost per year
C.7 Summary of alternative scenarios

Appendix D. **Model 2 Infrastructure Facility SIPOC Tables**

Appendix E. **Model 2 Results**

E.1 Reasonable worst case scenario results
E.2 Sensitivity analysis results