DEPARTMENT OF ELECTRONIC & ELECTRICAL ENGINEERING

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The Effect of Weather and Climate Change on the Operation of Meshed Power Networks

By

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Abstract

Weather outages affect power systems all over the world. In January 1998 Canada experienced the 'Great Ice Strom' which hit an area spanning from Eastern Ontario to Southern Quebec. 15 years later, it experienced another ice storm which left 600,000 people without power at the peak. Wind storms can also cause severe damage to power systems such as wind storms Lothar and Martin that hit France in December 1999. Due to never experiencing winds this high, nearly 3.4 million homes were left without power for up to 17 days. In the future outage rates may increase but we are unaware of what the current effects are, for example is there is any relationship between durations and the intensity of the weather or what the probabilities of these events causing an outage are. However, the weather experienced by each country, even areas within a country can vary. This thesis will present a five stage methodology that was developed for the analysis of both the current effects of weather on power transmission systems and also, the future effects. It also applied this methodology to the GB transmission network as a test case to identify the outcomes in terms of network reliability to possible changes in climate. To complete this analysis outage datasets, provided by the transmission companies of GB, were acquired to help understand what the current effects of weather are. It was determined that the three main weather types that cause weather related outages on the GB transmission network were, Lightning, Snow, Sleet, Blizzards & Ice and Wind, Gales and Windborne Objects'. It also compared observational weather data to reanalysis data and lightning strike data and a lightning strike proxy to verify reanalysis data as a suitable replicator of past weather data. A correlation analysis between weather variables and weather related outages was completed to identify the weather indicator for the associated outage. From this fragility curves of failure rates for the dominant weather-related outages based on the weather that is occurring were developed. Using climate projections seven weather test cases were developed for the state sampling model and eight for the sequential simulation. In each case a different weather variable was changed to understand the effect they will have.

It was concluded there are varying levels of confidence in climate change predictions making it difficult to assess the risk that poses to transmission networks. Reanalysis was found to be an acceptable replication of past observation data and CAPE was determined as a good proxy for lightning strikes. It was found there was an overall increase in failure rates and that there was an increase in all system indices, suggesting there would be increases in the magnitude and number of load shedding events.

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Chapter 1 - Introduction

This research has been conducted to gain a better understanding of the current and future effects of weather on transmission networks. This thesis shall present a methodology that enables the current effects of weather on transmission networks to be assessed as well as the possible effects of climate change. The developed methodology will be applied to the Great British (GB) transmission network as a test case. Due to their highly meshed topology, transmission networks are not considered to be vulnerable to weather except in extreme cases. This is particularly true when compared to distribution systems, which are generally more radial and more prone to outages that cause interruptions in supply to users. It is therefore, easier to quantify the direct impact weather has on distribution networks. However, transmission systems are vulnerable to weather, particularly to low probability but high impact events, as numerous historical occurrences have shown. It is therefore important to fully explore and understand the risks that weather currently poses and to subsequently use that information to identify the effects and risks that climate change may pose to transmission networks. This chapter shall discuss the current impacts of weather and climate change and an overview on previous research and adaptation methods. The chapter will conclude with research aims and contributions, publications and finally a thesis overview.

1.1 Weather Impacts

1.1.1 Weather Impacts

Many areas and sectors all over the world are affected by weather and climate change. After major events hit, people turn to their insurance companies to help rebuild their lives. With these events possibly increasing, insurance companies are taking an interest in looking at the risk of these events, and ultimately how it will and has cost them. Munich Re, Swiss Re, other reinsures and Lloyd’s of London insurance market are all on the same page as climate scientists when it comes to climate change: “there are no climate change deniers in the reinsurance industry” [1]. The governor of the Bank of England issued a stark warning at Lloyd’s of London in September 2015 stating that climate change poses a huge risk to global stability. The challenges that are currently faced due to climate change pale in comparison to what might happen in the future and that the current generation has little incentive to avert these future problems and the cost will fall on the future generations to pay [2].

Figure 1-1 comes from Swiss Re and shows an increase in insured covered losses from 1970 to 2012 for weather events. This trend of extreme weather events shows that their frequency has increased over the last 30 years [3] and if this increasing trend continues, without adaption, it will continue to cost billions each year.

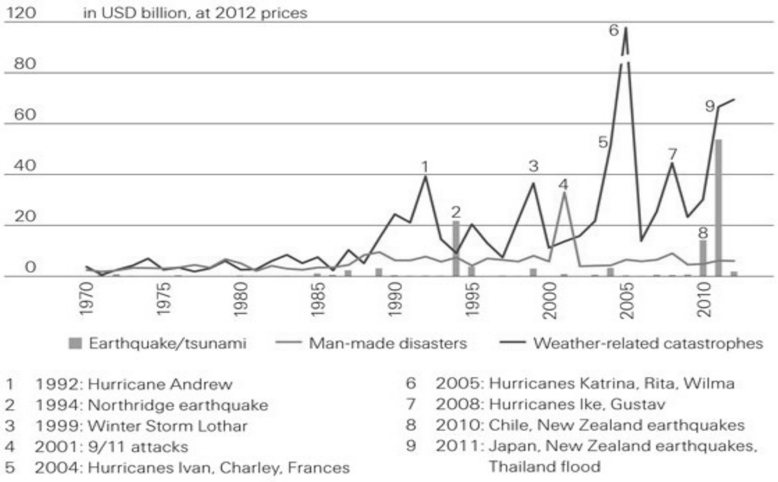


Figure 1-1 - Insured Catastrophe Losses 1970-2012 [4]

In 2012, a year of extreme weather in many countries, companies like Swiss Re, which deal with insurance-based forms of risk transfer, released studies that showed that worldwide disasters in 2012 caused economic losses of around $186 billion and around 14,000 lives were lost. These disasters can be broken down into a natural or a man-made disaster. In 2012 natural disasters cost insurers over $77 billion [5], making it the third most expensive year on record, beaten only by 2011 where claims were over $126 billion due to flooding and earthquakes in Asia and 2005 due to hurricane Katrina [4].In the USA the annual impact of weather-related blackouts ranges from $20 to $55 billion [6].

In 2012, nine of the ten most costly events occurred in the US with Hurricane Sandy topping that list. Hurricane Sandy was the second most expensive storm to hit the east coast of the US since 1900, second to the 1938 Long Island Express storm. [4] states that assuming a 10 inch rise in sea levels by 2050, that the frequencies of losses like Sandy are likely to increase in the future [5]. Table 1-1 shows the number of extreme events seen in different parts of the world and what percentage of these were weather-related [7]. While weather like hurricanes, tornadoes and earthquakes are not generally seen in the UK, it is still affected by adverse weather and it still costs billions of pounds. For example, the economic cost of the 2007 floods was around £3.2billion [8]. AXA is currently having work conducted by The Met Office which considers the effects climate change will have on wind and hail storms across Europe and the risks these changes could pose [9].

Table 1-1 - Fatalities, economic losses for disasters in different regions; estimates by insurance companies (85-99) [7]

	Africa	America: South	America: North, Central, Caribbean	Asia	Australia	Europe	World
Number of events	810	610	2260	2730	600	1810	8820
Weather-related	91%	79%	87%	78%	87%	90%	85%
Fatalities	22 990	56 080	37 910	429 920	4400	8210	559 510
Weather-related	88%	50%	72%	70%	95%	96%	70%
Economic losses (current $US billion)	7	16	345	433	16	130	947
Weather-related	81%	73%	84%	63%	84%	89%	75%
Insured losses (current US$ billion)	0.8	0.8	119	22	5	40	187
Weather-related	100%	69%	86%	78%	74%	98%	87%

1.1.2 Weather Impacts on Power System Operation

While whole economies are affected during adverse weather, power systems are also particularly vulnerable. Approximately 80% of large-scale power outages in the US from 2003-2012 were caused by extreme weather [3]. Different weather variables can affect power systems in different ways, but each can cause damage to the system though weather mostly affects overhead lines which are the most exposed system assets [10]:

- High winds and hurricanes can lead to outages on overhead lines for both transmission and distribution due to a mixture of flying debris and conductor galloping. In more extreme storms a tower or pole collapse is also a possibility.
- Ice and snow can build on the lines and insulators which can cause lines to snap, tower failures and collapse and flashovers.
- Lightning strikes on or near overhead lines can cause short-circuit outages, which will trigger protection settings. These types of faults tend to be less serious compared to wind and snow as they tend to be transient, i.e. the affected circuit does not suffer mechanical damage and can generally be restored to service within a short time e.g. by action of delayed auto-reclose (DAR). However, in some cases the voltage surge can be transferred along the line to substations and can cause other circuits to trip as a consequence of overloading leading to more a more severe impact on the system as a whole.
- High temperatures limit the transfer of power on the lines, as they increase line sagging and increase energy losses.
- Rain and flooding, while are not such a threat to overhead lines on their own, they are a threat to substation equipment if the correct flooding prevention is not in place.

Rain and flooding in combination with high winds and/or lightning can cause serious threats to both overhead lines and substations.

There are multiple examples of how adverse and extreme weather can affect the reliability and security of power grids all over the world and the consequences that they can have on individuals and companies alike when they occur. In January 1998 Canada experienced the 'Great Ice Strom' which hit an area spanning from Eastern Ontario to Southern Quebec. It caused major physical damage to the system with some reports saying that some network offices within the affected areas received more calls in one day than they receive during a normal year [11]. The damage left more than 4 million people without power, some for over a month in sub-zero conditions. The damage caused by this storm also affected some areas of Maine and New York in the USA and cost over $3 billion to repair and rebuild parts of the Hydro-Québec network [11]. This storm was the most severe storm that had been experienced in decades and the severity experienced was expected not to be felt again for decades. However, in 2013, 15 years later, Canada experienced another severe ice storm. This storm hit in December 22nd and around 600,000 people were without power at the peak of the storm and a large number still without power on Christmas Day [12]. And while the damage was not as extensive as it had been in 1998, as areas of the network did not require rebuilding, it still took over a week to reconnect all customers and over two months to complete the clean-up operations, at a cost of around C$12.9 million [13].

It is not just ice storms that can affect power grids; wind storms can also cause severe damage to power systems and cause major disruption to customers. In December 1999, wind storms Lothar and Martin hit France. The Meteo France archives have no records of such winds ever being recorded in France. The first storm hit north France on the 25th and 26th of December, with the second storm hitting southern France on the 27th. Due to never experiencing winds this high, the network was not designed to deal with them and therefore nearly 3.4 million homes were left without power for up to 17 days and the resulting repairs cost almost €1.5 billion [11]. At the end of January 2013 tropical cyclone Oswald hit parts of Queensland and New South Wales bringing with it severe winds and flooding that severely damaged the electricity network. Approximately 300,000 households were without power at the peak of the storm, which is around a quarter of the South East Queensland (SEQ) network. When the clear up began around 3600 powerlines had to be repaired and reinstated [14] due to the damage that was caused by the storm. The reconnection of 99% of customers took around 4 days with the clear up and restoration of the 1% taking longer due to major repairs being required [15]. Economic losses were estimated at around AUS$2.4 billion [16].

Extreme events can cause physical damage to equipment such as towers, poles and substations, which lead to long repair and restoration times which leaves the system vulnerable to further outages. The effects of adverse weather systems are arguably starting to be witnessed in the UK [17]. While these might not be as severe as the events described previously, they have still caused power outages and disruptions for many people across the UK. All of these examples show that while power grids are resilient to the day to day weather that is experienced, they are more vulnerable to extreme events. While extreme weather events only occur for a small proportion of time during the year, the failure rate during these events will be considerably higher than on a normal day [18]. This means it is important to understand the risks these events pose and what it means for power system reliability and security not only during normal weather days but also days when an extreme weather event occurs. By understanding and being able to model the current effects of weather, it will be possible to understand the effect that future weather changes, due to climate change, will have on network security and reliability. With the effects of climate change it is expected that the frequency, intensity and durations of extreme weather events are likely to increase [19], [20], combined with previous events and the scales of destruction the resilience of electricity networks has come under scrutiny along with network design and construction [21], [22], [23].

Under these circumstances resilience can be defined as the power systems ability to withstand high impact but low probability events, for example extreme weather events but also covers the ability of the power system to recover from such an event and learn to help soften the blow from similar events in the future [24] [25]. These adaptation methods refer to possible actions that can be taken to reduce vulnerability and increase system resilience [26]. Network operators have looked at reinforcing their networks to prevent such disruption in the future, using techniques such as undergrounding overhead lines, moving lines from exposed areas to more sheltered areas and having towers and line able to withstand heavier ice loading [11]. These adaptation measures to improve system resilience shall be discussed further in Section 1.4.

1.2 Climate Change

1.2.1 Climate Change Overview

Climate change is related to variations within the earth's average climate, usually over a long period of time and currently is a major issue around the world. It has been argued that the climate change currently being experienced is due to a mixture of natural causes and human contributions. Natural causes are defined as interactions between the oceans and the atmosphere and volcanic eruptions that the planet has experienced since the beginning of time. The main human contribution has been defined as the release of greenhouse gases. Energy that is radiated from the earth's surface, including reflected sunlight, is absorbed by these gases which causes the atmosphere to warm and global temperature increases [27]. In 2007 the Intergovernmental Panel on Climate Change (IPCC) backed up these assertions, stating that the climate has changed many times over the centuries but that most of the warming that has occurred in the last 50 years is attributable to human activities [28]. This was again stated during IPCC's 2014 Synthesis Report [29] which stated "Human influence on the climate system is clear, and recent anthropogenic emissions of green-house gases are the highest in history." Climate change does affect many different areas within society, and will amplify existing risks in sectors such as energy and governmental policies as well as creating unforeseen new risks within society [29]. In 2011 the World Meteorological Organization (WMO) produced a document looking at a decade of weather extremes that have been experienced between 2001 and 2010. Figure 1-2 shows the different types of extremes that were experienced during this time, for example in 2007 the UK experienced the worst flooding in 60 years while southern South America experienced the coldest winter in 50 years with unusual snowfalls [30]. After this the WMO also released a statement stating that "the sequence of current events matches IPCC projections of more frequent and more intense extreme weather events due to global warming" [31].

Events like El Niño, which is a prolonged warming of the Pacific Ocean, are known to disrupt weather around the world. An El Niño event five years ago was linked to a poor monsoon season in Southeast Asia, blizzards in the US, droughts in southern Australia, Philippines and Ecuador, heatwaves in Brazil, flooding in Mexico and the severe winter experienced in the UK [32]. Research now suggests that more extreme El Niño events are more likely as global temperatures rise [33]. Where El Niño is the warming, La Niña is the cooling and it is suggested in [34] that the frequency of extreme La Niña events, which usually follow an extreme El Niño, are likely to double. Suggesting there will be an increase in swinging from one extreme to another each year. The main changes in the climate can be seen when looking at the global average temperature and global average sea level change shown in Figure 1-3 and Figure 1-4 respectively. The different coloured lines indicate different datasets, but all agree that the global average temperature and global average sea level have increased over the last 50 years. It can be said with medium confidence that the last thirty years have been the warmest period in the last 1400 years [29].

Figure 1-2 - WMO 'A Decade of Weather Extreme' [30]

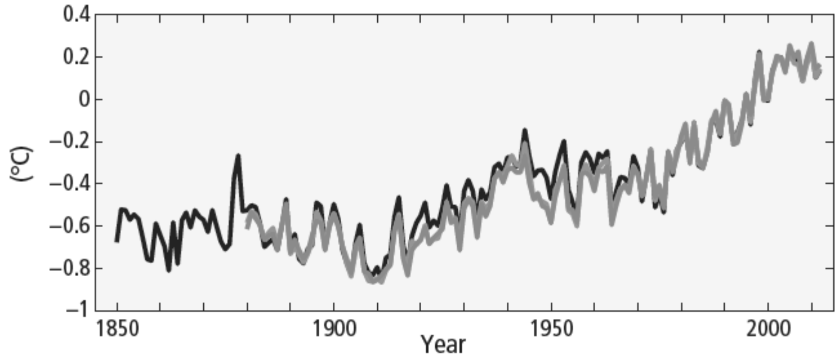


Figure 1-3 - Global Average Temperature [29]

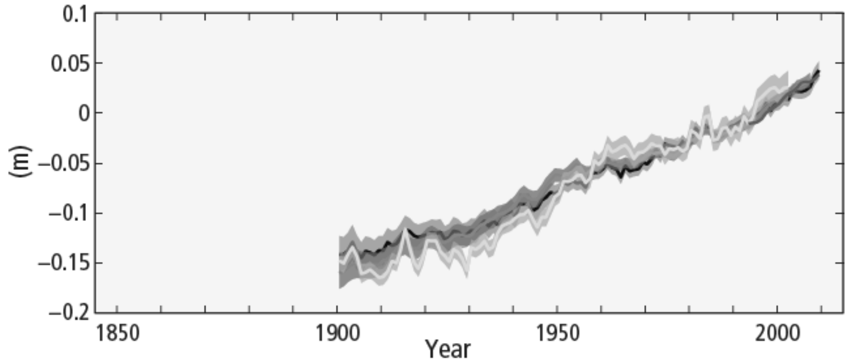


Figure 1-4 - Global Average Sea Level [29]

When discussing climate change it is important to understand that while attempts are made to state possible future scenarios it is impossible to be 100% confident, therefore confidence levels and agreements between different models are attached to all projections to help determine are the most agreed upon. The confidence levels in predicting these changes in weather can vary drastically depending on a number of factors, such as weather type, magnitude of extremes, quality of past data, understanding of the process, and the reliability of the simulation method that is used [20]. When discussing changes to climate and climate extremes it is important to understand the differences in confidence and agreement levels. For the IPCC Fifth Assessment Report a Guidance Note for lead authors was created [35] to communicate the key findings based on evaluations of scientific understanding of confidence levels. There are two main metrics used to define these measures: the confidence in the validity of a finding and the quantified measures of uncertainty. Figure 1-5 shows evidence against agreement, with the shading scale showing their relationship to confidence. As the evidence increases in robustness, so does the confidence in the data. As the agreement with the data increases, so does the confidence. With the flexibility in this relationship, different confidence levels can be assigned. Increasing levels of evidence and agreement are correlated with increasing confidence.

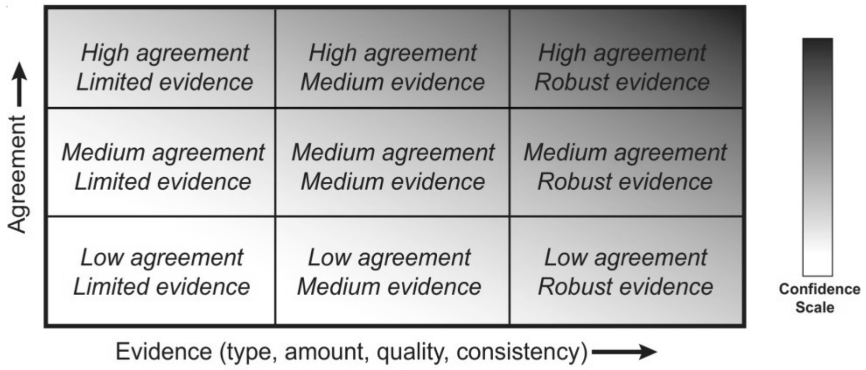


Figure 1-5 - Evidence vs. Agreement in relation to Confidence [35]

Extreme events are not common occurrences and therefore being able to ascertain long term changes in frequency or intensity is challenging – but while future extreme events might be marked with low confidence it does not make them any less likely to occur, there is simply low evidence and low agreement using current data [20]. For example it is very likely that there will be an overall decrease of cold days and nights and an increase in warm days and nights but there is low confidence in an increase tropical cyclone activity; however, this does not mean that an increase in tropical cyclones will not occur [35].

1.2.2 Emissions Scenarios

The future cannot be accurately predicted all that can be done is develop a selection of possibilities of what future weather could be like. Climate change is dependent on greenhouse gas emissions, and therefore dependent on whether emissions have increased or decreased. It is important to try to model future weather scenarios under different emission scenarios to see if there is any great effect on the outcome as this indicates what can be done with regards to emission reductions. According to [35], different emissions scenarios generally do not greatly affect the outputs of extreme weather changes, due to the complexity involved in predicating extreme weather, but it is still important to understand the different scenarios that are used when using climate change projections.

IPCC released emission scenarios to be used to develop climate change scenarios in 1992, the IS92 scenarios. These were further updated when a special report on emission scenario (SRES) was published in 2000 [36]. The SRES scenarios are designed to provide a baseline and therefore do not take into account any measures used to limit greenhouse gas emissions and do not state which scenario is more likely to happen, they are all just as possible as each other. There are four sets of family groups within the scenarios; A1, A2, B1 and B2. The A1 family group was then expanded to give A1FI, A1B and A1T giving six scenario groups in total. Altogether 40 SRES scenarios where developed using these six scenario groups. The assumptions made in the six scenario groups are as follows:

- A1 - a more integrated world, with rapid economic growth, a population that peaks in 2050 then declines and a rapid introduction of new and more efficient technologies.
    - A1F1 depicts an emphasis on fossil fuels as the main energy system
    - A1b depicts an emphasis on a balanced energy scenario
    - A1T depicts an emphasis on an non-fossil fuels energy system
- A2 - a more divided world with continuously increasing population growth, economic development is primarily regionally oriented and per capita economic growth and technology change are more fragmented and slow.
- B1 - same population growth and decline as A1 but has rapid changes in economic structures towards a service and information economy with reductions in material intensity and the introduction of clean and resource efficient technologies.
- B2 - increasing global population but at a rate slower than A2, intermediate levels of economic development and less rapid and more diverse technological change than in A1 and B1 scenarios. This scenario is also orientated to environmental protection and social equality but focuses on local and regions levels rather than global. [36].

To understand what the climate projections are saying and know the confidence levels one must first know the model and the emissions scenarios that were used to generate the projections. Most climate projection models use the emission scenarios that provide a mid-way point between an optimistic and pessimistic.

1.2.3 Climate Projections

Climate change projections are now a major interest for all sectors to see how they could be affected by the changes. Generally certain weather types have different levels of confidence when it comes to future predictions – temperature increases are cited with virtually certain confidence whereas there is generally low confidence in projections of extreme wind [35]. This confidence also greatly varies depending on what models are being used – from those developed by bigger organisations like the Met Office or IPCC, to those from smaller companies and individuals, which only look at one or two weather types and emission scenario. It is necessary to determine what projection has the highest confidence for the area and weather type that is being analysed.

IPCC [37] and the WMO [38] have summarised their main findings relating to climate change projections. They suggest that over all emission scenarios, the surface temperatures will increase, while global precipitation will increase in tropical regions and in high latitude areas but decrease in the subtropics. Precipitation extremes are also projected to increase. Due to the warming climate, snow cover and sea ice are projected to decrease, but a likely increase in the intensity of tropical cyclones, but not the frequency, is projected. Their models show that there will be fewer mid-latitude storms, averaged over each hemisphere, but that increased wind speeds could cause increase wave height during these storms.

As well as global projections, there are more specific climate changes projections on a more local scale. UK Climate Projections (UKCP09) [39] is one such climate projection, it uses the HadRM3 Regional Climate Model (RCM), which was developed by the Met Office Hadley Centre [40]. HadRM3 is used to produce regional future climate projection; these are then used when developing the UKCP09. A summary of the UKCP09 projections is as follows: the UK will be warmer but more so during summer rather than winter with the mean daily max temperature increasing and the mean daily minimum temperature also increasing during the winter. Annual precipitation will show very little change overall but during winter there could be increases up to 33%. During summer precipitation could also decrease by about 40%. However, they are unable to provide projections for snow and projected changes to storms are also unclear. UKCP09 also has a weather generator tool [41] which, based on the projections is able to provide a time series of weather variables thus allowing the user to develop different time series of the developed weather projections at a local scale. As an addition to the UKCP09 projections, the RCM models [42] were released for additional weather type projections focusing on lightning, snow, fog and wind speed. From these, the projections were as follows: lightning is projected to increase, for all seasons with the largest increase seen during summer; there is a projected reduction in snow days in all regions of GB, but there is uncertainty in this projection within GB as a whole; a decrease in fog for northern Britain is projected whereas an increase over the south is projected; and wind speed is projected to be slightly lower over mountain regions in Scotland but generally there is not much change on a GB wide scale. However, on a local scale, wind speed changes could be between -15% to +10%.

As well as UK specific climate projections there are also climate projections from other countries and organisations. The US is also looking at the effects climate change could have on the weather that the country experiences. Key US projections [43] include a projected temperature increase, leading to more frequent or extreme heat events, especially in areas that already experience heat events. Northern areas are projected to become wetter while the southern areas are projected to be drier with heavy precipitation events likely to be more frequent, going from once every 20 years to once every 4-15 years. It is also projected that more rain will fall rather than snow and the intensity of Atlantic hurricanes is likely to also increase but there is less confidence in the projections of frequency. Snow cover is projected to decrease, which will in turn contribute to rising sea levels. The snow season will also continue to shorten. NASA is also taking the threat of climate change seriously [44], and have summarised the IPCC report and what the effects are for the US. There are separate papers which look at specific weather types in the US. One such example [45] discusses the projections associated with lightning. It projects that lightning strikes will occur more frequently but the where and when is unclear. It states that for every two lightning strikes that occurred at the start of the century there will be three at the end. For certain parts of the US this is not a major issue; however, for areas such as the mid-west and Florida known as lightning alley this increase in strikes could cause serious problems. The US and GB are not alone when considering climate projections. There is also work being done looking at climate projections in New Zealand [46]. National Institute of Water and Atmospheric Research (NIWA) have many different projects relating to climate which consider how the effects of climate change will affect areas within New Zealand. One example considers the risk of drought and extreme wind under climate change [47]. It found that during winter the frequency of extreme winds would increase but decrease in summer, and that there would be an increased period of drought, spending 5-10% more of the year in drought.

Throughout all projections, it can be said with high confidence that temperature will very likely increase, lightning will likely increase, the number of snow days will likely decrease (although projections on the intensity of snow days are lacking) and due to the warming climate sea levels will very likely rise due to the melting sea ice. Low confidence exists within certain weather variables, such as wind and rain, and depending on local conditions can have different projections, making it difficult to find projections for these weather variables that have high confidence. Not all climate projections are statistical values, stating a percentage increase or decrease; some are large datasets that contain a vast amount of data based on climate model simulations. One such project is the ENSEMBLES project which was developed to create an ensemble prediction system for climate change [48]. This project aimed to provide a high resolution gridded dataset model for Europe to allow an objective probabilistic estimate of the uncertainty that exists within future climates for seasonal, decadal and longer timescales. There were over seventy partners that were involved in this project from all over Europe, including the UK Met Office and European Centre for Medium-Range Weather Forecast (ECMWF). However, unlike previously discussed climate projects the ENSEMBLES project has not developed definitive climate projections but instead created and stored different sets of climate model data. For the seasonal and decadal simulations, two sets of simulations were run and the data is available from ECMWF. The centennial simulations produced are stored by Program for Climate model Diagnosis and Intercomparison (PCMDI) and were used in the IPCC AR4 assessment. The following datasets are available from the different research themes (RT): the daily gridded observational datasets (RT5), the seasonal to decadal predictions for streams 1 and 2 (RT1 and RT2A), the global climate change simulations for streams 1 and 2 (RT2A), the regional simulations for the ERA-40 period (RT3), the regional climate change simulations, the quick-look analyses (RT2B), and the statistical downscaling (RT2B) [49]. All data is freely available to download and once collected it is then able to be manipulated as desired.

Further discussion will take place in Chapter 7 regarding climate projections used within this thesis and what they could mean for the test case of the GB transmission network. However, once the climate projections are known and the confidence levels understood, the next stage in the process is to consider how these will affect power systems. It is clear that the expected climate change will have significant effects on the weather that cause the main issues for power systems, not only for the assets discussed in Section 1.1.2 but also the operation of generation [50]. An increase in average temperatures will cause significant issues for power systems. An increase in temperature will affect the operation of overhead lines, which are governed by their temperature, and therefore reduce the maximum capacity that can be transferred through them – they will be derated. In addition to this an increase in temperature will also affect the thermal efficiency of thermal power plants and the efficiency of substation earthing [51], [52]. The rise of sea levels will also affect the security of coastal assets along with thermal and nuclear plants which use coastal or river water for cooling purposes. An increase in rainfall will increase the probability of flooding threatening already vulnerable assets, and an increase is high winds and storms threaten to cause more severe and more frequent damage to overhead line assets [21]. In addition to the effects on the power network assets climate change also leads to changes and growth in demand patterns, as has been investigated around the world [53], [54], [55]. If the climate changes at a slower rate than the development of power networks then adaptation measures implemented as this climate change occurs should allow the power systems to cope with changing weather. However, if climate change develops at a faster rate than the power networks then this will threaten the reliability and security of power networks. In order to face these challenges the next stage is to consider possible adaptation methods that can be used to help reduce the risk of climate change to the security and reliability of the power network.

1.3 Previous Research and Analysis on Weather Effects

Due to the importance and scale of this subject a large volume of work has taken place but with the range of challenges and the variations in climate around the world, the work has been far ranging. Previous work has looked at the overall effects of weather for example [56] summarises the different effects of weather on European and North American grids by analysing the current grid structure and what the current effects of extreme weather can have. From this some conclusions have been drawn on how adaptation could be used to lower the risk in the future. It states that due to climate change there is an increased risk to the system, both transmission and distribution, due to temperature, high winds, storms, ice and snow, lightning, rain and flooding, and droughts. But with correct system management and investment, system reliability shall be able to be maintained. However, it states that governments may to need to consider the need to allow energy companies to invest in adaptation measure for future changes to weather rather than just to measure adaptation against current weather. Reference [11] formed recommendations for distribution network operators (DNOs) by looking at four major storms and what their effects and consequences were, such as the demand to bury overhead lines to make them less vulnerable to the effects of weather. Another consequence of this investigation was the emergence of different functional demands for distribution networks, as well as more compensation schemes. However, the most important conclusion of this report is that there is no uniform solution that will be valid for every country and weather event. It is necessary to take account of the structure of the grid, the regulatory framework, location and weather type when coordinating adaptation methods and frameworks to reduce risk to system reliability to ensure the most cost-effective solution.

Others have looked at the effects of specific weather variables such as ice, wind and lightning. A main weather variable that has been investigated has been ice loading, which, as shown in Section 1.1.2, can be a large issue in some countries. Reference [57] summarises different modelling techniques that have been used to model ice build-up on overhead lines and has suggested a new model with improvements in relation to how water shedding is modelled. Some models consider no water shedding, whereas others consider all water shedding in form of icicles or that water not frozen on the cable is shed which are moderate and unreasonable assumptions respectively according to [57]. It suggests that the effect of water shedding and icicle growth contribute to ice loads and can be properly taken into account only by numerical modelling that includes all the relevant physical processes and there interaction. Reference [58] looks at developing a new type of distribution overhead line to withstand greater ice loading through practical experimentation and [59] discusses a method used to estimate the risk to transmission system components due to ice storms. Another weather variable that has a large effect on electricity networks and has therefore dominated areas of past research is wind. Reference [60] looks at predicting outages of power system due to hurricanes using Bayesian networks for Harris County's electric power system. It used 2008 Hurricane Ike as a test case for both distribution and transmission and is able to be updated for different networks. Reference [61] also uses Bayesian networks along with conditional probabilities to evaluate the effects of hurricanes on power systems, applied to the IEEE Reliability Test System. Reference [62] presents a method that predicts outages during hurricanes in order to support storm response planning for the whole of the US Eastern Seaboard. It also used historical data to develop a power outage forecasting model. Reference [63] also uses historical data to develop a probabilistic wind storm model for the distribution system in the Northeast US, combining a classification of wind storm events with Monte Carlo simulations. A final weather variable that effects electricity networks, and therefore also dominates past research is lightning. Reference [64] considers the effect of lightning storms on a distribution network in the Midwest region of the US, by identifying areas of the network that are more vulnerable to allow design changes to take place.

Reference [65] develops a 2 stage distribution model that is able to forecast storm outages, allowing the network operators to manage the network during a storm, based on these projected outages, more efficiently. It classifies different types of storms by wind speeds and temperature. When a storm approaches and the wind speeds and temperature are known, it can predict the possible number of outages. It also considers lightning outages by correlating between flash density and outages, which is simply stated as a linear function but can be added to the outages predicted for the approaching storm. Reference [66] develops two regression models, modelling outages on overhead distribution feeders. It compares the results to previously developed models [67] for the Kansas area of the US based on historical outage and weather data. As there is no general consensus to which models are better, multiple models are developed for comparison; out of the models they test in [66] the one which is the most accurate still underestimates at more extreme weather and overestimates at normal weather. Reference [68] discuss the need for other anti-lightning methods on high altitude lines in China which are frequently loaded with ice and snow, making the lightning protection inefficient. These indicate that one specific weather variable is not solely responsible for all weather outages that occur, but that multiple variables contribute to weather outages. For example, days after the snow falls it can still cause outages on the network if high winds or lightning also occur.

While looking at single weather types or specific weather type combinations that cause significant destruction is useful, it is also important to consider the combined effect of all these weather variables that affect the network and how their combined efforts can affect power networks. It is also clear that none of the above research considers modelling the failure as a function of weather variables investigated, which would involve development of seamless spatio-temporal simulation and infrastructure impact models of weather fronts moving across large-scale networks. More general modelling techniques have been developed that consider the possible effects of weather on different power networks. One such method that is the most commonly used is the two state weather model as shown in [69], [70], [71], [72], [73] where weather is represented two different states, normal and adverse, as shown in Figure 1-6 where *n* represents normal weather and *a* represents adverse weather. Reference [69] uses the two-state weather model on a composite system to assess the system reliability due to changing weather using sequential simulation. Reference [70] also uses the two-state weather model for modelling failure bunching in parallel facilities and in the adverse weather state it was confirmed, as would be expected, that there was a high increase in the number of failures. Both [71] and [72] use a Markov model in combination with the two-state weather model to assess the impact of weather on system reliability whereas [73] uses Monte Carlo simulation with the two-state weather model in a composite system for reliability evaluation.

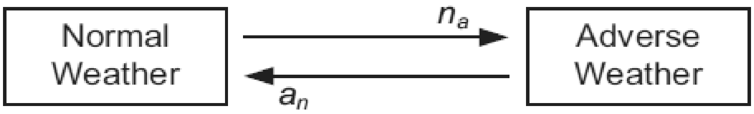


Figure 1-6 - Two-State Weather Model [70]

However, [74], [75], [76] all conclude that neither a single state or two state weather model reflect the outages during adverse weather as they underestimate the outages that do occur. They all propose a three state weather model: normal, adverse and extreme which has the ability to model the major adverse weather and therefore the outages that occur during this time more accurately as shown in Figure 1-7 where *n* and *a* are as in Figure 1-8 and m represents major adverse weather.

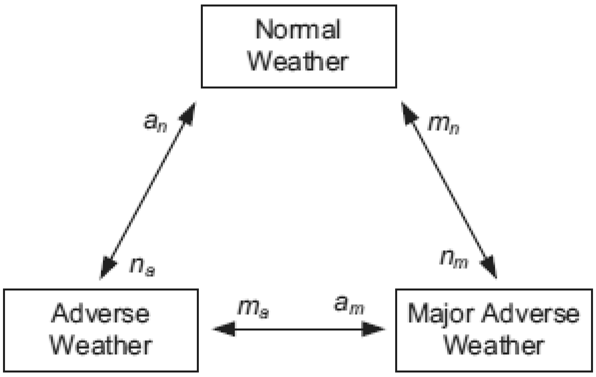


Figure 1-7 - Three-State Weather Model [75]

Reference [76] also considers the duration of weather events and failure rates under these three weather states. Reference [77] models the changing weather patterns to assess the security of supply on an active distribution network. They generate a normal weather situation then use Monte Carlo to capture the change in weather and conclude that a change in weather patterns by 50% of the nominal weather can result in impacts on security of supply up to three times the nominal impacts. These show that it is important to consider the different states of weather and distinguish between them, but as described earlier, it is also important to consider the differences in the weather type; a lightning strike is very different from a snow or wind storm when considering the impact on power networks. Other modelling techniques look at changing normal weather to different weather states with different parameters to see the effect on power system security. Reference [77] considers the effects of moving winds and ice storms on the reliability of power systems based on a Monte Carlo technique where each scenario represents different situations with pre-defined parameters and can represent not only the outage risk but the mean time to failure. However, for each scenario a weather impact model needs to be developed where the risk of the transmission outage is connected to the weather situation. Looking at a time dependent phenomenon, based on a Monte Carlo simulation, [78] presents a methodology to perform a cost/benefit analysis for establishing the value of security, with one feature modelling the effect of weather. It is stated that more work is required in order to more accurately model the probabilities of failure due to weather. It is also important to not only consider the past effects of weather on power systems but also the probabilities of past weather events.

Reference [79] presents statistical results of a detailed analysis of Alberta Power Limited's transmission line outage database and Alberta Environmental Service weather databases over a 20 year period. For the entire population of lines in Alberta, [79] found a stronger correlation between line location and fault rate than between line length and fault rate. This could be due to the wide range of altitudes and latitudes of the lines found in Alberta. Other research has included a time varying model that uses the stochastic nature of severe weather plus its intensity and duration to model variations in failure rate. Both [80] and [81] consider a non-homogenous Poisson process (NHPP) to study both high winds and lightning on Sweden's distribution system. These weather variables, however, are considered as standstill unlike [82] which considers weather as a time sequential variable. All three, however, use time-varying failure and a restoration rate to consider the effects of weather on distribution systems reliability indicators using a sequential Monte Carlo simulation. Reference [82] concludes that time-varying failure rates increase the unreliability cost indices for frequency sensitive loads. Reference [83] models major storms on the distribution system in Finland using storm and interruption data gathered from electricity distribution utilities, while [84] looks at component reliability when combining aging and weather on a Medium Voltage (MV) French electrical system. Additionally, based on the New Zealand network using insurance risk analysis data, [85] highlights the need to understand multiple outage consequences, looking at high impact low probability events which contain some weather events on the transmission system. Beta Probability Density Functions (Beta PDFs) were used as part of a simulation method that modelled system failures due to adverse weather in South Africa by running power flow simulations using DIGSILENT and reliability analysis using MATLAB to run Monte Carlo simulations [86]. All of these focus on analysis of past weather on the countries' specific networks which is an important first step to understanding the effects of weather on electrical network. However, to the author's knowledge this type of analysis is missing on the GB transmission network on a regional basis.

On top of considering the effect of different weather types both separately and then as a whole, it is also important to understand the differences in outage numbers under different weather conditions compared to what has been experienced in the past to allow operators to adjust system performance. Reference [87] develops two models: a Poisson regression model and a Bayesian network model that predict yearly weather-related outages for distribution overhead lines and then uses MC to determine the prediction bounds. It states that the Bayesian network analysis model is better as it is more flexible and the conditional probabilities provide more accurate results but again the weather scenarios are pre-determined. Another such project conducted by NIWA looked at climate and the electricity system to help understand how climate will affect the electricity systems in New Zealand [88]. It considered various aspects including how these changes will affect generation capacity, demand and how to minimise risk to their infrastructure. During the project so far they have developed weather generator models to help identify answers to these risks. The weather generator is a valuable tool in itself but is yet to be applied to the electricity network. This research shows that it is important to not only consider each weather type's effect on the network and their combined effect but also the different states that can be experienced as well as the random nature of weather by developing weather generator models that can be applied to the network to understand the risks.

Fragility curves as discussed in [89], can be used as a method for modelling the effects of weather. This is done by analysing a component's probability of failure based on different weather variables. This allows the failure probability of any given component on a network, such as towers, lines or poles to be given in terms of individual weather variables or a combination of multiple weather variables such as wind speed and/or lightning strikes. Reference [90] develops fragility curves for distribution system components for Harris County, USA, using historical weather data. In the Resilient Electricity Networks (RESNET) project, which will be discussed further in Section 1.4.2, [91], fragility curves are used to determine the probability of failure of transmission towers based on wind speeds. It is proposed in [92] that fragility curves developed in [91] in combination with Monte Carlo simulation would allow for system resilience to be analysed. This method was applied to the IEEE 6 bus reliability test system for illustration of the propose methodology. And finally [93] develops fragility curves analysing past historical data of earthquakes in LA, using a systematic network analysis approach allowing the probability of failure for electrical components to be developed based on the peak ground acceleration which is a measure represents the intensity of the seismic ground motion. The research that currently exists within this topic is far ranging from focusing on specific weather types, specific countries, network types, weather events, general summaries of past events and consequences to more broad modelling techniques, meaning that many areas still have not yet been investigated. It also highlights peak areas of interest as well as areas that could be improved upon such as considering not only one prevalent weather variable but all prevalent weather variables that can affect a network. Different weather states are required to achieve a full understanding of how electricity networks are affected. To enable accurate modelling of the probabilities of failure due to weather it is necessary to consider not only the past effects of weather but also the probabilities of past weather events.

Reference [94] proposes and a test a model of a power distribution system which is effective for modelling power blackouts and improves system robustness. It tries to handle multi-fault events, for example weather induced events, as well as single fault events. The model is a mixture of an admittance model and the probability model of failures of network components; it also includes a Monte Carlo method to estimate the probability density function of the blackout size. This model is tested on the IEEE 118 bus model and plans to apply this model to analyse existing networks using real data. Reference [95] presented a methodology to build machine learnt proxies able to predict the outcome of real-time reliability management response in a look-ahead operation planning context and investigated the use of machine learning, in particular supervised learning to predict some outputs of real time reliability management, this analysis was conducted on a modified version of the IEEE-RTS96 network. Reference [96] proposes a methodology for the evaluation of reliability in radial distribution networks through the identification of new investments to reduce the repair time and failure rate, leading to a reduction of forced outages and an increase of reliability. It presents a case study using a 33-bus distribution network is presented to illustrate the application of the proposed methodology. Blackouts especially weather related becoming more frequency, [97] introduces a restoration process to examine important issues in restoration, and survey the state of the art in the research and practice of power system restoration planning. The case study demonstrates the capability of the proposed framework in generating effective and executable restoration plans. References [98] and [99] reviewed and discuss the basic definitions of dependent, common mode and cascading outage events, identified major causes of common-mode, dependent and cascading outages, and assessed the impact of weather related outages and extreme events on the performance of the Bulk Electric System, including weather outages. Part II looks at summarising outage data analysis, and how it is stored across North America and Europe. Reference [100] presents a dynamic Bayesian network approach for the modelling and predictive resilience analysis for dynamic engineered systems, an industrial based case study on electric power distribution system in Sedgwick County, KS is studied to demonstrate the effectiveness for resilience analysis. Based on internal and external mechanism which will lead to failure [101] proposes Ageing-Load-Health-Weather-PHM (ALHW-PHM), which is applicable to characterise the failure probability. The model adopts temperature-based aging model as the baseline hazard function, and utilizes health status, weather condition, and load rate as covariates in the link function. It concludes that the calculation of failure probability plays an important role in the risk assessment of power system. Reference [102] presents a risk-based security assessment methodology which allows the assessment of operational security of a power system's future state under uncertainty deriving from varying topology scenarios and forecast errors. The methodology models input uncertainty with a copula function based Monte-Carlo framework. Reference [103] investigates how historical data coming from the lightning detection network and measurement stations capturing associated weather conditions can be utilized to provide a predicted assessment of risk of insulation breakdown for a given exposure and associated weather threats. With this model components geographical configuration is taken into account for a prediction. The worth of loss assessment that effectively differentiates the impact of different outages on the overall system economic performance has been performed. These show the importance of testing methodologies on test cases, and using actual data and real systems where possible.

Previous work considers different methods in order to analyse the effects of weather, such as; Markov chain models, Monte Carlo models, non-homogenous Poisson process (NHPP) & Poisson regression models, Bayesian networks, and fragility curves. While all have benefits when analysing weather effects on power systems there are some disadvantages to some of the techniques. Markov chain modelling would require every state of weather and outages to be represented, which is hard to develop from scratch and within the scope of this research would be a massive task to undertake. Bayesian networks are a type of Probabilistic Model that can be used to build models from data and can be used for a wide range of tasks including prediction. Monte Carlo techniques are estimators and are repeated samplings of random walks over a set of probabilities. Fragility curves can be used as a method for modelling the effects of weather by analysing a component's probability of failure based on historical data. One disadvantage of the Poisson is that it makes assumptions regarding the distribution of the underlying data. In particular, that the mean equals the variance, while this is acceptable in some circumstances, they are less appropriate for the data collected and used within this study. With this in mind, Reference [87] states that Bayesian modelling is better than Poisson regression modelling for failures. Therefore, it is suggested that Bayesian networks could be a suitable method to understand the effects of weather on power networks.

Where the prior and observed information is used to compute the posterior or fragility curve analysing a component's probability of failure based on different weather variables and using Monte Carlo simulation predictions can be made using the calculated posterior.

1.4 Adaptation Measures

1.4.1 Universal Adaptation

As discussed in Section 1.1.2, weather does affect power networks and with the threat of climate change it is forcing network operators and governments alike around the world to consider adaptation methods to reduce the impact of weather and climate change. After a major weather event in a country, methods are considered to help prevent such a disaster from being seen again. For example after the wind storms in 1999, Germany and France started looking at short, medium and long term adaptation methods to prevent such disruption happening again [104]. France and Germany are not alone in recognising the need for adaptation to a changing weather environment; utilities, regulators and consultancies alike have all conducted research into adaptation measures [105], [106], [107] and [108]. Nor are they alone in considering the after effects of a large storm on the energy network and what could have been done differently [109] and the ability to adapt to extreme weather events is now considered a key business goal by some [110]. As stated in [104] a multi measured approach will be required, as no single measure on its own would be enough. IPCC state that multiple adaptation and mitigation options will be required [29]. The main short term measures that have been considered are: load management, as by understanding the load they can then be adjusted and adapted to the rise and fall of demand to optimize generation; accurate estimation of weather location and severity; estimation and preposition of repair and recovery crews; system configuration and monitoring; quick assessment and prioritisation for restoration [104], [10]. Medium term measures considered include research into impacts and possible adaptation methods to help mitigate the effects of weather. Long term measures considered were: changes to the design of the network such as replacing overhead lines on the network with underground cables; improving operation of the network under abnormal events; adding redundant transmission routes; changing designs of power plants, especially plants that require water cooling, or plants on the coast [104], [19].

While each event is different, and therefore the impact is different, it is important to take into account and prepare for all cases, even the worst case which may have a low probability of occurring but could cost much more than taking the time to invest in measures to limit its impact [13]. By studying weather events around the globe and by looking at the effects of these events some general lessons that were learnt could be put in place to help in the future events. Reference [13] suggests that not only are strategic planning options needed to improve long-term resilience, but also workforce mobilisation and communication between managers, staff and the public. Again short term, medium term and long term planning options were important and suggested to be developed, even at just a broad level basis to help when an extreme event hits. Reference [111] promotes three main steps that need to be taken to address climate change: new operating tools to take into account the impact of climate change, training dispatchers on how to manage the power grid during extreme events and establish crisis organisation skill and additional countermeasures at local levels.

Adaptation to climate change is not solely limited to industry; academia is also considering possible methods for adaptation that could help build resilience. Reference [112] develops possible research areas to investigate the effects of climate change to help with adaptation planning. These research areas include: combining climate projections of extreme weather with blackout risk assessment techniques, exploring monitoring and control techniques of power systems to help when weather events hit, to review climate change prediction studies for all regions and use these to estimate the rate of change of power systems design parameters, and to design a better service restoration methodology that can be applied during weather events. These investigations into the effects of climate change will help with adaptation planning for before, during and after weather events. Other research suggests that change to how the system is currently operated is the way forward for dealing with extreme events. For example [113] looks at the possibility that dynamic line rating might be one useful answer among many. Others look at adaptation to policy and how that would help adaptation measures. [114] recommends that in order to properly adapt to climate change and its effects it needs to be included in infrastructure planning as a mainstreamed component and not an additional extra that is often overlooked. It is proposed in [115] that the best way to adapt to climate change is to make sure that climate change adaptation is not only considered from all angles but also be in line with planned public adaptation.

In the UK, in 2008 the Climate Change Act (CCA) [116] was brought into law and required all companies that are responsible for vital services and infrastructure to report on adaptation measures to deal with climate change [117]. The three Transmission Network Operators (TNOs) in GB – National Grid (NG) [52] , Scottish Power (SP) [118] and Scottish Hydro Electric (SSE) [119] – all released reports relating to climate change adaptation. The Office of Gas and Electricity Markets (OFGEM) [120] and the Energy Networks Association (ENA) [121] also released adaptation reports detailing their action plans to the Department for Environment, Food and Rural Affairs (DEFRA). These adaptation reports look into many areas that climate change will affect, including:

- Areas of strength – Industry-level collaboration (see discussion in Section 1.4.2), adaptation reports from areas of the sector attempting to understand climate change and the risk that it may pose allowing them to start taking adaptation measures, and multiple research programs from all the GB network operators.
- Areas of key risks – reduced overhead line ratings due to increases in temperature, increased flooding due to rising sea levels, structure integrity due to summer drought, changes to vegetation growth and season lengths, changes to lightning, ice and wind which all effect equipment on the network.
- Areas where further research is required – Adjustments required to both the regulation and management of the network during and after extreme events which may become more frequent due to climate change, clarity around the discussion on de-rating factors, risk posed and the impact of climate change and low probability and high impact events, changes to demand, evaluation of current adaptation plans/strategies and the cost of the necessary adaption and who pays.

For some of the companies this was the first time they had considered the effects of climate change on their network [118] whereas others had previously considered the effects but only certain specifics had been looked at, such as flood prevention [52]. All of these companies' adaptation reports were later summarised by Cranfield University for DEFRA [122]. The summary report notes that although the companies are aware that climate change will impact their business they are unclear what the exact risks are meaning that more research is required in order to demine the risks to the electrical infrastructure and supply.

1.4.2 The GB Power Network and Previous Adaptation

There are 14 distribution network license areas within Great Britain (GB) which are in turn owned and maintained by 6 different distribution network operators (DNOs) [123], as shown in Figure 1-8. The distribution systems operate at 132kV and below in England and Wales and 33kV and below in Scotland. The transmission system in GB is owned and maintained by three transmission network operators (TNOs): NG for England and Wales, SP for Southern Scotland, and SSE for Northern Scotland [124] as shown in Figure 1-9. However, the whole GB transmission system is operated by National Grid. The transmission system operates at 275kV and above in England and Wales and 132kV and above in Scotland. Both transmission and distribution networks are made up of many different types of equipment, including overhead lines (OHLs), cables, protection equipment and substations. All equipment is susceptible to outages, which can be caused by a variety of reasons such as: age, lack of maintenance, interference or damage by third parties and weather. The transmission network is more resilient to outages, due to its mesh topology design whereas the distribution network tends to be more of a radial design and therefore will see many more disconnections of demand [125]. However, the transmission system requires a certain level of redundancy as part of system resilience to allow scope for planned outages and corrective actions when an outage does occur. Power system reliability metrics and historic GB performance will be covered in Section 2.1.

This image has been removed by the author of this thesis for copyright reasons

Figure 1-8 - DNO Companies [124] **Figure 1-9 - TNO Companies [126]**

As an extra response to the CCA a set of GB network operators commissioned work from the UK Meteorological (Met) Office's Hadley Centre [127], [128], [129] called the EP2 project which looked at the risk of weather to the electricity network, mainly focusing on the distribution network. The EP2 project broke weather-related faults into smaller categories and used the ERA 40 weather dataset [130]. A large portion of the work focused on the distribution network due to the volume of outages and the ability to easily classify the impact on the network. For the DNOs the Met office produced reports detailing the relationships between weather types and weather-related outages. However, due to the low number of outages on the transmission network the report looks at transmission faults across the whole of the GB system. In these individual reports the Met Office developed a risk assessment of the electricity network to the climate. Risk was defined as a function of the climate hazard and the vulnerability of the system. The climate hazard looked at formalising the relationship between weather and outages, whereas vulnerability looked at the magnitude of impact on the network. The Met Office used customer interruptions as the measure of vulnerability, which generally is not recorded for the transmission network. Only the hazard analysis was completed for the transmission network. Their overall findings were that wind and gale outages increase when winds gusts are above 22m/s. Snow, Sleet, Blizzard and Ice (SSB & Ice) outages tend to occur on snow days with wind gusts over 35m/s and lightning outages increase when Convective Available Potential Energy (CAPE) is above 735J/kg. This work looked at the GB system as a whole system, rather than regional which is quite important when considering the differences in weather between the North of Scotland and the South of England. This work is also now several years old, and so missing the more recent outage data and due to what the network companies regard as the sensitive nature of the data, the results and resulting reports were only available per company, for both the transmission and distribution, making it difficult to get the original analysis.

The final stage of the EP2 project looked at trying to predict the effects of future weather scenarios on the network using the baseline they had created previously and applying future climate scenarios. But since no vulnerability analysis was undertaken on the transmission network, a full climate risk assessment was not undertaken [129]. Due to the uncertainty that is associated with climate change related predictions for the future weather, effects for the distribution areas were quite far ranging, from significant decreases in outages to significant increases [131]. However, the transmission system is also affected by weather and there is a possibility of increasing outages in the future due to the effects of climate change and it is therefore an important area of research. This focus on the distribution systems occurs within large amounts of current work leaving a gap in transmission system operators' knowledge not only relating to the current effects of weather on the network but also the future risks that they could be facing due to climate change.

Other projects in the UK concerned with similar questions are Adaptation and Resilience in Energy Systems (ARIES), Resilient Electricity Networks (RESNET) and Adaptation and Resilience of Coastal Energy Supply (ARCoES). ARIES is based at the University of Edinburgh and Heriot-Watt University and they have created bespoke supply and demand models to enable the future changes in energy demand and what effect they can have on energy provision in the future climate to be accounted for [132]. They have also investigated the impacts of climate change on large-scale renewable energy generation for different future climate scenarios. RESNET is conducted by teams from Manchester and Newcastle

Universities. Here they have developed tools to help quantify estimations around the potential futures of electrical demand within the UK [133]. They use the range of climate scenarios from UKCP09 and explore the social implications that could result from a future of both climate and technology change. This allowed them to address the challenges of resilience of the UK's electricity energy networks. ARCoES is led by the University of Liverpool but is a multi-partner consortium and has developed a decision-support took that is able to assess the risks that might face coastal energy deployment in the future [134]. By considering the risks that may be experienced by power stations, substations and the distribution grid informed decisions on how to adapt due to climate changes can then be made. While these projects all function separately they also work together linking all the sections to allow the bigger picture to develop on how to adapt to climate change through the Adaptation and Resilience to a Changing Climate Coordination Network (ARCC CN) [135].

The main project of relevance to the work presented here is the RESNET project which consists of multiple smaller projects under this heading which look at the potential change to the existing electricity supply mix, a shift of currently non-electric energy usage onto the electricity network, and the challenge faced by a change in climate to both the demand and infrastructure resiliency. For analysing the resiliency of the electricity network descriptive statistics were developed in the form of wind fragility curves of National Grid's electrical assets. These allow the robustness of the system to them be tested under the threat of extreme winds. Another output of the RESNET project was the development of a possible methodology that could be applied to assess the influence of extreme weather and climate change on electrical network resilience [136]. It is a brief three-stage process consisting of a weather model and possible weather types that could be used, a component which uses the weather model to evaluate the component resilience, a system model which, using the component model, can assess the system under different weather condition and what possible indices may be used to evaluated the system resilience. After this analysis is complete it further suggests that adaptation studies should be conducted to improve system resilience. It is an interesting outline of a methodology to assess the influence of extreme weather and climate change on electrical networks and the ability to assess the effects of weather and climate change on electrical networks is a major area of interest. However, it lacks detail of what is required to undertake this assessment and no test cases have been completed.

1.5 Summary of Previous Research

The key points from the previous three sections are summarised here and are as follow:

→ All power systems are vulnerable to extreme weather events which cause physical damage to equipment and lead to long repair and restoration times, leaving the system vulnerable to further outages, meaning the risks to power systems need to be understood to enable adaption to climate change.

→ IPCC's 2014 Synthesis Report [29] stated that "Warming of the climate system is unequivocal." But within different weather variables and models the confidence of climate projections can vary. Where high confidence exists with a weather variable the different projections models will produce similar results, for example, lightning is predicted to increase in most climate projection models. When low confidence exists, different models will produce different results. Such low confidence is described in respect of wind and snow weather variables and storm predictions.

→ Modelling components' failure rates as continuous functions of weather parameters represents a key novelty in reliability and resilience research, as it allows the development of seamless spatio-temporal simulation and infrastructure impact models of weather fronts moving across large-scale networks.

→ Power system owners are generally aware that climate change will impact their business but are unclear what the exact risks are.

→ Past work tends to consider whole networks as one area rather than considering that different areas of power networks can experience different weather conditions at the same time, which can provide inaccurate results for future predictions.

→ Due to the ease of quantification of the impact of weather on power network, a large quantity of past work focuses on distribution networks and ignores the transmission network or imagines that it is fine during extreme events, which is not the case.

→ Models have been developed in the past based on a high level outline of how to analyse outages. However, they can be vague and lack complete detail about how they may be used to analyse a real system or different systems around the world. It can also be difficult to compare results between different geographies. This ambiguity stems from a lack of outage data available to base this analysis on.

→ When considering the effects of weather on power networks there is a tendency to consider a sole weather variable, a single weather state, or only specific weather combinations and to ignore all others, or to consider weather as a whole represented by just two or three different aggregate states rather than separate individual variables. This leads to an incomplete picture of how each weather variable can affect the systems being analysed and how their combined effects can affect the power system as a whole.

→ To be able to accurately model the probabilities of a network failure due to weather, it is important to consider the relationship between a particular weather variable and the rate of occurrence of power network failures in different classes of prevailing weather. This relationship of probability of an outage to a weather variable should be quantified and used as part of an assessment that considers the probability of occurrence of different values of weather variables. This provides the basis for understanding the possible impacts of changes to weather patterns due to climate change. Determining future risk due to climate change.

1.6 Research Aims and Objectives

This thesis aims to provide a detailed methodology for the analysis of both the current effects of weather on power transmission systems and also, given a postulation of changed weather, the future effects. It also aims to apply this novel methodology to the GB transmission network as a test case to identify and illustrate the outcomes in terms of network reliability. This analysis will enable a comparison between current and possible future weather effects due to climate change and hence the determination of possible risks. The following specific objectives have been identified in order to fulfil these research aims:

1. To summarise and critically evaluate existing work modelling weather and the possible future effect that climate change could have on power networks.
2. To develop a methodology that is used to assess the impact of weather and climate change electrical networks.
3. To complete an analysis of outage datasets, provided by the three transmission companies of GB, for both weather and non-weather-related outages, to check how accurate their records are and to understand what the current effects of weather are on the GB transmission network. Weather outages are defined as outages that have been classed as weather related by the transmission companies, and non-weather are outages that have been classed as caused by non-weather related circumstances.
4. To compare observational weather data and reanalysis data and lightning strike data and a lightning strike proxy, Convective Available Potential Energy (CAPE), in order to verify reanalysis data as a suitable replicator of past weather data.
5. To develop a correlation analysis between different weather variables and weather-related outages and identify the most useful weather behaviour indicator for the associated outage.

6. To establish fragility curves or the conditional probability distributions of failure for the dominant weather-related outages based on the weather that is occurring as well as standard probabilities for other outages that occur on the transmission system.
7. To develop weather test cases using climate projections that can be used within the model to determine the risk to the GB transmission network.
8. To investigate if a relationship exists between the duration of an outage and the weather variable that caused the outage.
9. Using the model results and reliability indices analyse the effects of different climate models on the GB test case.

1.7 Novelty and Contributions

The main contribution of this research is the development of a methodology that can be used to assess the current effects of weather on given power system and what the possible future effects of climate change will be. Weather causes a large number of outages on both transmission and distribution power networks; as a consequence, it is important to understand and assess the risk that it poses to system security and reliability.

A particular contribution of the proposed methodology will be that it is primarily applicable to the transmission network. While considerable other work worldwide has set out analysis frameworks, mainly distribution system risks are discussed. Transmission system risks to outages are considered less often and therefore the changing failure and repair rates associated with climate change have not been investigated as inputs to such frameworks. Consequently, a methodology that can be applied to assess the transmission network is an important piece in understanding the effects of weather and climate change on power networks. This methodology, unlike the majority of previous research, considers each weather variable as one continuously varying weather state rather than a two or three weather state model, allowing for a much more realistic modelling of the weather conditions. In addition the GB network is split into four areas, allowing each area’s weather to be treated differently granting the ability to treat extremes differently for each area. This would allow the ability to model storms passing through the UK, allowing a GB based storm management system. A further contribution which is the development of GB transmission system specific overhead line outage fragility curves. An additional contribution of this research will be to apply this methodology to a test case of the GB transmission network. By applying the developed methodology to a test case it shows the importance of the stages and how they can be used to assess different effects of weather. While the transmission companies within GB understand the need to adapt due to climate change they are unclear what the exact risks are and so are unclear on how to adapt showing that research is required in order to determine the risks but no previous work to the authors knowledge has addressed possible changes to transmission failure and repair rates or system impacts.

While the analysis itself is an important contribution to GB network operators' understanding, the methodology developed will applicable to different networks and different countries that experience different dominant weather variables allowing other network operators in other countries to more confidently predict possible changes to failure rates, and therefore system security and reliability due to climate change.

1.8 Publications from the Thesis

The following papers have been published by the author based on work in this thesis.

1.8.1 Conference Publications

K. Murray, and K. R. W. Bell, "Weather Related Fault Outages on the GB Transmission Network," CIGRÉ Conference on Innovation for Secure and Efficient Transmission Grids, Brussels,12-14 March, 2014.

K. Murray, and K. R. W. Bell, "Wind related faults on the GB transmission network," 2014 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Durham, 7-10th July, 2014.

1.8.2 Prize Winning Presentations

Durham Risk Day Presentation (2013), "Weather related fault outages on the GB transmission system", Best student presentation prize. This was presented at Durham University, Durham, 13th November 2013.

Poster at Hubnet (2014), "Weather Related Fault Outages on the GB Transmission Network", Best poster presentation. This was presented at Manchester University, Manchester, 9-10th April 2014.

1.8.3 Additional Publications

Poster at IEEE PES GM (2014), "Outages on the GB Transmission Network due to Adverse or Extreme Weather". This was presented at the IEEE Power and Energy Society General Meeting in Washington DC, 27-31st July 2014.

Poster at Renewables and Future of Energy Meteorology (2012), "Effect of Climate Change on Design and Operation of Meshed Power Networks". This was presented at Imperial College, London, 17th October 2012.

1.8.4 Additional Work

In addition to publications, aspects of the work that is contained within this thesis have been implemented by SSE in their control centre, to be used on a daily basis for better network operation during extreme or adverse weather. This was implemented by Bellrock Technology as an addition to the distribution network fault predictor that was developed by the University of St Andrews for SSEPD with the final intention to use the methodology developed within this thesis for the transmission network alongside the distribution network fault predictor using the Lumen web platform. The first stage of implementation uses the conditional probabilities that are developed and displayed in Chapter 6 of this thesis. This is done by feeding current weather data into the program and with the developed conditional probabilities, and the route length, the risk of failure per branch can be calculated. This allows for the network to be operated more securely when extreme events occur. This has been completed for the 400kV and 275kV network in the SSE area in the North of Scotland for the weather variables of Wind Gusts and Wind Gusts on Snow Days. Lightning has not yet been implemented due to lack of current weather data. The second stage is to implement a similar application for the 132kV network, which was implemented in table format at the end of January 2016 with the same weather variables being analysed. It is hoped that lightning will be added shortly once a source of lightning weather data can be found. A further stage is under development which will allow the overall impact assessment and reliability indices to be determined based on the daily forecast using the later stages of the methodology developed within this thesis.

1.9 Thesis Overview

The eight chapters following this introduction are outlined below:

Chapter 2 - Discussion on Statistical Modelling and Power System Reliability

The following chapter will contain the discussion relating to different statistical methods used for data analysis, and possible modelling methods that could be used to model weather and will finally discuss current reliability methods that are used in power system analysis. It will also contain a discussion on power system modelling techniques.

Chapter 3 – The Methodology

This chapter will discuss the main methodology that has been developed and will be applied within this thesis to a test case of the GB network. This methodology contains five stages: pre-analysis, correlation analysis, conditional probabilities, Monte Carlo (MC) simulation and finally power flow and impact analysis. Each stage will be discussed in detail, explaining the process involved in order to apply this methodology. This chapter will meet the second aim of this thesis as set out in Section 1.6.

Chapter 4 –Analysis of Weather Sources, Weather and Non-Weather-Related Outages

This chapter will form Stage One of the methodology applied to the test case of GB - pre-analysis. To fully understand the effects of climate change on different power networks, it is first important to understand the current effects of weather on the power networks being analysis, i.e. which weather variable is predominant in causing outages and if seasonality exists within the data. It is also important to develop a highly accurate weather profile; to do this it is first necessary to understand the weather that currently affects the power grid being analysed. It will initially cover different historical weather sources and contain a comparison between past observational weather and reanalysis weather data as well as a comparison between lightning strikes and a lighting strike proxy, Convective Available Potential Energy (CAPE), to assess accuracy at reproducing past weather data. Following this, analysis will be presented relating to the outage datasets provided by the three transmission companies in GB; National Grid Electricity Transmission plc (NG) for England and Wales, Scottish Power Transmission Limited (SP) for Southern Scotland, and Scottish Hydro Electric Transmission plc (SSE) for Northern Scotland. This chapter will meet aims three and four of this thesis as set out in Section 1.6.

Chapter 5 – Correlation Development between Weather-Related Outages and Weather

This chapter will present the second stage in the five stage methodology that this thesis will present applied to the test of the GB system – correlation analysis. It will begin by discussing further dataset refinement and the processes involved in assigning exact weather values to each outage. Subsequently, it will address the process involved in determining the weather variables that are the main cause of the dominant three weather-related outages in GB, i.e. what weather variable shows the strongest correlation for each weather-related outage class. This will meet the fifth aim of this thesis as set out in Section 1.6.

Chapter 6 – Quantification of Weather Dependent Outage Probabilities

The application of Stage three of the methodology to the GB network will be presented within this chapter – the derivation of conditional probabilities. This stage uses Bayes' Theorem to determine the conditional probabilities for each of the top weather-related outage classes for each area. It will also cover the standard probabilities of non-weather-related outages and Other Weather-related outages, which are not able to be analysed using Bayes' Theorem. These values will then be transformed to per area, per year per 100km and compared. This will meet the sixth aim of this thesis as set out in Section 1.6.

Chapter 7 – Weather and Outage Sampling

This chapter will examine the set up required for the final two stages of the developed methodology applied to the test case of GB. This chapter will initially discus the inputs that are required for the simulations and then will focus on development of these inputs for the GB test case. It will cover a discussion of state and sequential sampling simulation setup and an investigation of outage durations as another input to the MC simulations. There will be a discussion on weather extremes, the development of the set of weather test cases using climate projections and the generation and load set up of the simplified GB test model. This chapter will meet aims seven and eight of this thesis as set out in Section 1.6

Chapter 8 - Assessment of the Impact of Changed Weather on Power System Reliability

The chapter will cover the output results for stages four and five of the presented methodology applied to the test case of GB. It will discuss the differences between the basecase models and the weather test cases, allowing the changes to the network's security and reliability to be assessed due to the possible future effects of weather. This chapter will meet aim nine of this thesis as set out in Section 1.6.

Chapter 9 - Conclusions and Future Work

The final chapter will examine the main conclusions that were drawn from this thesis and then suggestions for future work and improvements to develop this work further.

Chapter 2 - Discussion on Statistical Modelling and Power System Reliability

This chapter aims to provide discussion on the known techniques and methods that will be used throughout this thesis in order to develop and implement the proposed methodology. It will initially contain a discussion on different reliability indices that are used within the power industry as when analysing power systems it is necessary to consider the current reliability methods that are used, as understanding them will allow changes in climate to be assessed and then understand how and where to adapt. Another component of the proposed methodology requires different statistical techniques to be used and applied and therefore the second section of this chapter will discuss the different techniques that will be used within this thesis. The final section of this chapter shall cover different power system modelling techniques that were considered and could be used for modelling the effects of weather on power systems.

2.1 Quantification of Power System Reliability

2.1.1 What is Reliable?

In order to determine how to quantify impacts on reliability, stability and security due to weather it is first important to define what is meant by these terms. Although reliability, security and stability are often confused or considered to be the same there are important differences. Within the power systems literature, reliability relates to the ability of the power system, or the system's components to perform as required or expected under stated conditions for a specified period of time [137]. Stability is defined as the ability of a power system to remain in a state of equilibrium when under normal conditions and have the ability, after a disturbance, to regain a state of equilibrium [138]. Security is the ability of a power system to maintain the flow of electrical power to customers, under both normal and disturbed conditions [139]. However, it is critical to understand that a power system is never 100% secure, no matter how much planning, preparation and money is spent and therefore the risks that will affect security must be understood.

Reliability, stability and security are clearly interlinked; the reliability and stability of supply are dependent on the security of supply [140]. Reference [141] discusses that in 2002 only 1% of interruptions were caused by generating plants or the transmission system, indicating that it might not be worth the research on how to improve security of these areas. However, it goes on to argue that neglect of generation and transmission would be a mistake as the situation is not as clear cut as the 1% statistic represents. The author of [141] describes a situation that argues for investigation into improving security and reliability: a mid-week fault during rush hour and with some cascades that lead to a system blackout would cause issues for millions of people country-wide. Although this was just one event, it would nevertheless be a major problem and is worthy of attention even though the UK has never experienced a similar major disturbance that would require a black-start [141]. Transmission failures that cause serious problems are rare, and are generally known as low probability but high impact events (HILP), but, because of the impact they cause, they are a risk to the security and reliability of the system. Reference [142] states that HILP events can be many different things and can be grouped together depending on the level of preparedness that should be expected. Different HILP events include: pandemics, extreme weather conditions, terrorist attacks, climate change and nuclear accidents. To secure against all these types of events would be impossible even before considering the cost implications to both companies and customers, making it critical for system operators and planners to not only balance cost against impact but also against risk which is defined in [140] as the product of the probability of an event and the event's impact, summed over all possible events. Reference [85] introduces a framework that demonstrates how to identify key HILP exposures which can lead to some cost effect ways to protect against them but first you have to understand the risk and impact of each type of event, meaning that they require as much information as possible about the risk and impacts each HILP poses on power networks.

There are certain measures that an operator must watch to ensure system security and reliability. Variation in frequency, voltage, and thermal limits can affect system reliability and can contribute to demand not being meant. National Grid's balancing principles state that the frequency should not be unacceptably high or low. During steady state operating conditions the frequency should remain between 49.5Hz-50.5Hz, with an ideal frequency of 50Hz. During a transient state if the frequency goes outside these limits, it has 60 seconds to return to the limits before being classed as Unacceptable High or Low Frequency Conditions [143]. For each voltage level, within steady state operation there are set tolerances that they must be kept within. 400kV should normally be kept within +/- 5%, but is allowed a maximum range of +/- 10%; these values are only acceptable for 15 minutes. For 275kV and

132kV under normal conditions should remain within +/- 10% and for voltage levels below 132kV the tolerance level is +/- 6% [144]. Thermal limits of equipment are also considered when operating the system as overheating a piece of equipment due to allowing too much current to travel through it can lead to a breakdown of electrical insulation and a short-circuit which should be rapidly detected and cleared by protection equipment which acts to take the affected circuit out of service. Excessive temperatures might permanently damage the equipment. This means that all equipment has a maximum current that can be carried and is limited by the temperature [125]. Similar limits exist within all stable power grids to provide electricity on demand. An outage on the transmission system does not always mean that there will be an interruption to demand as the transmission system tends to be designed and operated to the security of N-1, where the system should be able to withstand one major outage. It is therefore necessary to monitor system limits to ensure they are not violated when an outage occurs. When an outage occurs on the system it will cause the system frequency to fluctuate. During steady state operation of a power system there is what can be classed as a single system frequency but when an outage occurs this is not the case as there will be different voltages responses throughout the system depending on the type of outage and location of outage. Loss of network branches typically cause increases in the power carried on other branches, possibly overloading them. Loss of generation in importing areas also causes power flows into those areas to increase. These breaches of voltage and thermal limits are unsustainable for the power systems and while sections of the system may not be outside of operational limits, it will still leave the system as a whole vulnerable to further outages which could trigger further instability and possibly a system collapse. Ultimately, the main measure of success or failure of the power system is what proportion of demand is met. Losses of demand connections clearly lead to failure to meet that demand; overloads, voltage deviations and instability also entail risks of failing to meet demand.

2.1.2 Current Methods

Reference [145] asserts that operation of power systems can be considered in three hierarchical levels which are shown in Figure 2-1. The first level solely considers generation facilities and the balance with demand, level two considers the integration of the generation facilities to the transmission system and the third level considers also the integration with the distribution system so the system as a whole.

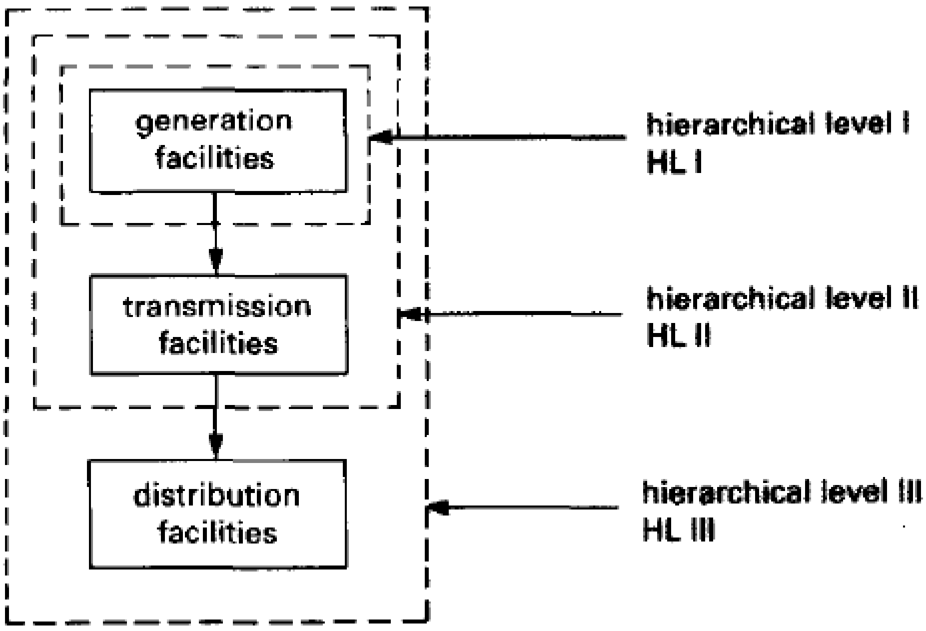


Figure 2-1 - Hierarchical Levels [145]

For the Hierarchical Level 1 (HL I) it is necessary to consider the current probabilistic methods that are used to determine that the generation capacity on the system is enough to meet required demand. There are three main indices that are used: Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE) and Loss of Energy Expectation (LOEE) or Expected Energy not Supplied (EENS) [145]. LOLP is the oldest index and is defined as the probability of the load exceeding the available generation. However, it is unable to display the measure of severity of the event, just the likelihood of an event happening. LOLE is generally the most used index and is the average number of days or hours on which the daily or hourly peak load is expected to exceed the available generation so it is able to indicate the number of days or hours that demand is not met. This enables this measure to be better than LOLP but it is still unable to display the severity. LOEE is the expected energy that might not be supplied on the occasions that load exceeds available generation. It is used less than LOLE but it is able to both indicate the likelihood of this occurring as well as the severity [145]. LOLE can be extended to include Frequency and Duration Indices (F&D) which identify the expected frequency and durations of the insufficiency of generation but these are not widely used in practice [145]. LOEE can also be expanded to include energy index of reliability (EIR), energy index of unreliability (EIU) and system minutes (SM). EIU is the value of LOEE divided by the total energy demand, and EIR is one minus EIU, these values are generally used to make difference sized system comparable [145]. SM is LOEE divided by the peak load all multiplied by 60 and is used by a number of utilities. It is however, an index with time as a unit so is impossible to use in real time and is better suited to annual values [145].

The distribution system has a different set of indices that are used to analyse how the system performs while in operation. The most basic indices are: failure rates, average outage durations, the annual unavailability, Customer Interruptions (CI), and Customer Minutes Lost (CML) [146, 147]. Other more complicated indices are; System Average Interruption Frequency Index (SAIFI), Service Average Interruption Duration Index (SAIDI), Customer Average Interruption Frequency Index (CAIFI), Customer Average Interruption Duration Index (CAIDI), Average Service Availability Index (ASAI), and Average (Expected) Energy Not Supplied (AENS/EENS). CI and CML are the most commonly used within GB operation, whereas worldwide, SAIFI and SAIDI are the most commonly used indices to track a distribution system's performance [18] though the effects of weather can drastically effect these indices especially during storms. For example in Canada in 1998 the value of SAIDI was 30.31 hours but 1998 saw an extreme ice storm, discussed in Section 1.1.2. By removing the storm the value of SAIDI was 3.32 hours [18]. This indicates that the indices are very sensitive to extreme weather, and large outages that weather cause will greatly increase the index values. Due to the more radial design of typical distribution systems, where if an outage occurs there will be an interruption to a customer meaning that the values of CI can be directly inferred from fault rates, though the CML values depend on the time taken to restore each customer which depends on the exact network configuration and the availability of remote control of normally open points [148]. However, due to the meshed topology of the transmission system, when an outage occurs it does not always lead directly to an interruption for a customer meaning that estimation of CI and CML or other indices depends on at least moderately detailed modelling of the system. The index estimation methods used, e.g. Monte Carlo simulation or truncated state enumeration approaches that only consider certain combinations of states, must also be selected with care due to the relative rarity of demand interruptions which generally depend on the occurrence of simultaneous or overlapping outages.

2.1.3 Current Suggestions about Reliability Measurements

As discussed above, there are methods for defining and measuring the reliability of the generation capacity (LOLP, LOLE, LOEE, etc.) and the distribution network (SAIFI, SAIDI, etc.) but these cannot be used to accurately monitor the reliability of the transmission network as they are dependent on whether there is adequate generation capacity to meet the demand or the effect a local network outage has on a customer, neither of which takes account of the impact of outages on the transmission network [149]. The transmission network is not only there to provide adequate transmission capacity to ensure that demand is met it is also required to do this within the voltage, frequency and thermal limits, mentioned in Section 2.1.1, and cope with an outage and other possible disturbances on the network [149]. Reference [149] states that because of this the reliability of the transmission system can be broken down into two categories: system security and adequacy where adequacy relates to the ability of the system to meet the demand and security refers to the ability of the system to cope with outages or disturbances on the network. Indices that measure the adequacy of the system include: system unavailability, unsupplied energy, number of incidents, number of hours of interruptions, number of voltage limit violations and number of frequency violations [149].

Security is harder to determine as while it is important it is reliant on probabilistic security assessment [149]. As a probabilistic security assessment can be difficult, to maintain security the transmission system is often operated in such a way that it is able to uphold security for a set of credible contingencies. Therefore it has been suggested that a risk based methodology is a better option [150-152] which is also computationally heavy but will allow for better balancing between the risk to system security as well as the cost implications. These risk based methods tend to look at the probability of failure for each equipment type or the probability of failure overall. Reference [152] discusses that while developing a basecase to measure against is important it is not good enough to only develop contingences based only on the most severe situations; you also have to look at all situations by evaluating both their probability of occurrence and the consequence of occurrence. So while the number of failures and duration of failures are important to consider it is also important and necessary to consider the probability of failure and what the consequences could be.

National Grid publishes yearly reports showing the availability, unavailability and ‘reliability’ of the GB transmission system during the previous year [153]. They define availability of the transmission system as the average percentage of hours a circuit is available for use as displayed in equation 2-1 .

$$\left(\frac{The\ sum\ for\ all\ circuits\ of\ hours\ available}{(No.of\ circuits)\ x\ (No.of\ hours\ in\ period)}\right)\ x\ 100 \tag{2-1}$$

Circuit unavailability is caused by four things, three of which are planned: maintenance outages, system construction outages and user connection outages and one of which is not planned: outages that occur as a result of plant failure or equipment failure. To maintain the expected levels of security and supply a high availability and reliability of the network is required. ‘Reliability’ is defined by National Grid as the percentage of energy that is supplied relative to that which it is estimated would have been supplied had the transmission system been perfectly reliable, as shown in equation 2-2.

$$\left[1-\left(\frac{Estimate\ Unsupplied\ Energy}{Total\ energy\ that\ would\ have\ been\ supplied\ by\ the\ transmission\ system}\right)\right]\ x\ 100 \qquad \textbf{2-2}$$

The reports also define a loss of supply incident as an incident that causes a loss of supply to a customer. However, not all unplanned outages on the transmission network lead to a loss of supply incident. Chapter 6 will compare the values that are reported in these reports to the initial analysis on outages and Chapter 8 will further discuss the approach used in this thesis for quantification of power system reliability subject to weather-related outages.

2.2 Statistics Background

2.2.1 Basic Statistics

The central tendencies (mean, median, and mode) are often the first investigated when analysing a dataset. The mean or the average looks at what the average value in the data set, and is affected by outliers, while the median is the middle number and less affected by outliers. The mode is the most frequently occurring value [154]. The central tendencies have limitations and are recommended for use only in certain situations as indicated by Table 2-1.

Table 2-1 - Best Measure of Central Tendency [154]

Type of Variable	Best Measure of Central Tendency
Nominal	Mode
Ordinal	Median
Interval/Ratio (Not Skewed)	Mean
Interval/Ratio (Skewed)	Median

Not all datasets are normally distributed; skewed datasets are more common in real life and can be either negatively or positively skewed [155]. A general rule of thumb for skewness is that for negatively skewed distributions the mean<median<mode, positively skewed distributions the mode<median<mean and for a normal distribution the mean=mode=medium [156]. However, this does not always hold [157]. The Kurtosis value of a dataset is a measure of the peakedness. There are three main types of Kurtosis:

leptokurtic – a high peaked distribution, positive kurtosis value; platykurtic – a flat-topped distribution, negative kurtosis value; and mesokurtic for a neither peaked nor flat distribution, zero kurtosis value [158]. The standard deviation is used to measure the variation from the average, a high standard deviation indicates a population with a wide spread from the average and a low standard deviation indicates a closely packed population around the average [159]. Quartiles or percentiles are useful measures to show the dispersion of a dataset, where the middle values represent the median [158]. The semi-interquartile range is another measure that is used to show the dispersion of a dataset. For a normal distribution the range from one semi-interquartile range for below and above the median will contain half the values. This does not hold for skewed distributions, but since this measure is not affected by outliers in the data, it can show the spread of a skewed distribution [158]. The standard error is used when it is not 100% guaranteed that the dataset is the full population [159]. Another measure is the upper and lower confidence limits, which calculate the 95% confidence limits of the mean [158]. The confidence limits are calculated based on the assumption that the data is a normal distribution, and sometimes will not be valid on skewed distributions unless the sample size is large [160]. Box charts are used as graphical representation of the maximum value, minimum value, the quartiles or percentiles (or both), mean, median and the confidence limits, allowing at a glance, quick evaluation of the dataset [158]. For larger datasets that need to be summarised, it is useful to create frequency distributions. This representation of the data makes it possible to evaluate the spread. Each category or bin generally has an upper and lower limit which determines the conditions [159]. This can be taken further to develop the cumulative frequency and the cumulative relative frequency. The former is the running total of the frequencies [161] in each category and the categories before and the latter is the percentage total of occurrences that occurred within that particular category and the categories before [158].

2.2.2 Probability Techniques and Bayesian Analysis

To complete a probability analysis of a dataset, a correlation analysis between variables and outside influences can be considered first. The correlation coefficient can range from -1, which represent a perfectly negative correlation, to +1, which represents a perfectly positive correlation [162] and is used to represent how strong the relationship is between variables being tested [158]. The coefficient of determination (R^2) is the square of the correlation coefficient (R, equation 2-3). R^2 is a measure used to determine the unexplained variation between two variables. A high value of R^2 indicates that variation of variable one causes a high variation of variable two; a low value of R^2 indicates that variation of variable one causes a low variation of variable two [158].

$$R = \pm\sqrt{\frac{explained\ variation}{total\ variation}} \tag{2-3}$$

The variables can be plotted on a scatter diagram to determine if there is a linear relationship or non-linear relationship [158], but it can often be difficult to spot if the data contains outliners [162]. When working with skewed distributions it can be difficult to see an initial relationship because the correlation analysis is based on a normal distribution, where skewed distributions tend to be more closely related to a logarithmic or lognormal distribution [163]. The log transform can be used, to allow the relationships between variables to become much more interpretable [164]. For datasets with zero values a constant must be added to prevent errors [165]. An example of data that has no clear relationship before a log transform is applied can be seen in Figure 2-2.

Probability is the chance that an event will occur and will be between the value of 0 and 1, where a probability of 0 indicates that the event will never occur and a probability of 1 indicates that the event will definitely occur [166]. There are different types of probability that can be used, a summary of different types of probabilities are shown in Table 2-2.

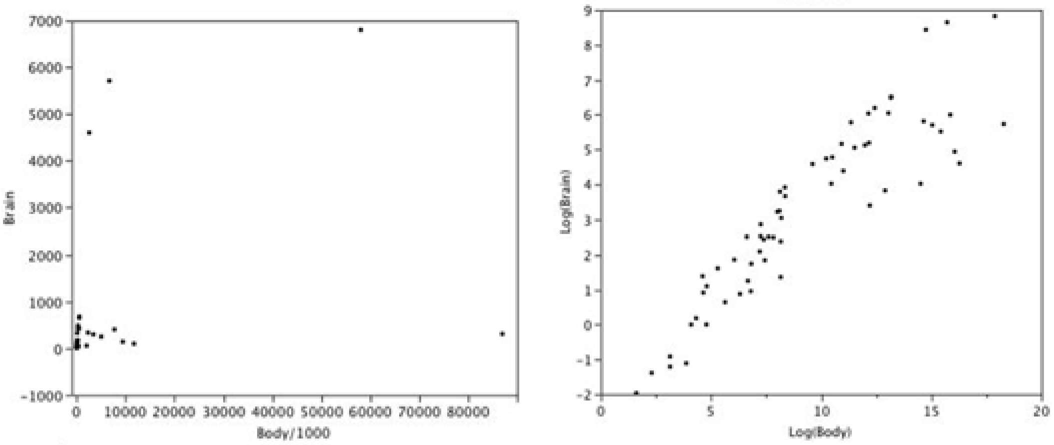
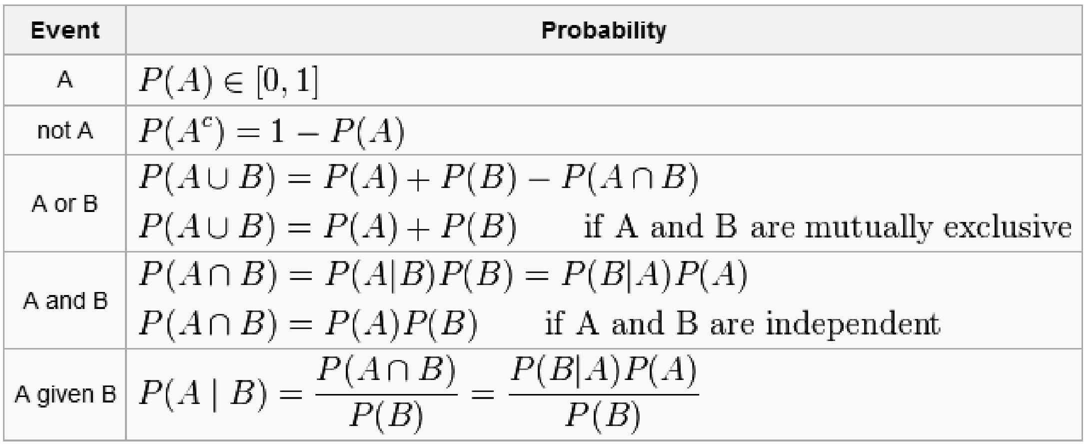


Figure 2-2 - Log Transform Example [164]

Table 2-2 - Probability Summary [167]



Event	Probability
A	$P(A) \in [0,1]$
not A	$P(A^c) = 1 - P(A)$
A or B	$P(A \cup B) = P(A) + P(B) - P(A \cap B)$ $P(A \cup B) = P(A) + P(B) \qquad \text{if A and B are mutually exclusive}$
A and B	$P(A \cap B) = P(A\|B)P(B) = P(B\|A)P(A)$ $P(A \cap B) = P(A)P(B) \qquad \text{if A and B are independent}$
A given B	$P(A \mid B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B\|A)P(A)}{P(B)}$

The classic method of calculating a probability is based on the assumption that the dataset is a random sample. Another method is the Bayesian Methodology where parameters are treated as random variables [168], where subjective probability and conditional perspective are the main concept and the observed data is considered the only data, the statistical interpretation is based on the observations [168]. Bayesian analysis tries to estimate variables of a distribution based on the observed distribution [169]. One main part of Bayesian analysis comes from Bayes' Theorem, which is used to express a conditional probability and to allow the calculation of a probability of A occurring given that B has occurred [168]. The equation used for Bayes' Theorem is shown in equation 2-4. Where *P(B)* is the probability of B occurring, no matter A, *P(B|A)* is the probability of B, given A has occurred and *P(A)* is the probability of A occurring, no matter B [166].

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \tag{2-4}$$

2.2.3 Sampling and Modelling Techniques

Once the relationship between variables and the probability of events occurring is determined, it is then possible to sample these results and use them to generate models. There are different ways to generate models using the data and this depends on what outcome is required from the model, with random sampling being a popular option. Proportionate stratified random sampling is one such technique and is a method used to sample the population in their respective subpopulations or stratum generating a smaller population that can be used to reduce the size of the dataset being used, as long as proportionally the smaller population on each strata agrees with the ratios from the larger population [170], and can be useful for modelling systems as a stopping criterion.

Monte Carlo sampling technique is used as a tool to understand the impact of risk and uncertainty in forecasting models [171]. It solves a problem by randomly generating a value and based on this random value the model can be solved. This random value can be based on the data that is being sampled or based on an outside factor. The Monte Carlo sampling is then repeated for as many time steps as desired or until the stopping criteria is met [171]. The more times you sample the lower the chance for error. Where the probabilities of individual outcomes are known, and the interactions between random variables are simple, it is likely to be more practical to work out the probabilities of combined states by hand than to go through a Monte Carlo sampling process. However, more complicated problems are unable to be solved by hand. For example, Monte Carlo can be used as a method for assessing risk in power system operation where the outcome in terms of meeting demand depends on a very large number of interacting factors [172], [173], [174]. In [175] Monte Carlo simulation is used to calculate critical line temperatures due to fluctuating power flows and meteorological conditions. These show that Monte Carlo simulation is highly adaptable and suited to modelling outages on power lines. Monte Carlo simulations can be developed in two formats – state, or non-sequential sampling, and sequential sampling. State sampling is when the input to the next iteration is not dependent on the output of the previous iteration, whereas sequential sampling moves through time chronologically [176]. Sequential sampling is generally run at hourly intervals [145] and requires a more complex implementation due to the link between outputs and inputs. State sampling is therefore often regarded as an acceptable first approximation when considering Monte Carlo methods as it is easier to implement, and, as previous states do not need to be stored and processed, computational time is quicker [177].

Latin Hypercube sampling (LHS) is a type of stratified sampling and an alternative to Monte Carlo simulation. Unlike Monte Carlo which randomly generates numbers and can therefore have clusters of samples in one area of the sample space and have blank areas in other sections of the sample space, LHS tries to control the way random samples are generated to make sure the samples are more evenly generated [178]. While it offers better precision it does contain some disadvantages. Unlike Monte Carlo, which can end if a stopping criterion is met, LHS is designed to run for the full number of time steps. It is also more difficult to extend the number of samples, and due to having to pre-stratify for each distribution and store these numbers which can take time and use up memory [178]. Both LHS and Monte Carlo could be used to randomly generate outages based on underlying relationships and then from this a power flow can be run on the system to test the effects of these outages on the test network. Another modelling method that has been used extensively when modelling weather effects on power systems is Markov modelling [71], [72], [179]. A Markov model is a stochastic model that is used to model randomly changing systems. However, it is generally assumed that the future state of the system being modelling depends only on the present state and not on the events that preceded it [180]. There are four basic types of Markov models; Markov chain, hidden Markov model, Markov decision process and partially observable Markov decision process. A Markov chain model uses random variables that change through time to model the state of the system. This means that the next state is dependent only on the previous state [181]. The hidden Markov model works where there is a sequence of states but not all of the states and the sequence they occur in are visible [182]. The Markov decision process allows for decision making in situations where the outcomes are in part random and in part in the hands of the user or decision maker but the user gets to observe the current state fully when making the decision [183]. The partially observable Markov decision process is similar to the Markov decision process but with an element of the hidden Markov model, instead of having a full view of the current state the user is only able to see some of the observations depending on the state that the model is in [183].

Of the methods that were researched, Monte Carlo simulation is not only popular but also flexible and applicable to modelling the effects of weather on the transmission system; it is also able to be combined with load flow analysis when generating random outages on the network based on underlying probabilities as discussed in [63], [80] and [87]. Monte Carlo will provide a modelling platform to model the randomness that exists within all-weather variables that are required to be modelled. Implementation of Monte Carlo simulation will be discussed further in Chapter 7.

2.3 Power System Modelling Techniques

When modelling power systems there are many different techniques and methods that can be used depending on what is required from the model but it is often found that the areas of interest are around the stability of the system and its ability to return to equilibrium or a steady state after being subjected to a physical disturbance [184]. There are minimum standards that a power supply must meet with regards to frequency constancy, voltage constancy and the level of reliability. But a power system in highly nonlinear and can influenced by a wide array of devices and disturbances [138], which are often the areas of interest. These different stability issues can be modelled using various techniques to assess the ability of the system to return to a steady state condition. If it is unable to return to a steady state condition then the user can decide what actions would be required for this to happen, for example load shedding. These actions are usually performed by the system operator through a manual operation. When initially considering power system modelling, steady state analysis is often a good enough indication of the state of a power system, but when considering this type of modelling it is important to consider the input data, such as the slack or reference node, PV node values and PQ node values and limits [185].

When modelling power systems, the components of the system are required to be modelled. Therefore consideration of how these components are modelled need to be taken into account. Components include: generators, transformers, transmission lines, load, excitation systems and system stabilisers. Additional complexity can be added when High Voltage Direct Current (HVDC) systems are also required to be included [186]. Within this thesis the model of the power system that will be used has been developed previously [187], where branches are defined using per unit values for positive phase sequence series resistance and reactance and winter post-fault thermal ratings are used. No transformers are explicitly represented but they are implied in the branch data. It is necessary for the user to choose the inputs for the operating conditions being investigated in order to solve the power flow. These input conditions for the purposes of this thesis shall be discussed further in Chapter 8 -. Optimal Power Flow (OPF) model sets the outputs of the generators to minimise the total cost of operating the power system but is still able to maintain that no elements of the power system are overloaded [188]. OPF uses economic dispatch in combination with power flows to allow for the minimal cost generation units to be dispatched when the load requires it but also takes into account limitations in the transmission system. Another method that can be used to reduce the complexity of the modelled system is to use a merit order. A merit order is an additional way to rank the available generation, based on their price and energy that will be generated in order to dispatch it but it is not guaranteed to satisfy the systems thermal limits [189]. It can be used when different technologies are required to take precedent over other types of generation. This can be the case when wind generation is required to be dispatched first before anything else, then other renewables, nuclear and fossil fuels and thus allows the user to control the generation profile.

There are many different software packages that are available for use that allow for all of these aspects of power system modelling to be achieved. Examples include DigSilent, PSSE, MATPOWER, IPSA, and PowerWorld. For this research all load flows will be undertaken using MATPOWER [190] as this allows easy integration between Monte Carlo simulation and an OPF AC load flow system with the addition of merit order for generation dispatch.

Further discussion relating to how MATPOWER solves the power flow equations can be found at [191].

2.4 Summary

This chapter presented discussion on the known techniques and methods that will be used throughout this thesis in order to develop and implement the proposed methodology.

This chapter displayed different definitions of power system reliability and how a power system will never be 100% reliable, therefore understanding the risk is important as HILP events can cause significant risks to security and reliability. It also discusses the current methods that are used to measure system reliability and security and how this differs for generation, transmission and distribution networks due to the differences in network topology. The measures that work for one type of network are generally not applicable to the other types, making the quantification of impact on the transmission networks due to weather a difficult task that will be discussed throughout this thesis.

It further discussed different statistical methods that can be used to analyse data, such as the historical outage and weather data, and different methods that can be used to develop relationship between variables, such as correlation analysis and Bayes' Theorem. Additionally, methods that can be used to model risks and uncertainty were also discussed, for example Monte Carlo simulations, LHS and Markov modelling were presented. This chapter finally presented a discussion about different power system modelling techniques that concluded with the methods that will be used within this thesis.

Chapter 3 - The Methodology

As described in Sections 1.6 and 1.7 a main aim and contribution of this research has been to develop and present a methodology that can be applied to transmission networks around the world to assess the effects of weather and climate change. This chapter will present the five stage methodology that has been developed, presenting a discussion on each stage and why it is necessary and important in the assessment of the effect of weather and climate change.

3.1 The Five Stage Methodology

The five stage methodology that will be presented and applied within this thesis is shown in Figure 3-1. This extensible methodology has the ability to model the dominant weather variables and the ratio between extreme and normal weather to allow modelling of changing weather patterns. This is done by using historical weather data to understand the current risks that weather can have on a transmission network in order to develop a basecase. The impact on the transmission network can be analysed by feeding this basecase, as well as weather changes from climate change projections, into the model.

3.1 Stage One - Analysis of Weather Sources, Weather and Non-Weather-Related Outages

When starting to analyse large datasets to define relationships between variables, it is first important to investigate the datasets with the basic statistical tools discussed in Section 2.2.1. This is an important and necessary first step in the process of analysing weather on electricity networks as it allows the dataset to be defined, determines which weather variables dominate the network, and provides an understand of the different weather datasets that are able to be used. This pre-analysis stage comprises of two parts: the weather data pre-analysis and the outage data pre-analysis. The first step is to find different weather datasets that are available that cover the network area that is being analysed. For each network area that this methodology is applied to there may be different weather variables that effect it and different available weather datasets covering the area. There are two main types of weather data: observational weather data and reanalysis weather data. An observational weather dataset will contain weather information that is recorded at weather stations, whereas reanalysis weather datasets may be available from multiple different sources and provide interpolations to fill gaps in recorded observations. Reanalysis data will be discussed in further detail in Section 4.1. However, if using a reanalysis weather dataset it is important to compare it to an observational dataset to understand how accurate it is in comparison to the observation data.

The second part within this stage is to analyse the outage dataset for the network area that is being investigated. For this second part a dataset of outage data for the area is required that when analysed will provide information about the weather variables that affect the network the most and it will also allow for the weather classes to be defined. A weather class is a group of weather variables that are grouped together because, alone, their effects are very difficult to distinguish, for example Wind, Gales and Windborne Objects, or Snow, Sleet and Blizzard. This section can also be used to analyse the seasonality within the outage data, if there are any yearly trends in the data and if trends within the equipment type or voltage level exist. Transmission networks tend to cover large areas and can experience different weather; it is therefore important in the pre-analysis section to analyse the different areas to determine what the optimal split is to accurately reflect the weather. The outputs from this stage are the definition of the main weather variables that affect the transmission network, verification of the weather data being used and the area split that would best define the way weather affects the network. All of this information is important as it will be required for the following stages and will allow for a deeper understanding of the data that is being used and how weather affects the network that is being analysed.

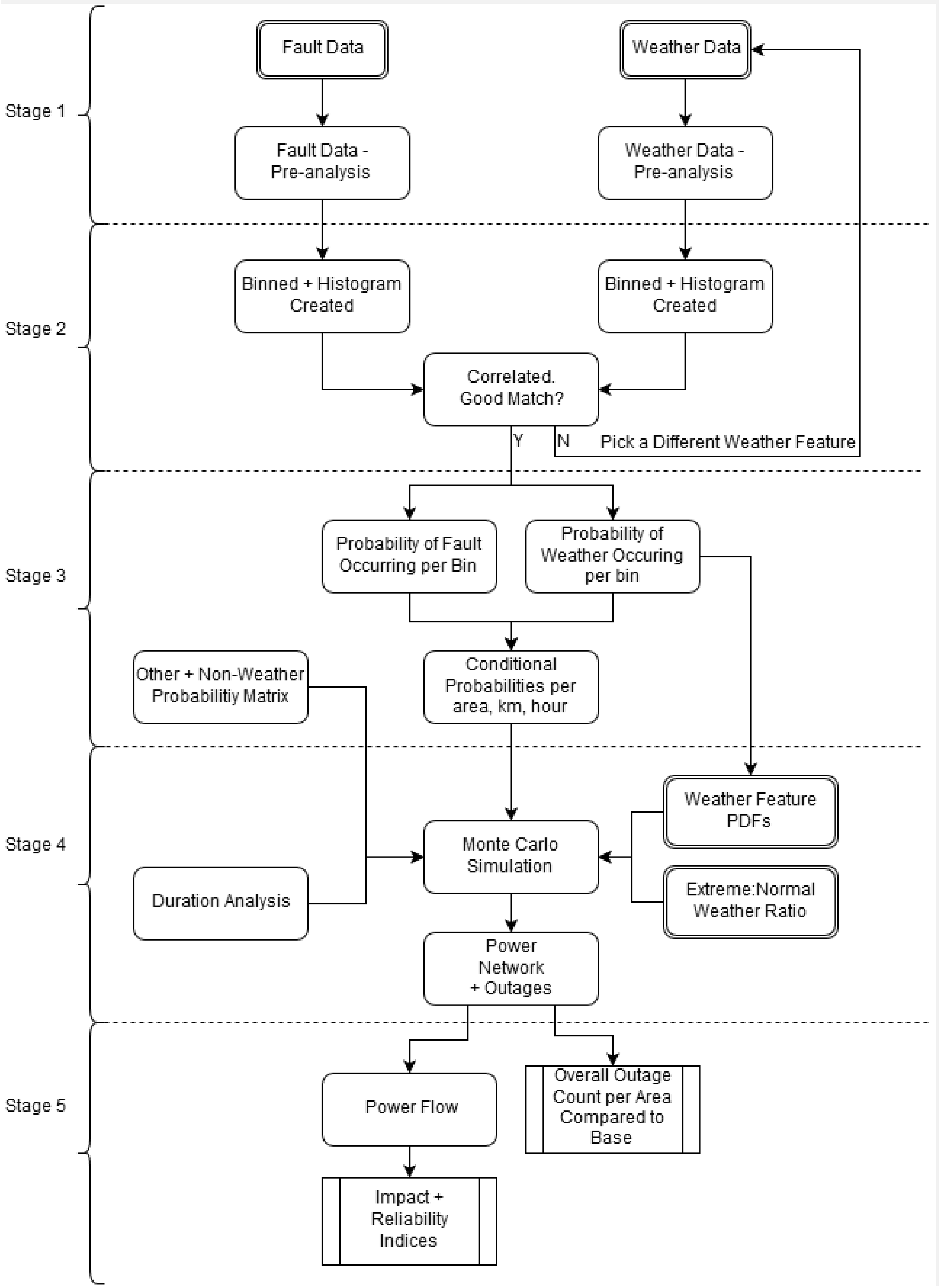


Figure 3-1 - Five Stage Methodology

3.2 Stage Two - Correlation Development between Weather-Related Outages and Weather

The second stage of the methodology is to develop a correlation relationship between a weather variable and a weather outage class. It uses the development of the main weather variables from the pre-analysis stage to determine which weather variables will be suitable for this type of assessment. Not all weather variables that affect the transmission system are able to undergo this stage due to lack of data, and therefore only the main weather variables are able to be analysed. This analysis produces a weather variable that is a strong indicator of a weather outage class by using available weather datasets and the outage cause noted in transmission fault records. Weather-related outages tend to be classed in broad categories for example, wind, gales, snow, and lighting. However, this methodology requires an exact value of weather, e.g. 21m/s wind gust as the outage cause. Due to the complexity of weather, it can be initially unclear what weather variable is responsible for an outage. For example, within a weather outage class of ‘Wind, Gales and Windborne Objects’, two weather variables available from datasets of weather observations in Britain could be strong indicators of an outage: (i) 10m Wind Speed, and (ii) 10m Wind Gusts. Therefore, all possible indictors should be assessed and the strongest indicator chosen. If there is no clear indicator, because they are all strong indicators, then the variable most likely to cause outages should be chosen. However, if none show a strong indication then other weather variables should be tested or combinations of different weather variables might provide the strongest correlation or the weather outage class may need to be reassessed. The frequency distribution, cumulative frequency distribution and the correlations between each weather variable and each weather outage class are then generated. From these it is possible to determine the strongest weather variable indicator for a weather-related outage.

3.3 Stage Three - Quantification of Weather Dependent Fault Probabilities

Stage Three uses the weather variable indicator of a weather outage class that is developed in Stage Two to determine the conditional probability density functions for each weather outage class based on the weather variable. For weather outage classes that are not within the main weather variables of the network, conditional probabilities based on weather are not able to be calculated as they are not analysed in Stage Two due to lack of data. However, in order to complete the analysis standard probabilities are also calculated. This is done to include the outages that are caused by the other weather types experienced on the system being analysed. For example, generating a 5% chance of another weather outage occurring no matter what the weather occurring is.

To calculate the conditional probabilities for each bin individually Bayes' Theorem is used, as shown in equation 2-4. In this case P(A|B) is the probability of a weather-related outage occurring based on a particular weather variable value occurring in a particular range or bin; P(B) is the probability of a weather variable value in the relevant bin occurring, based on historical records; P(B|A) is the total number of outage occurrences in the relevant bin divided by the total number of occurrences over all bins; and P(A) is the outage rate for weather-related outages. When calculating P(A) it is necessary to take into account the number of weather-related outages that are misreported to take into account of misclassification errors that exist within the data. To do this, misclassified outages, that is outages with weather as their cause but the exact weather variable is unknown, are randomly assigned to the known weather classes in the same proportion as for the rest of the dataset for which weather causes are noted. This is done after attempting to match weather cause to weather outages, given the weather that was occurring at the time of the outage. This ensures that all outages are included in the analysis, which is important as this can be a large proportion of an already small population size. To compare probabilities by area it is necessary to have them on a comparable scale, so they are transformed in each area to per 100km per hour. To do this the total OHL + cable lengths within each of the areas should be calculated and each weather variable identified as either continuous or discrete.

3.4 Stage Four - Weather and Outage Sampling

Stage Four uses Monte Carlo simulation to generate outages on the network using the conditional probabilities developed in Stage Three. This determines the network state before an AC load flow in Stage Five can be performed. Both a state and sequential sampling version of the model have been created where the sequential sampling model is built upon the state sampling model. For the GB test case both sets of simulations are run in hourly time steps, but as the conditional probabilities can be adapted they could be run in different time sequences. As well as the conditional probabilities there are four other inputs that are required for the Monte Carlo simulation. These four other inputs are;

- Additional outage probabilities for non-weather outages and other weather outages to allow for a complete outage picture of the network to be developed.

- Duration analysis information to allow for outage durations to be determined based on historical duration information.
- Weather histograms developed from current weather and used to create the basecase of the model and then, using climate projections for the area being analysed, further developed to allow the effects of the projections to be evaluated.
- The electricity network's characteristics, the area split, branch locations and lengths.

There are two steps of Monte Carlo sampling in the presented methodology. The first samples weather values at different locations on the modelled system. Then, using the sampled weather value, the second step samples whether an outage will occur. This first step requires one input, the weather histograms per area; these can either be based on historical data, or based on climate projections. This allows the model to be used to create a basecase for analysis as well as assess the impact of changes to the climate. The second Monte Carlo sampling step requires two inputs: the electricity network that is being tested along with each branch's line length, and the outage conditional probabilities based on the weather variables determined in the first Monte Carlo step. The sequential sampling also requires outage duration information. It uses these values to develop the probability of an outage per branch and determines if an outage will occur on the branch. Within each time step, this is repeated for every branch on the network, building a complete picture of network outages which is then used as the input to Stage Five. The other output from this stage is the average failure rate per area per weather variable. These values can be used as one method to evaluate the impacts of changes to the weather and climate on the electricity network that is begin tested.

3.5 Stage Five - Assessment of the Impact of Changed Weather on Power System Reliability

Stage Five is where power system analysis is undertaken in order to assess the impact of a particular pattern of outages on the system state and the sustainability of a particular operating condition. In particular, whether any demand needs to be shed, in addition to that which outages have directly disconnected. The form of this analysis can be chosen by the user to give the level of accuracy required, though assessment of system stability, in particular, requires advanced methods and considerable extra data. In the studies conducted as part of this work, an AC load flow has been used on the electricity network that is built during Stage Four of the proposed methodology. The outputs of the load flow can be used to consider the impacts of weather and climate change on the power system that is being analysed. Validation of the modelling approach and data should be carried out with respect to historic conditions for which performance data are readily available. Although it might be considered that modelling of a future, post-climate change condition requires modelling of the system assets as they are planned or forecast to be then, actually this would prevent the drawing of any conclusions with respect to the impact solely of climate change. This is because results of Monte Carlo simulation of the future system would include the effects of both the changed system and the changed weather. In order to compare the effect of present day weather with future weather, all other system parameters should be kept the same. As discussed in Chapter 2 -, the main impact measure concerns the reliability with which demand is met. This might be measured simply by the probability of failing to meet all of it, but this neglects the magnitude of each failure event. The energy not supplied seems to be a better metric but this depends not only on how much demand was initially disconnected but also on when it is restored. To model, with any confidence, the restoration of disconnected demand is extremely challenging due to the large number of unknown factors, e.g. availability of manpower, equipment, seriousness of the fault and the ability to re-arrange maintenance schedules. As a subject for future work it is recommended that this should address not only the system technical measures such as starting up of reserve generation and network reconfiguration but also logistical issues such as availability of staff, access to sites and communications which are particular issues in especially severe events. When conducting a load flow analysis it is important to set the initial conditions correctly to represent credible operating conditions. The inputs that are required for this stage of the methodology are:

- The network that is built in Stage Four containing all the branch outages.
- A demand profile for the time period and network area that is being modelled. This can be altered depending on the user requirements.
- If a weather variable is used to generate power on the network, then the values of this weather variable are required to be known. For example wind power, solar power or hydro power. These values would be determined in Stage Four.
- The relationship between the weather variable and power that value can generate is then used to determine each area’s weather dependent renewable power contribution.
- Availability and merit order, or price information, for dispatchable generation per area and the volume of generation per area.

Once these inputs are established the model can then use the information to determine how to dispatch the generation based on the demand and the power that can be generated, including weather dependant generation. The model first uses the demand profile to determine the volume of generation that is required then will determine the weather dependant generation that is dispatched based on the weather variable values determined in Stage Four. It is suggested as a point of future work that the weather variables that are generated in Stage Four are used to influence the demand profile, as on wet and windy days the demand is higher, and on hot days the demand tends to be lower. For this to be possible, a power curve for the generation, based on the weather variable, is required. In the GB version of the model, wind speeds are used to determine the generation of wind power, using wind speed to power curves. The merit order is used to dispatch the required generation to meet the demand profile. Once the generation, demand and network information are all known the AC load flow can be run. The outputs that are generated allow an evaluation of changes to failure rates, increased occurrence of equipment overloading or voltages outside limits, potential system frequency instability, lost load and energy not supplied, as well as countless others. The outputs can be tailored to suit what is required for the system being analysed. The outputs of Stage Five presented in this thesis will be; system reliability and unreliability, unavailable system minutes, LOEE, LOLP and LOLE (day and hours).

3.6 Summary

This chapter has presented the five stage methodology that was developed for this thesis and meets the research aims that were presented in Sections 1.6 and 1.7. Stage One of the methodology is a pre-analysis stage, which allows the datasets that will be used to be explored and allow characteristics of both the weather and outage datasets to be understood. Stage Two develops strong relationships between weather variables and outages types. Stage Three uses these relationships to develop conditional probabilities that can be used to determine the probability of an outage based on the weather variable value. Stage Four is the weather and outage sampling step in this methodology where Monte Carlo simulation uses historical or climate projections to generate weather variable values and then determine if outages occur on the network based on the conditional probabilities that are developed in Stage Three. The final stage of this methodology, Stage Five, uses the network built in Stage Four to provide the basis for a power system analysis, in this case a load flow, to determine the effects of weather on the network that is being analysed. The demand profile for the load flow is provided by the user, and the generation is dispatched based on a merit order, and weather dependant generation uses the weather variable values determined in Stage Four. These five stages allow for a thorough investigation of the effects of weather and climate on transmission networks and can be easily adapted to suit the network under analysis. The following chapters of this thesis shall present these five stages in use on a test case of the GB system showing the effects that weather and climate change can have.

Chapter 4 - Analysis of Weather Sources, Weather and Non-Weather-Related Outages

The first stage of the proposed methodology described in Chapter 3 - is to examine the necessary weather and outage datasets to understand the current effects that weather poses on the transmission network that is being analysed. This is an important stage, as without it, it is impossible to understand what the main weather types are that affect the transmission network and it would not be possible to build relationships between weather and weather-related outages. For the purposes of demonstrating the effectiveness of this methodology, it has been applied to the GB transmission network as a test case. For the GB transmission network analysis past outage data was collected from the three transmission operators of the GB network. Past weather data was collected from ERA-Interim Reanalysis weather from The European Centre for Medium-Range Weather Forecasts (ECMWF) and Met Office Integrated Data Archive System (MIDAS) from The British Atmospheric Data Centre (BADC). Lightning Strike data was provided by EA Technology. This chapter will initially contain a discussion about these weather datasets and will continue with an initial analysis of the historical outages. This chapter aims to meet research aims 3 and 4, as discussed in Section 1.6 to complete an analysis on outage datasets, provided by the three transmission companies of GB, for both weather and non-weather-related outages; and to compare observational weather data and reanalysis data as well as lightning strike data and a lightning strike proxy, Convective Available Potential Energy (CAPE), in order to verify reanalysis data as a suitable replicator of past weather data.

4.1 Weather Data

4.1.1 Weather data gathered

In order to develop relationships between weather and weather-related outages it is first important to collect past weather data in order to assign weather values to outages and develop frequency distribution and cumulative relative frequencies. There are several sources for past weather data, but the main providers in the UK are BADC and ECMWF. BADC has available a large variety of data sets, but for the reasons outlined below, two sets were selected for investigation for this analysis: Met Office MetDB system: Surface, upper air and satellite data [192] and MIDAS Land and Marine Surface Stations Data (1853-current) [193]. The MIDAS dataset is land and marine surface observations from the Met Office station network and other stations available worldwide. The MIDAS data set contains a range of different data including UK Daily Rainfall Data, UK Hourly Rainfall Data, UK Soil Minimum Temperatures, and UK Daily Temperatures. The set used for this analysis was the UK Hourly Weather observation data, which was the only set with the required time resolution to be able to determine exact weather conditions around the time of a fault. The MetDB system contains data extracted from the Met Office's MetDB system which includes surface and upper air observations and some satellite data. The MetDB data set contains a range of different data (Aircraft Meteorological Data Relay, Land Based Synopsis (SYNOP) Messages, Radio Acoustic Sounding System Messages, Ship Based SYNOP Messages and Wind Profiler Observations). The dataset used was the Land Based SYNOP Messages. MetDB data is only available up to 2009, which is a shorter period than historical outage data was available making it not ideal for analysis and therefore it was decided not to use MetDB dataset for this analysis. The MIDAS dataset is available from 1974 till present, access to the data set needs to be requested and once granted all files can be downloaded. For this analysis the hourly weather was downloaded from 1989 till 2012. Both MetDB and MIDAS are based on land station data, which means that the data can contain gaps if the stations are not online, require to be manned or it is a date outside the stations operational time period. Therefore, sometimes these datasets will not have any available weather data for a specific date and time, which makes them undesirable for analysing outages which could happen at any date and time.

ECMWF uses forecast models and data assimilation systems in order to reanalyse past weather data observations [194]. This means that unlike observational data, reanalysis data is not totally reliant on stations' recordings as it uses the multiple sources of data to interpolate and fill the gaps. This allows for a much fuller dataset which is better suited to analysing outages at specific dates and times. ECMWF has developed four iterations of its reanalysis datasets, with the newest being the ERA-Interim [195] dataset where data is available from 1979 until the present. ERA-Interim contains many atmospheric and surface parameters which are available in 6-hourly atmospheric fields on model levels, pressure levels, potential temperature and potential vorticity, 3-hourly surface fields and daily vertical integrals, monthly averages of daily means, and synoptic monthly averages at 0 Universal Time Coordinated (UTC), 6 UTC, 12 UTC, 18 UTC [194]. ERA-Interim data was downloaded directly from ECMWF using information provided by [196] and a table of parameters that were used to extract weather data for this analysis is found within Appendix A. Weather data is available in grid square format; Figure 4-1 shows the weather grid squares that cover GB and therefore what grid squares are required for this analysis. Data was extracted over each licence area for the same time period that outage data was available for. The final weather dataset that was used was lightning strike information. While both the MIDAS and ERA-Interim datasets provide comprehensive weather data parameters, neither contains information on lightning strikes. As lightning causes a large proportion of weather-related faults on the GB network, it is critical to have the weather data available for lightning strikes. Lightning strike data is recorded by EA Technology [197], who provided data relating to lightning strikes and their strength from 1995-2010 to allow analysis between lightning data and lightning related outages on the GB system to take place.

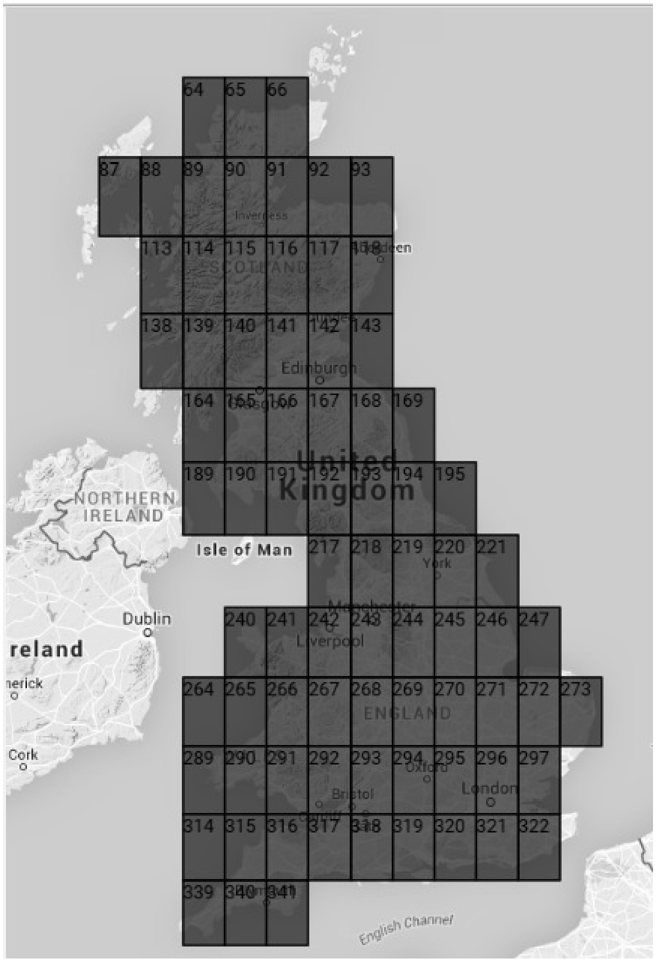


Figure 4-1- GB Weather Grid Squares

4.1.2 Reanalysis Verification

As discussed in Section 4.1.1, reanalysis weather data would be ideal for analysing weather outages in this research as it is a fuller dataset and will have a weather value for every outage. However, before using reanalysis weather data, it is crucial to compare it to observed weather data to verify how accurately it reproduces past weather data. To this end, the ERA-Interim reanalysis weather data sets that were used in this thesis are compared in this section against the MIDAS data set provided by BADC. Different weather metrics were required from ERA-Interim for outage analysis and each was compared against the same weather metric from MIDAS; 10 metre wind gust since previous post-processing, 10 metre U wind component & 10 metre V wind component, Minimum temperature at 2 metres since previous post-processing, and snow depth and snow density for 3 hour periods. To facilitate this comparison, the correlation between the two datasets values was considered and the coefficient of determination (R^2) was measured. The reanalysis data must be able to accurately reflect the observed situation on the ground at a grid square level as that is as good a resolution that is required for this analysis. The data was compared from 1st January 1989 to 31st December 2008.

Wind Gusts

A wind gust is defined as short sudden bursts of high speed wind followed by a lull [198]. ERA-interim wind gusts are recorded at 10m above ground level at 3 hour intervals. Each observed wind gust has a latitude and longitude based on the station, which in turn allowed the ERA-Interim grid square of that station to be determined. For every observed wind gust, the reanalysis wind gust value within the grid square during the same period was taken and compared. The result of this analysis is shown in Figure 4-2. It is clear that the correlation in the range up to 40m/s is reasonable; indicating that the observations above this value are rare, so year-round network reliability performance is dominated by wind gusts below 40m/s. For the assessment of the whole network on a year-round basis, it was judged that the use of reanalysis data is reasonable as a proxy for observed wind gust. Large scale variability was also investigated, for each grid square the observed wind gust values were averaged for each period, allowing the average observed wind gust and the reanalysis wind gust in each grid square to be compared. From Figure 4-2 it can be seen that ERA-Interim in unable to fully capture wind gusts variability at a locational scale, Figure 4-3 shows that ERA-Interim is able to cope with large scale variability, as the R^2 value is 0.949. This high value indicates the reanalysis dataset is able to successfully reproduce wind gust values on a grid square level successfully.

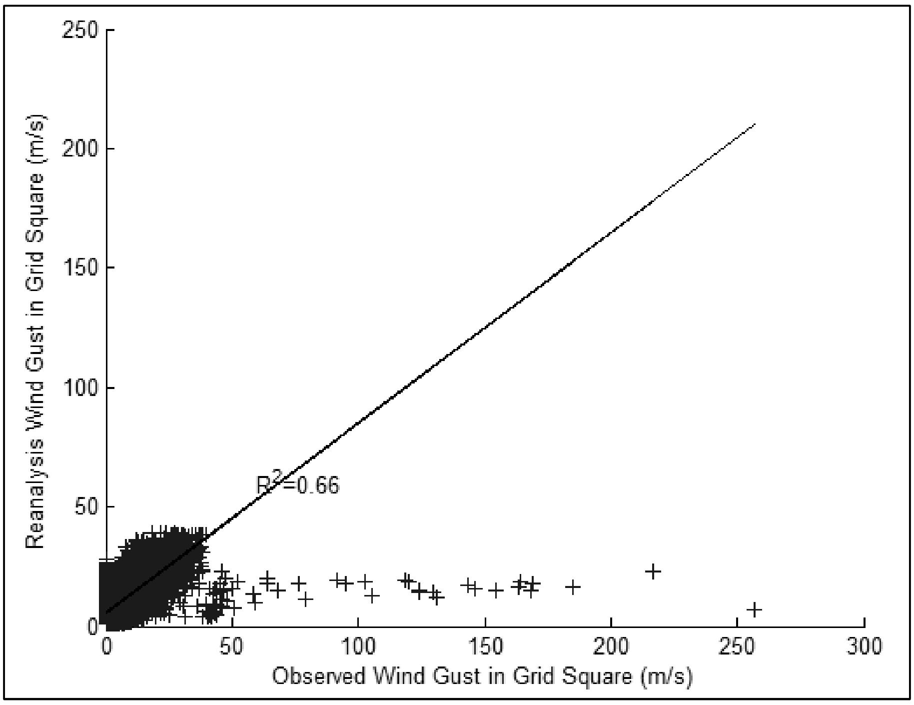


Figure 4-2 – Comparison of MIDAS observed wind gusts (m/s) with ERA-Interim reanalysis wind gusts (m/s)

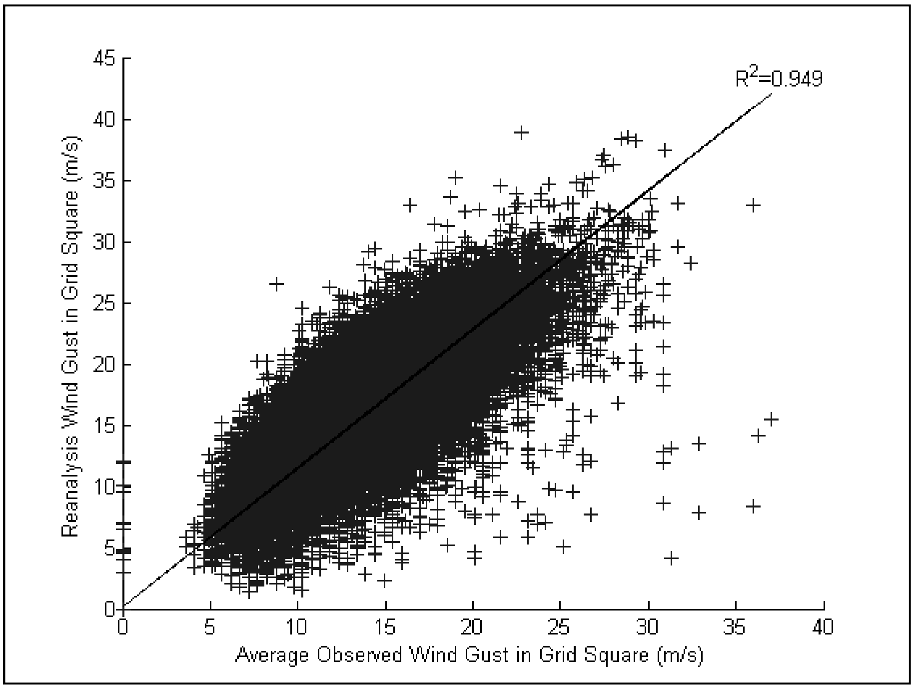


Figure 4-3 –Comparison of MIDAS averaged observed wind gusts (m/s) to ERA-Interim reanalysis wind gusts (m/s)

Wind Speeds

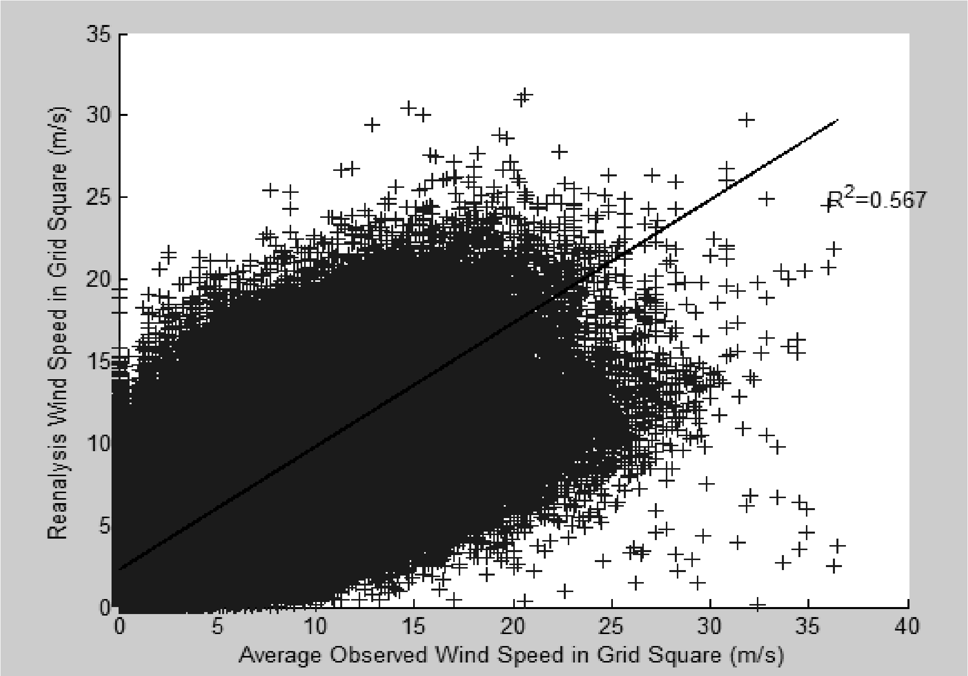


Figure 4-4 - Comparison of MIDAS averaged observed wind speeds (m/s) with ERA-Interim reanalysis wind speeds (m/s)

Wind speed is defined as a measure of motion of the air [199]. ERA-interim wind speeds are in their U and V components, are at 10m above ground level at 3 hour intervals and are a possible metric for weather-related outages. The same method used for wind gusts were used to analyse wind speeds, as with wind gusts, wind speeds for each grid square were averaged for each three hour period allowing the average observed wind speed and the reanalysis wind speed in each grid square to be compared. The result is shown in Figure 4-4. Unlike wind gusts, the reanalysis average wind speeds are not as successful at reproducing observed wind speeds with an R^2 value of 0.567. This could be for many reasons: human error in obtaining comparable values, errors in observed values, or errors in the data used to calculate the reanalysis values. However, while the R^2 is lower than expected, when looking at Figure 4-4 it is clear that there is some correlation between the observed and reanalysis data, indicating that ERA-Interim would still be a reasonable source for wind speeds.

Minimum Temperature

Minimum temperature was also considered as a possible metric for weather-related outages and therefore observed minimum temperature and reanalysis minimum temperature were compared. The observed weather dataset that is used is Air Temperature and from that the minimum temperature can be extracted per station. This was then plotted against the reanalysis minimum temperature value and the outcome is shown in Figure 4-5. There is high agreement between the observational values of minimum temperature and reanalysis values of minimum temperature, with a R^2 value of 0.891. This indicates that ERA-Interim strongly reproduces values of observed minimum temperature.

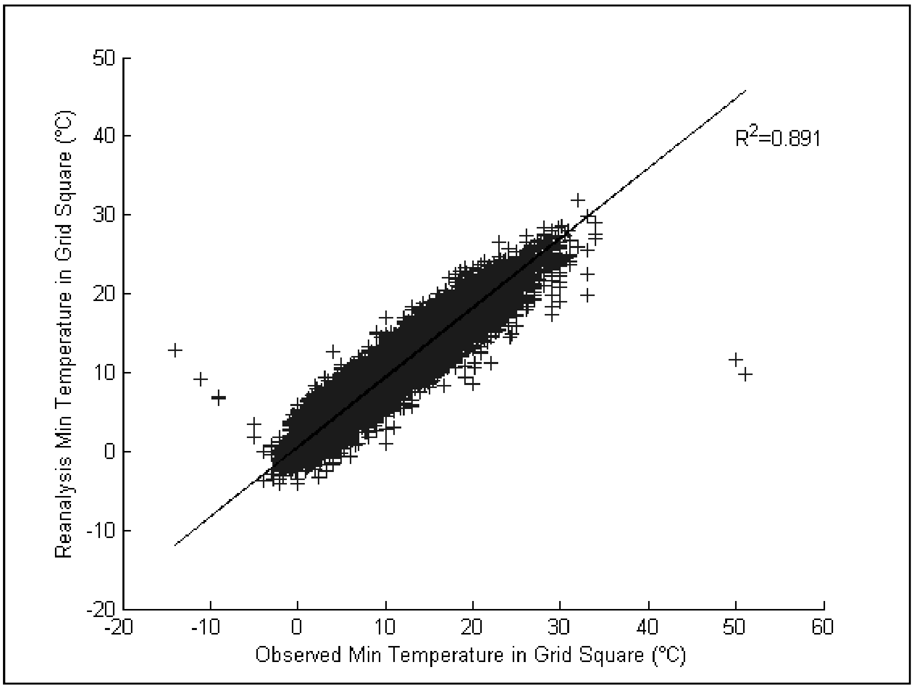


Figure 4-5 - Comparison of MIDAS observed minimum temperature (°C) with ERA-Interim reanalysis minimum temperature (°C)

Snow Depth

Snow depth is more difficult to compare than the previous weather variables. Observed snow depth in MIDAS is measured by a person with a ruler. In contrast, the reanalysis data represents snow depth as snow water equivalent (SWE). This is the depth of water that would result if the entire snowpack was melted. Alone, these two values are incomparable and therefore snow density is also required to allow a snow depth value to be calculated. This is done using Equation 4-1 [200].

$$Snow\ Depth\ (m) = \left(\frac{SWE\ (m)}{Water\ Density\ (\frac{kg}{m^3})}\right) x \left(Snow\ Density\ \left(\frac{kg}{m^3}\right)\right) \qquad \textbf{4-1}$$

Once this has been completed for the reanalysis values of snow depth, it is then possible to compare observed and reanalysis values of snow depth using the same methods as described previously. The resultant graph is shown in Figure 4-6. While the R^2 value is not as high as it was for the other weather comparisons, at 0.615, it is important to note the errors that exist within the snow depth data: human error in the process involved in obtaining comparable values, errors in observed snow depth or the assumption of constant snow density. Despite these issues, ERA-Interim is still able to positively reproduce snow depth.

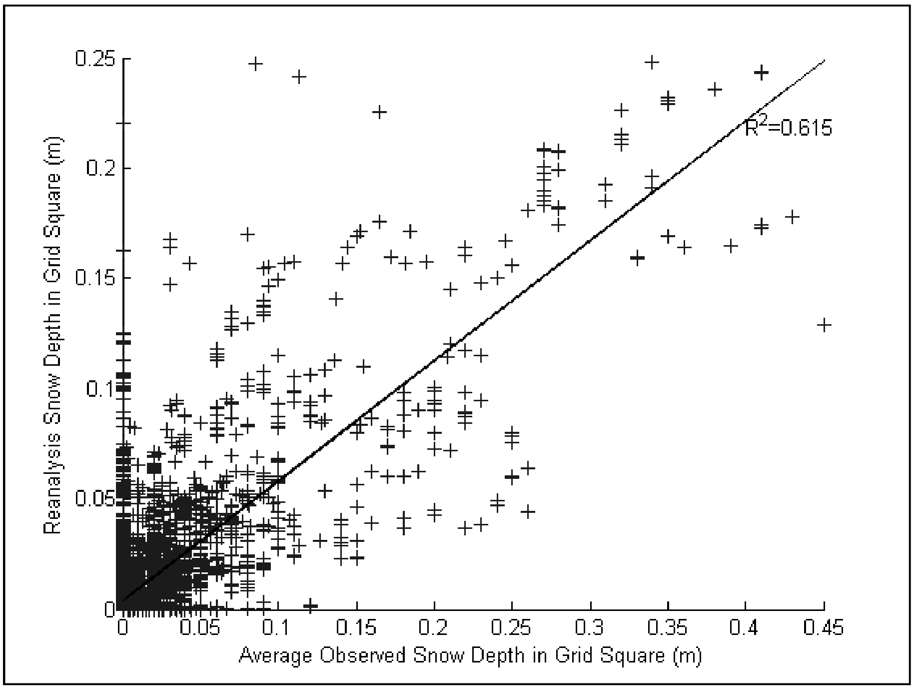


Figure 4-6 - Comparison of MIDAS observed snow depth (m) with ERA-Interim reanalysis snow depth (m)

4.1.3 Lightning Strike Proxy Verification

As mentioned in Section 4.1.1 lightning strike data is an important aspect of analysis as a large proportion of weather-related outages are caused by lightning strikes. Lightning strike data was provided by EA Technology, their lightning location system locates lightning strikes that have occurred within the UK. It was set up to help the electrical companies determine when lightning had caused damage to overhead lines (OHLs) and only detects cloud-to-ground lightning activity, which are what cause damage to power networks [197]. The lightning location system is able to detect up to 100 strikes per second and works by detecting the Very Low Frequency (VLF) electromagnetic waves created by the electrical discharge when the lighting strike occurs [197]. There are six stations throughout the UK that detect the electrical discharge, record where and when the strike took place, the strike strength, and then report back to the control centre where all the data is stored, or displayed "live" to customers [197]. However, this analysis is not only looking at the effect of current weather it is also considering the effects of weather due to climate change. Lighting can be a hard weather variable to predict and harder to determine future changes and tends not be available in climate projections. It is suggested that CAPE is the best proxy for lightning [128, 201, 202] and changes to CAPE are available in climate projections. CAPE is directly related to the maximum potential vertical speed within an updraft; thus, higher values indicate greater potential for thunderstorms and lightning [201]. This section will determine if the CAPE data from ERA-Interim is a good proxy for lightning strike data by comparing it with the lightning strike data that was provided by EA Technology. CAPE data that was used was available in the format of daily max CAPE (J/kg) for each grid square over GB as shown in Figure 4-1, from 1995-2010, the same time period that lighting strike data was available for. Lightning strike data was organised into daily number of strikes in each area, each day allowing the number of strikes to be plotted against CAPE. As discussed in Section 2.2.2, sometimes relationships between values are not always clear until transformed; in this case the data is transformed using the logarithmic transformation. Figure 4-7 shows the logarithm of the number of strikes against the logarithm of CAPE.

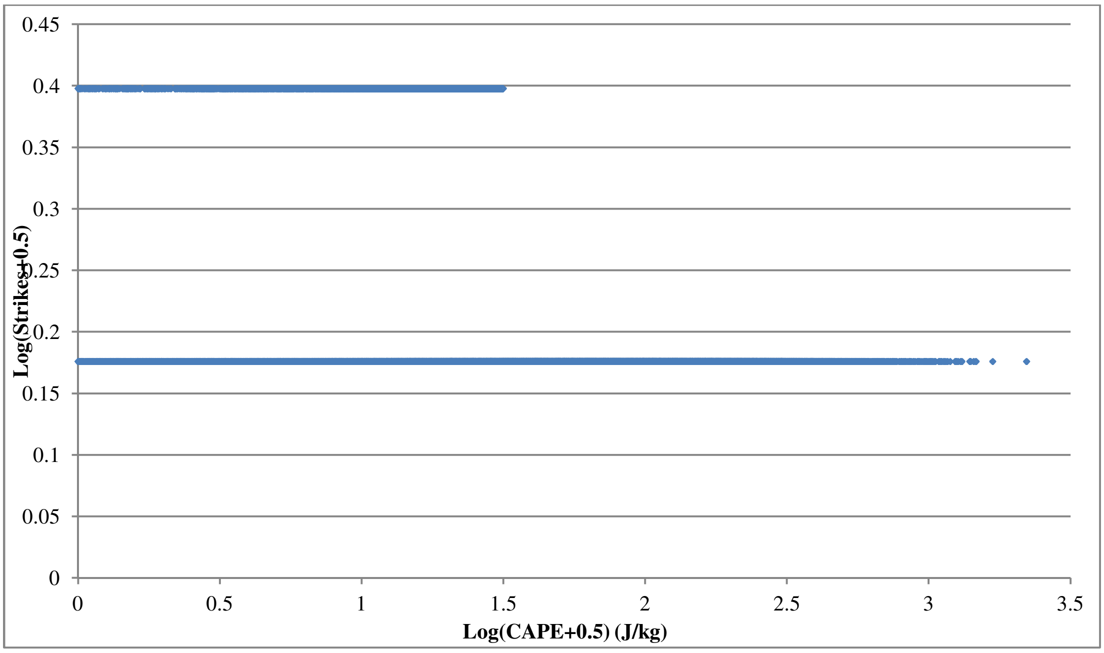


Figure 4-7 - log (Number of Strikes) against log (CAPE) (J/kg)

While it is difficult to see a relationship at the lower values of CAPE and lightning strikes, as these are commonly occurring values, as the values of CAPE increase there is an increasing trend in the number of strikes indicating a relationship between CAPE and lightning strikes. However, this relationship is non-linear and therefore complex and due to time constraints it is not possible to explore this relationship further and is not within the scope of this research.

4.2 Outage Data

4.2.1 Outage Data Gathered

Outage data was provided by the three transmission companies that own and operate the GB transmission network. Due to the sensitive nature of the outage data that was provided it was requested that the data be anonymised. Therefore the three transmission network owners will be known as Company A, B and C from this point forward. Data was provided for Company A, via the Met Office (as part of the EP2 project works discussed in Section 1.4.2) in January 2012 and contained a range of data from 1996 to 2009. This data had already been processed by the Met Office so each weather-related outage had been already been assigned a weather variable. Data for 2010 and 2011 was later provided by Company A directly but did not contain specific weather variables information. Data was provided from Company B directly in May 2012 and contained a range of data from April 1999 to April 2012. They also provided the data that they had provided the Met Office with for the EP2 project which contained weather outages only from April 1984 till February 2008. Company B records a weather-related outage not only as weather-related but by what weather variable caused the outage. Data was provided from Company C directly in July 2012 and contained a range of data from April 1986 to April 2012. They also record the weather variable that caused the outage. The time period for the provided data is displayed in Table 4-1. To be able to assign exact weather values to an outage it is necessary to not only know the time and date of the outage but also the location of the outage. To enable this, the latitude and longitudes of all GB substations were provided. The outage data only considers three phase faults, not single phase faults.

Table 4-1 - Outage Data Availability

Category	Company A	Company B	Company C
Weather Outages	1996 – 2011	1984 – 2012	1986 – 2012
Non-Weather Outages	2000 – 2011	1999 – 2012	1986 - 2012

4.2.2 Outage Data Organisation

The data recorded varied quite dramatically not only between companies but throughout the years within the same company as data recording techniques changed. This variation was not only on what was recorded but also how it was recorded, making it difficult to filter out unnecessary data and get a consistent dataset over all three companies. In order for easier analysis of the data the three sources were merged into one dataset using a common format.

This allowed for data from all three companies to be grouped together and unnecessary information removed. The main fields of interest were:

- Weather Cause
- Date and Time of Failure
- Failure Duration
- Location of Failure
- Equipment
- Voltage
- Customer Data
- Failure Description

Due to overlaps between weather causes e.g. rain/wind, wind/gales, flooding/wind, fog/pollution, heavy rain, wind/gales, etc. the weather categories used when combining the data originated from the EP2 project as mentioned in Section 1.4.2 and are as follows:

- Lightning
- Snow, Sleet, Blizzard (SSB) & Ice
- Wind, Gales and Windborne Objects
- Rain and Flooding
- Salt, Condensation & Corrosion
- Pollution, Mist & (Freezing) Fog
- Fire not due to Faults
- Other Weather (Tree faults, Solar Heat, Earthquake etc.)
- Blanks and Unknowns

The 'Blanks and Unknowns' category are outages that are caused by weather, as classified by the companies, but the actual weather variable that caused the outage is unknown. The initial analysis was completed using these nine categories, but for later analysis, due to the small amount of data available, the following categories were combined into a single 'Other Weather' category: 'Rain and Flooding', 'Salt, Condensation & Corrosion', 'Pollution, Mist & (Freezing) Fog', and 'Fire not due to Faults'. Other important properties that were required were voltage rating, equipment type and Return to Service times (RTS times). The voltage categories were; 132kV, 275kV and 400kV, but there were a large proportion of outages that did not have an assigned voltage level. Equipment categories also vary across the companies, after analysis all failures were found to fit into eight of the categories that were used by the companies:

- OHL
- Cables
- Circuit Breakers
- Protection Equipment
- Power Transformers, Reactors, etc.
- Other Switchgear, Fusegear and Busbars
- Miscellaneous
- Blanks

Table 4-2 shows the percentage of data complete for each company in each of the aforementioned categories. From Table 4-2 it is clear that there are some data limitations within the data. Company A has 20% of weather causes missing which was an issue as is it means a large number of outages were not useable in their original state. The data limitations of Company A were not only restricted to the weather classifications of the outages: only just over 8% of outages contained a RTS time. Companies B and C generally have fairly complete datasets. However, all three companies have a large quantity of outages that have no voltage value assigned. Section 4.2.3 will discuss the processes that were used to complete the datasets. It is important to remember, that it is recorded by people in the field and already contains a certain amount of human error. When attempting to complete certain blanks it is important to consider certain assumptions so as not to add to existing errors.

Table 4-2 - Completeness of outage records

Company	Number of Outages	Equipment (%)	Voltage (%)	RTS Time (%)	Weather Cause (%)
A	1670	86.59	44.97	8.08	80.00
B	1532	89.22	0.00	100.00	99.15
C	1719	97.32	0.00	94.82	99.77

4.2.3 Filling of Data Blanks

As with a lot of datasets, the datasets provided by the companies contained blanks within certain categories, as was discussed in Section 4.2.2. It was important to include as it still contains useful information, on weather type and by filling in blanks it allows the entire dataset as one coherent whole rather than have to have partitions of the data with each treated in different ways. While some of these blanks (voltage, equipment and substations) were able to be filled by reading the attached comments for each outage, others such as the RTS time and weather cause were more complicated to fill. Some of the data for Company A data was provided directly, and the rest was not. The data provided indirectly by Company A had been part of the EP2 project by the Met Office, and so had been processed by them. The data provided directly by Company A does not record the weather variable that caused the outage. Therefore, it is required to use past weather data to assign a specific weather variable to each outage. To do this the latitude and longitude of an outage had to be established and matched with past weather data at the time and date of occurrence. If any weather variable had an extreme value then it was assumed that it had caused the outage. The definitions of extreme weather values are discussed in Section 7.3. This, however, did not work for all outages if no obvious extreme weather was occurring at the time. These outages were left recorded as weather outages but the weather cause was left blank and these were grouped into the 'Blanks and Unknowns' weather category as described in Section 4.2.2. When it came to how to complete the RTS times there were multiple options:

- Calculate the average RTS times for each category and apply to the blanks then do a sensitivity analysis
- Create data bins and complete a proportionate stratified sampling, where the ratio between the bins for the historical data is the same when the blanks are added
- Create a random distribution using the historical distributions best fit.

Based on the assumption that the distribution of return to service times for the fault outages where no RTS time was recorded would be the same as for those where the RTS time was recorded, option number three was determined to be the option that would provide the most accurate results. This method would allow for random results based on historical values and allow use of the complete set of records without biasing the overall distribution of RTS times for each weather type, separately. This method was used in order to fill RTS time blanks. The historical distribution was resampled to populate the missing RTS times for each weather category. This process was completed using MatLab where the histogram of the historical data was generated and then the best fit distribution for the data obtained. From this distribution the parameters are noted and then used to create a random sampling to fill the RTS blanks. Due to the repetitive nature of this stage an example for lightning will be shown and the rest of the results will be shown Appendix B:. For each company, the numbers of outages that contained a duration and that did not were counted as shown in Table 4-3. For lightning-related outages there were 9 out of the 877 outages with durations that are outliers: values over 150 hours. As discussed earlier in Section 2.2.2 outliers can have a large effect on the outcome of analysis especially when resampling - these outliers were considered exceptional occurrences and removed from the resampling analysis as they represented a very small proportion of the data. Using Matlab's dfittool, a histogram of the durations can be created and then the best fit distribution to be determined. Once determined it is important to note the parameter of the dataset in order to create a random distribution based on the current data. For the lightning durations the exponential distribution was the best fit. Figure 4-8 shows the distribution and histogram of the lightning duration data on the left and then the resampled data with the distribution on the right.

Table 4-3- Lightning Outages RTS Time Count

Company	With RTS Times	Without RTS Times
A	67	710
B	293	0
C	518	34
Total	**877**	**744**

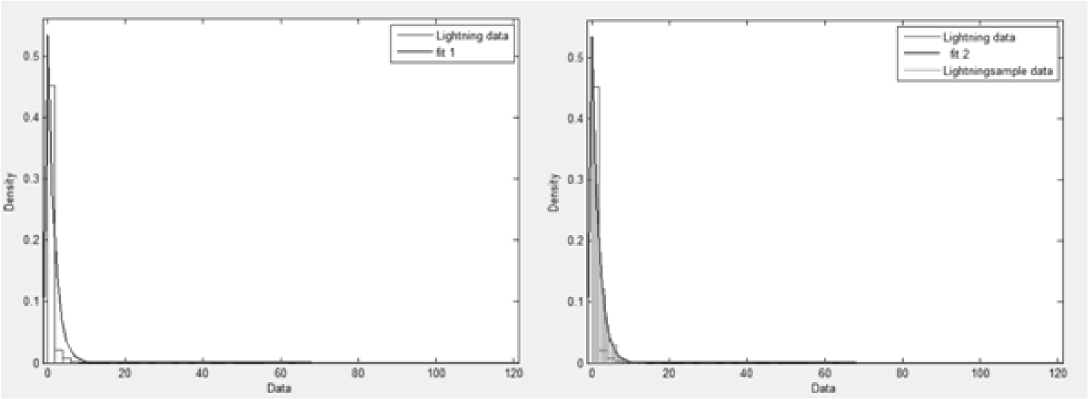


Figure 4-8 - Lightning Fit

The same process was used for all other weather-related outage categories as well as non-weather-related outages which also contained duration blanks. However, instead of being organised by weather cause, non-weather faults were organised by equipment type. This was due to the many different causes of outages that were recorded over all three companies making it very difficult to organise by cause. The number of RTS time blanks compared with the filled RTS times are shown in Table 4-4. Once these randomly generated distributions were generated, the durations (hrs) are randomly applied to each outage with a blank duration, allowing the RTS times and dates to be calculated.

Table 4-4 - Non-Weather RTS Time Counts

Equipment Type	Total	With RTS Times	Without RTS Times
OHL	590	482	108
Cables	186	125	61
Circuit Breaker	257	110	147
Protection Eq.	1346	1038	308
Transformer	1311	443	868
Other Switchgear etc.	645	524	121
Miscellaneous	152	143	9
Blanks	314	305	9

Company A's data contains a combination of outages with date, time or neither for the RTS times and so a more complicated process of applying the generated data was needed. This process is shown in Table 4-5. Table 4-6 shows the percentage of data that is no longer blank after this analysis has taken place. The voltage availability is dramatically increased for all three companies, as is the RTS time information for Company A. The dataset is not perfect as there are a large number of Company A's outages not assigned a weather variable but as they do not recorded the weather that causes the outage, it is impossible to reach 100% of outages with an assigned weather cause as the overhead of effort required to search the weather database when no clues on weather type were given was judged to be too high.

Table 4-5 - Company A's RTS Time Allocation

Category	Available RTS Times	Missing RTS Times	Date Only RTS Times	Time Only RTS Times
Total (%)	8.08%	85.33%	0.84%	5.75%
New RTS Time Information	Keep what was provided	Use generated duration	Keep date provided, use generated duration to calculate time	Use generated duration to calculate RTS Time and date

Table 4-6 - Completeness of records after (and before) resampling

Company	Equipment (%)	Voltage (%)	RTS Time (%)	Weather Cause (%)
A	**86.59** (86.59)	**98.68** (44.97)	**100.00** (8.08)	**83.35** (80.00)
B	**99.87** (89.22)	**99.34** (0.00)	**100.00** (100.00)	**99.15** (99.15)
C	**98.25** (97.32)	**97.50** (0.00)	**100.00** (94.82)	**99.77** (99.77)

4.3 Initial Outage Analysis

4.3.1 Initial Weather Outage Analysis

Before developing relationships between weather and outages it is first useful to understand several characteristics of the outage data such as: failure rates for each area, if specific weather variables dominate outages in any area, how do the areas compare with each other, is there a seasonality to weather-related outages, or a yearly trend. In order to analyse these outages the statistics discussed in Section 2.2 will be used. The available data for this section is displayed in Table 4-1.

Weather Analysis

Figure 4-9 shows the percentage split of weather-related outages per company. It shows clearly that Company A is dominated by 'Lightning' outages whereas Company B is dominated by 'Wind, Gales and Windborne Objects' outages. However, Company C has an almost equal spread between 'SSB & Ice', 'Wind, Gales and Windborne Objects' and 'Lightning' outages. As shown in Section 4.2.3 Company A also contains a significant percentage of unclassified outages, whereas the number of unclassified outages is very small for Companies B and C. Company A's second and third main causes of weather-related outages are 'Wind, Gales and Windborne Objects' and 'SSB & Ice' outages respectively whereas Company B's second and third top causes of outages were 'SSB & Ice' and 'Lightning'. The top three categories of outages for all three companies are the same three weather variables. These categories cause 85% of weather-related outages. It is also clear from Figure 4-9 that the smaller weather categorises are not as significant as the main three weather categorises. Figure 4-10 shows the split between the weather categories with the less significant weather categories combined to complete the 'Other Weather Types'. This is done because while these weather types cause outages on the transmission network there currently are not enough of them to create a dataset to allow for further analysis, therefore will be considered together.

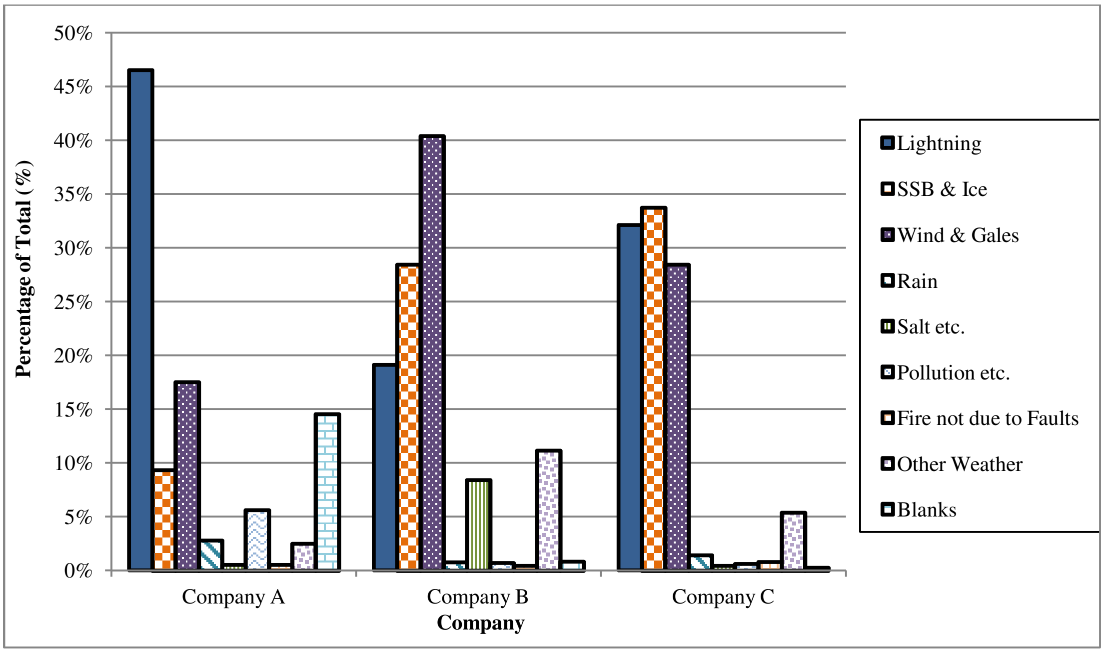


Figure 4-9 - Percentage of Total per Weather Category

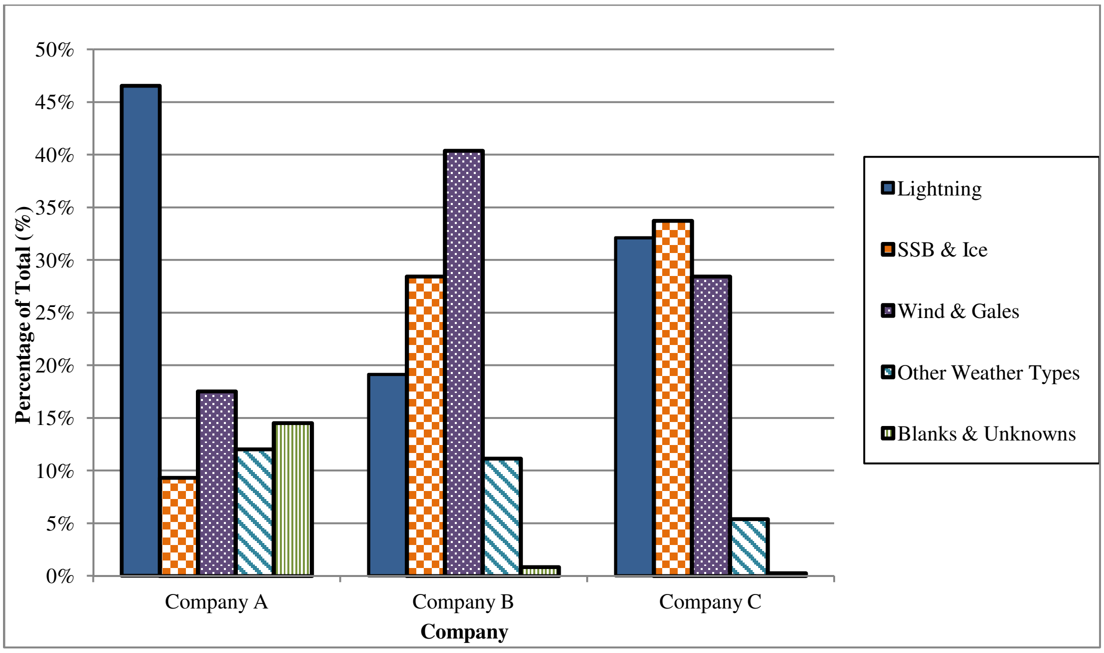


Figure 4-10 - Split between Outage Categories

Seasonal Analysis

Figure 4-11 shows that the outages that occur for all three companies experience seasonality.

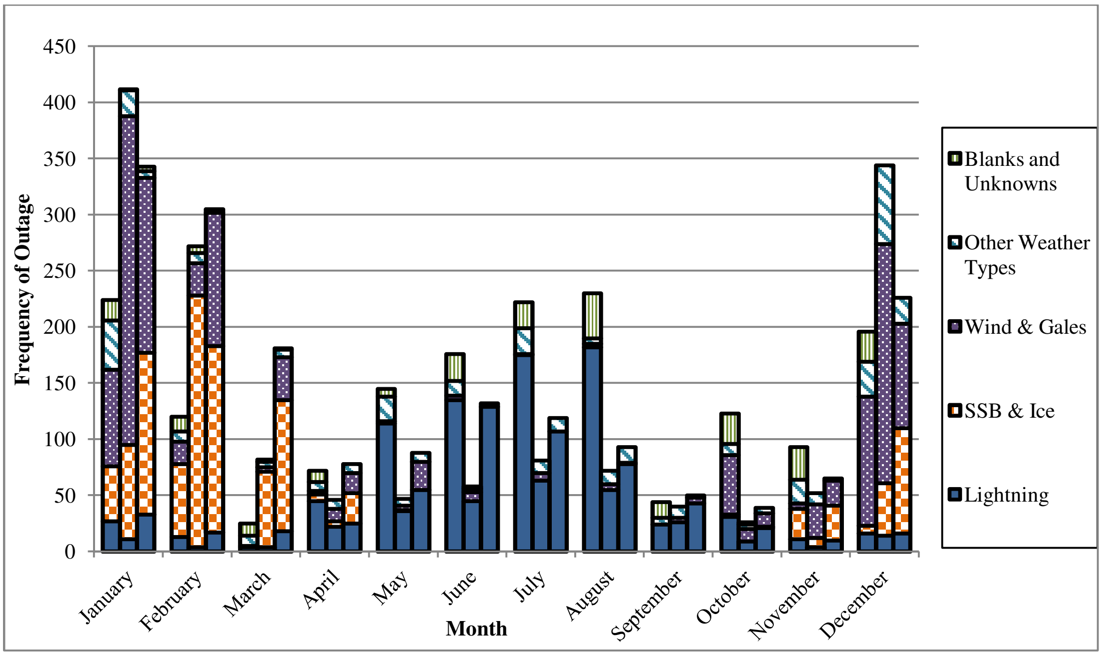


Figure 4-11 - Seasonal Spread of Weather-Related Outages

It is very clear that 'Lightning' outages dominate the summer months, whereas outages caused by 'Wind, Gales and Windborne Objects' and 'SSB & Ice' dominate during the winter months. This is unsurprising since worse weather is generally seen during the winter months and more lightning is seen during the summer due to moisture and rapidly rising warm air occurring. A clear relationship between 'Other Weather Types' and seasons is difficult to see as there are so few occurrences. A large proportion of the 'Blanks and Unknowns' occur during the summer months and it could be suggested that due to the dominance of 'Lightning' outages during these months that these are mostly 'Lightning' outages that have been misclassified but by doing this without further evidence that the outages are 'Lightning' could add to errors that already exist within the datasets.

Yearly Analysis

There is also a trend in the yearly outage data due to some years seeing less extreme weather than others. The years with more extreme weather will see a much higher number of weather-related outages compared to years without extreme weather. This is clear from Figure 4-12, where 2001 and 2010 experienced extreme snow storms [203, 204] and as such experienced a large number of 'SSB & Ice' outages. It is also clear that the years 2002 and 2011 experienced extreme wind storms [205, 206] as there are higher numbers of 'Wind, Gales and Windborne Objects' outages on these years. 'Lightning' outages are relatively consistent throughout the years showing that they do not occur in one off extreme events, but as more regular, commonly occurring storms. This difference between extreme years and non-extreme years is further discussed in Section 7.2.

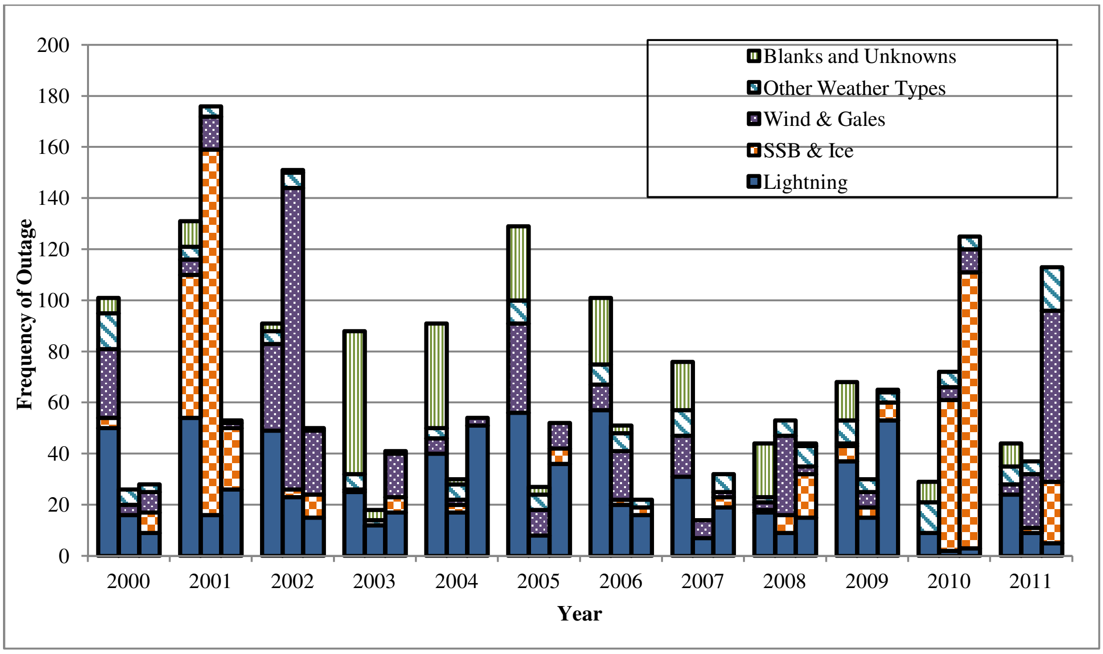


Figure 4-12 - Yearly Weather-Related Outage Spread

Skewness & Kurtosis

It is also important to consider if the distribution of outages per year is a normal distribution; if it is not then how asymmetrical and peaky is the distribution? This can be done by determining the distribution's values of skewness and kurtosis. Figure 4-13 shows that, for all three companies, outages per year are skewed. They are all positively skewed as the data has a long tail that extends to the right. This is more evident in Table 4-7 which displays the skewness value per weather type for each company. Since a perfect normal distribution would have a skewness value of 0 it clear that 'SSB & Ice' and 'Wind, Gales & Windborne Objects' are very asymmetrical as they have a high value of skewness, whereas 'Lightning' has a much smaller value of skewness. This reinforces the previous assertion that weather variables such as 'SSB & Ice' and 'Wind, Gales and Windborne Objects' cause grouping of outages whereas weather types such as 'Lightning' are more consistent.

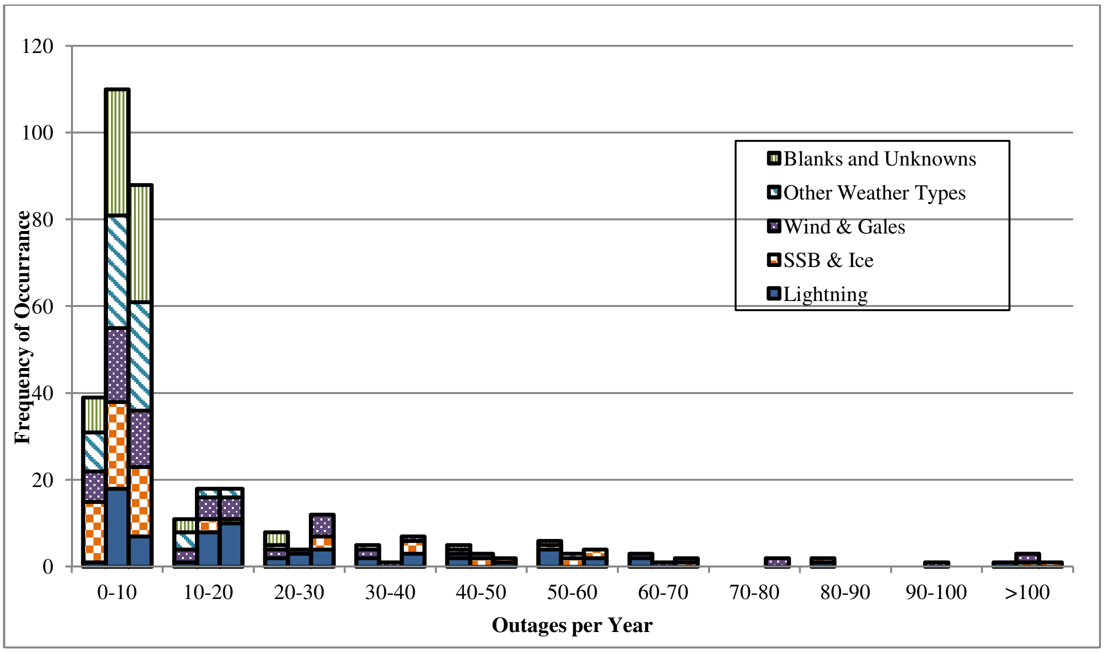


Figure 4-13 – Weather-Related Outages per Year per Range

Table 4-7 displays the kurtosis value for each outage class for all three companies. It is clear that overall both companies A and C have a flat topped distributions whereas company B, overall, has a peaked distribution. However, when looking at the individual weather types it is clear that they all have a positive kurtosis values, indicating that they have a peaky distributions, which is clear when looking at Figure 4-13. Weather types such as 'SSB & Ice' and 'Wind, Gales and Windborne Objects' have a much higher value of kurtosis indicating that they are 'peakier' in comparison to 'Lightning' outages. This again backs up previous assertions that 'SSB & Ice' and 'Wind, Gales and Windborne Objects' outages occur in peaks and troughs, whereas 'Lightning' outages are much more consistent.

Table 4-7 – Weather-Related Outages – Skewness and Kurtosis per Weather Type per Company

Weather Category	**Company A**		**Company B**		**Company C**	
	Skew	**Kurt**	**Skew**	**Kurt**	**Skew**	**Kurt**
Lightning	0.59	0.10	0.92	0.46	1.04	0.41
SSB & Ice	2.69	7.16	3.17	11.69	1.88	4.05
Wind, Gales & Windborne Objects	1.37	1.70	2.18	3.86	1.87	2.82
Other Weather Types	1.68	2.42	4.47	22.25	1.88	3.95
Blanks and Unknowns	1.28	1.47	2.37	4.56	4.00	17.18
Total	**0.46**	**-0.15**	**1.52**	**1.35**	**0.69**	**-0.48**

Equipment and Voltage Analysis

Another section of initial analysis is to consider if any equipment or voltage type is more susceptible to weather-related outages. From Table 4-8 it is discernible that the majority of weather-related outages occur on OHLs, as expected. Company A sees a smaller percentage of outages on OHL, but this could be attributed to the outages that were not assigned an equipment type in the original dataset. The next highest affected categories are Protection Equipment, Transformers and Switchgear but these are far less affected.

Table 4-8 – Weather-Related Outages: equipment Percentages

Equipment	Company A	Company B	Company C
OHL	73.23%	89.95%	94.07%
Cables	0.36%	1.04%	0.06%
Circuit Breaker	0.54%	0.07%	0.00%
Protection Equipment	4.91%	1.44%	1.57%
Power Transformers, Reactors, etc.	4.61%	2.28%	0.99%
Switchgear, Fusegear and Busbars	2.46%	4.24%	0.93%
Miscellaneous	0.30%	0.72%	0.58%
Blank	13.59%	0.26%	1.80%

Table 4-9 shows the split of outages over different voltage levels. It is important to note the difference in classification of transmission voltage levels between Scotland and England and Wales. In Scotland 132kV is classed as transmission whereas in England and Wales it is distribution and therefore certain companies have not provided 132kV data. At the time of the data collection not all of the companies had records for the 400kV transmission network. The majority of weather-related outages occur on 132kV and 400kV. This could be because they are more exposed, as the lower voltage transmission networks are present in mountainous areas and larger voltages are used to travel long distances, or that there is more 132kV or 400kV transmission network in certain regions compared to other regions.

Table 4-9 – Weather-Related Outage: voltage level Percentages

Voltage (kV)	Company A	Company B	Company C
132	3.89%	43.73%	82.55%
275	27.72%	21.54%	14.89%
400	66.77%	34.07%	0.00%
Blank	1.62%	0.65%	2.56%

Statistical Analysis

Figure 4-14, Figure 4-15 and Figure 4-16 show box charts showing basic statistical analysis per year for Company A, B and C respectively. For all three companies the mean and median of 'Lightning' outages are close suggesting little variation in outage spread, whereas the mean and median of 'Wind, Gales and Windborne Objects' and 'SSB & Ice' outages are further apart suggesting that there is variation in outage spread. Generally the 'Lightning' outages statistics are represented by a relatively small box and whiskers suggesting that again throughout the years the frequency of outages are similar, but the boxes and whiskers representing 'Wind, Gales and Windborne Objects' and 'SSB & Ice' outages are much more spread again suggesting variation in the outages per year. 'SSB & Ice' outages show a large gap between the maximum value and 95th percentile suggesting that just 5% of years' experience a large number of outages due to 'SSB & Ice'.

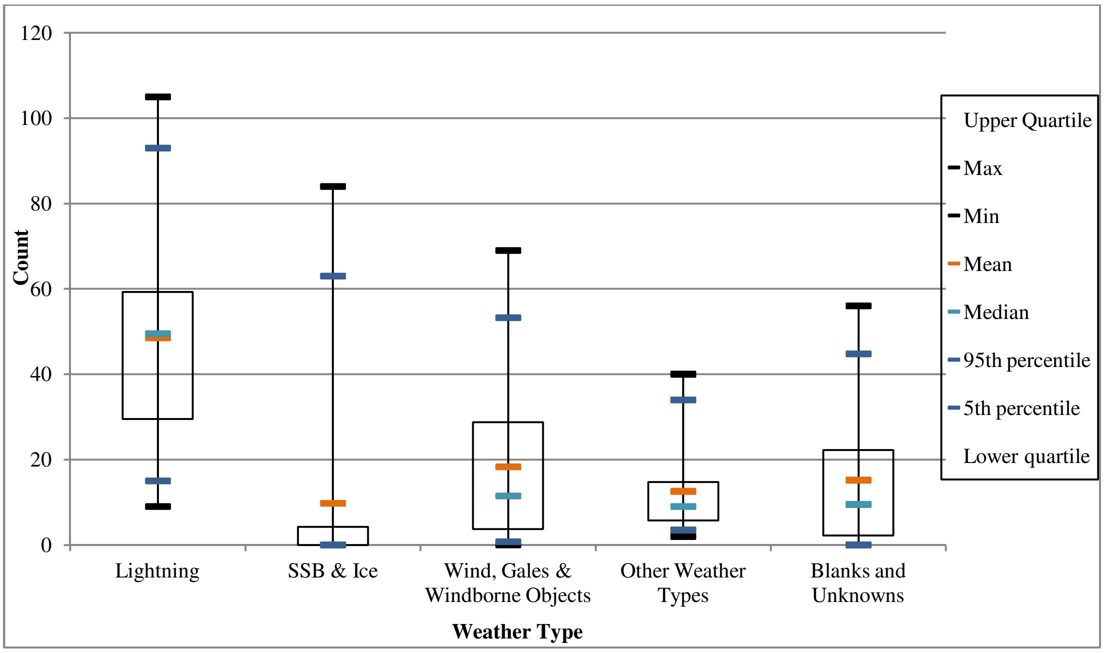


Figure 4-14 - Company A Box Chart: number of weather-related outages in a year

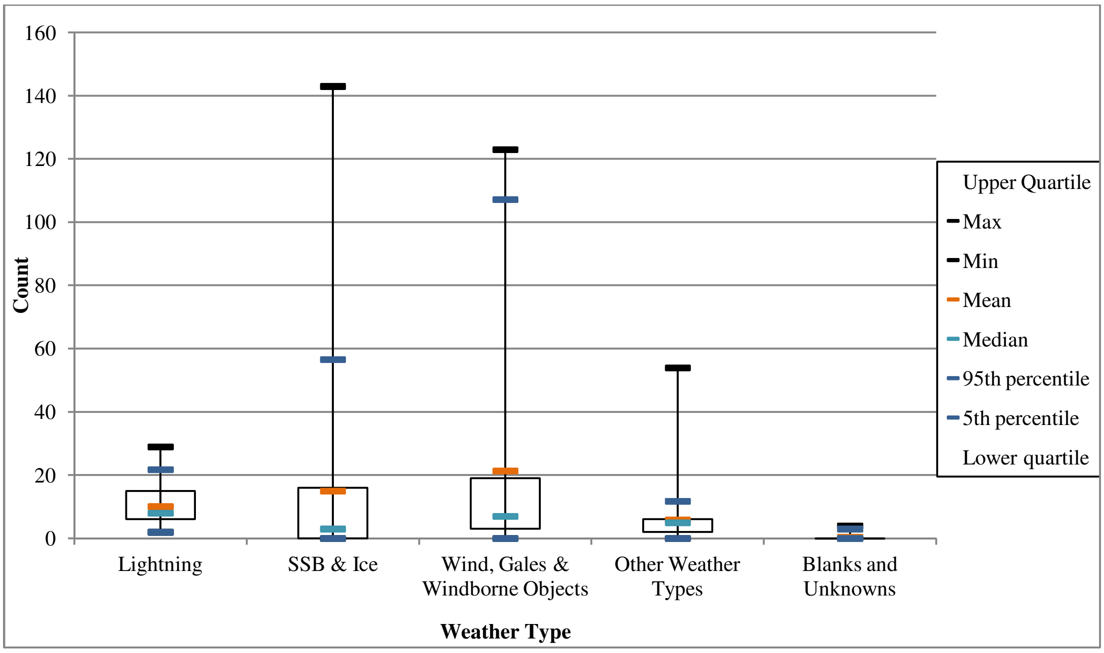


Figure 4-15 - Company B Box Chart: number of weather-related outages in a year

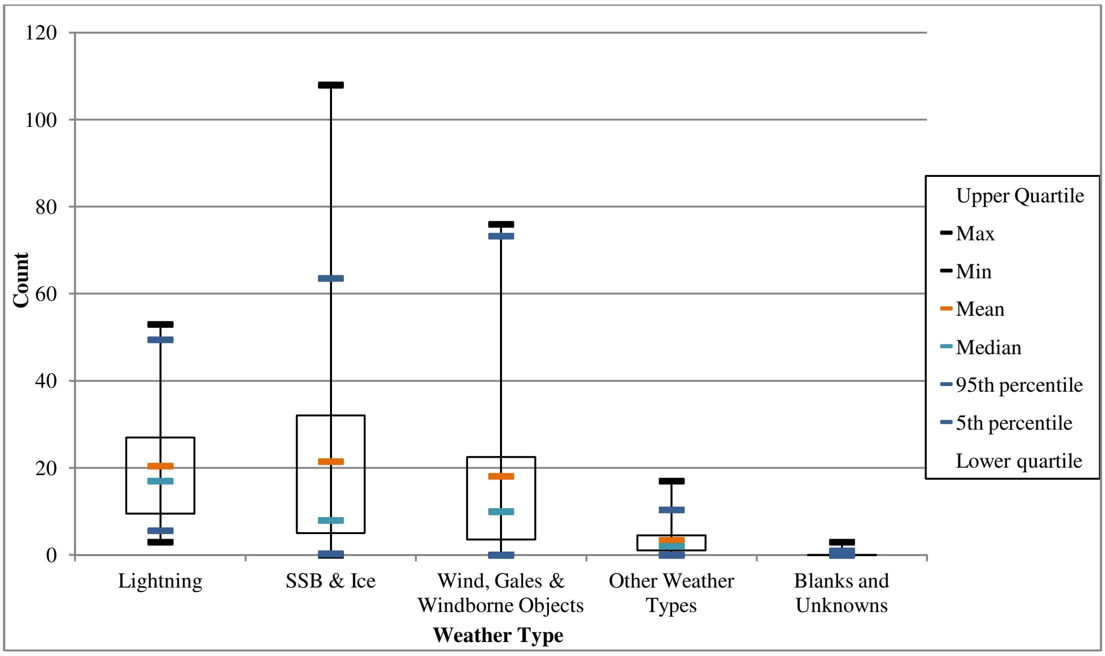


Figure 4-16 - Company C Box Chart: number of weather-related outages in a year

The data provided by the transmission companies is from different sized networks as well as spanning different time periods; this makes the raw data not comparable. In order to be able to compare the data for future sections it was normalised to a per year per 100 km format. The data relating to equipment numbers was unavailable from the transmission companies, the only available information relating to system equipment was the OHL and cable lengths. It was assumed that the equipment would be distributed within each company's circuit km evenly and that the differences in km would compensate for the difference in size of the areas. Initially, this was completed for each equipment type. However, as shown once the data was broken down into equipment types it was found that this was not feasible for some equipment types as hardly any outages occur or no information was available about the numbers of equipment on the system. This would mean that the numbers would be too small to extract meaningful results or would rely on a best guess of equipment numbers. Table 4-10 shows the standard terms of analysis mean, median, and the standard deviation of outages per weather, per company, per year, per 100km of circuit length. Equation 4-12 shows the calculation used to calculate the mean outages per weather, per company, per year, per 100km. The standard error, the upper and lower confidence limits of these estimated statistics are shown in Appendix C:. It is clear from Table 4-10 that on average Companies A and C see more 'Lightning' outages compared to Company B. However, Company B experiences on average more 'Wind, Gales and Windborne Objects' outages and Company C sees the highest numbers of 'SSB & Ice' outages. It is also clear that the average failure rate per year per 100km for 'Other Weather Types' is relatively small in comparison to the main three weather types. On average Company C sees the most weather-related outages per year per 100km, followed by Company B and then final Company A experiences the least number of outages per year per 100km. Comparing the mean, median and the standard deviation again shows that 'Lightning' outages are generally consistent throughout the years and that 'Wind, Gales and Windborne Objects' and 'SSB & Ice' outages can vary. This is due to the effects of extreme or major events which skew the data for these weather types.

Table 4-10 - Mean, Median, Std. Deviation per year per 100km of Weather-Related Outages

Category	**Mean per year per 100 km**			**Median per year per 100 km**			**Std. Dev per year per 100 km**		
Company	A	B	C	A	B	C	A	B	C
Lightning	0.34	0.26	0.42	0.35	0.21	0.35	0.18	0.18	0.28
SSB & Ice	0.07	0.39	0.44	0.00	0.08	0.16	0.16	0.77	0.51
Wind, Gales & Windborne Objects	0.13	0.56	0.37	0.08	0.18	0.20	0.13	0.88	0.44
Other Weather Types	0.09	0.15	0.07	0.06	0.13	0.04	0.07	0.25	0.08
Blanks and Unknowns	0.11	0.01	0.00	0.07	0.00	0.00	0.11	0.03	0.01
Total	**0.74**	**1.38**	**1.30**	**0.68**	**0.78**	**1.08**	**0.34**	**1.36**	**0.71**

$$Mean\ per\ year\ per\ 100\ km = \frac{\left(\frac{\sum Yearly\ Weather\ Outages}{No.Years}\right)}{Area\ Circuit\ km} x\ 100 \qquad 4\text{-}2$$

4.3.2 Major Events

An ‘extreme’ or ‘major’ event is an event that causes multiple outages when it occurs but that currently does not occur regularly. For example, a large snow or wind storm that is above average, and so is classed as a HILP event. As Section 4.3.1 showed, there was a small difference between the mean and median for “Lightning” outages for all three companies, which suggests lightning, is quite consistent throughout the years. In contrast the difference between the mean and median for “SSB & Ice” and “Wind, Gales & Windborne Objects” outages is quite large suggesting that they occur in large numbers in only certain years, which is consistent with the fact that large snow storms and wind storms do not occur every year but when they do occur, they can cause significant damage and disruption to the electrical network. This is highlighted in the following examples. During 1998 there were 226 wind-related outages over the whole year. However, 82.3% of these occurred over two consecutive days during high winds that were experienced on the 26th and 27th of December that year during The Great Boxing Day Storm of 1998 [207]. Comparing that to the following year, only 48 wind-related outages occurred. During 2001 there were in total 223 snow-related outages, due to a large snow storm during late February (26th-28th) [203]. During these three days 87.4% of the total year’s outages occurred, with the 27th of February seeing 190 snow-related outages. Compared to the following year where there were no large snow events, only 12 snow-related outages occurred. The largest number of lightning-related outages was seen during the year 1999 where in total there were 135 lightning-related outages. In comparison to wind and snow-related outages where a large percentage of outages occurred over the course of a few consecutive days the highest percentage of outages over consecutive days was only 11.85% which occurred during the height of summer. In comparison to the following year, during 2000 there were 75 outages which compared to differences experienced year on year by snow and wind-related outages is not as large. This shows that snow and wind storms can cause large numbers of outages to the transmission network when they occur and that it is vital to understand if they could be more frequent in the future.

4.3.3 Initial Non-Weather Outage Analysis

It is imperative to also consider the effects of non-weather-related outages to allow a comparison between weather-related outages and non-weather-related outages and assess the overall impact on reliability of supply that would arise from changes to weather patterns. The same methods were applied to the non-weather-related outages as were applied to weather faults. The data available for this analysis is shown in Table 4-1.

Seasonal Analysis

Unlike weather-related outages, non-weather-related outages show no seasonal variations. This is shown in Figure 4-17. While slightly more outages occur during the summer months, this could be due to more strain experienced on the system during the summer months as this tends to be when the majority of maintenance is completed on the system or human errors during maintenance.

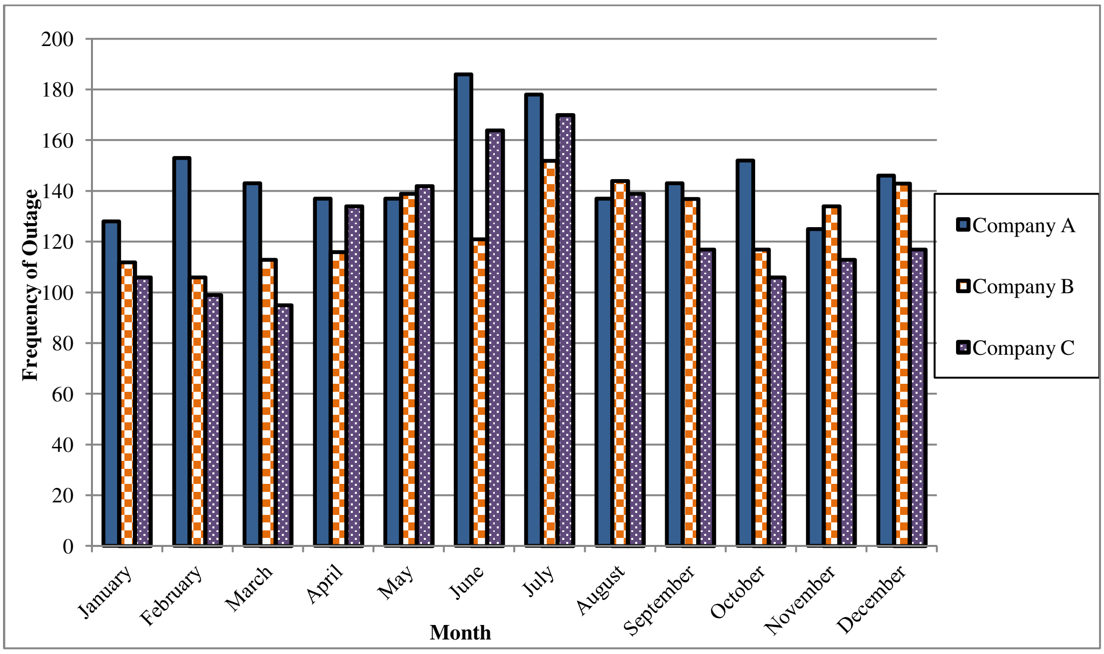


Figure 4-17 - Seasonal Spread of Non-Weather-Related Outages

Yearly Analysis

Figure 4-18 shows that there is no discernible yearly tread for non-weather-related outages, but does indicate that the outages for each company are relatively consistent throughout the years.

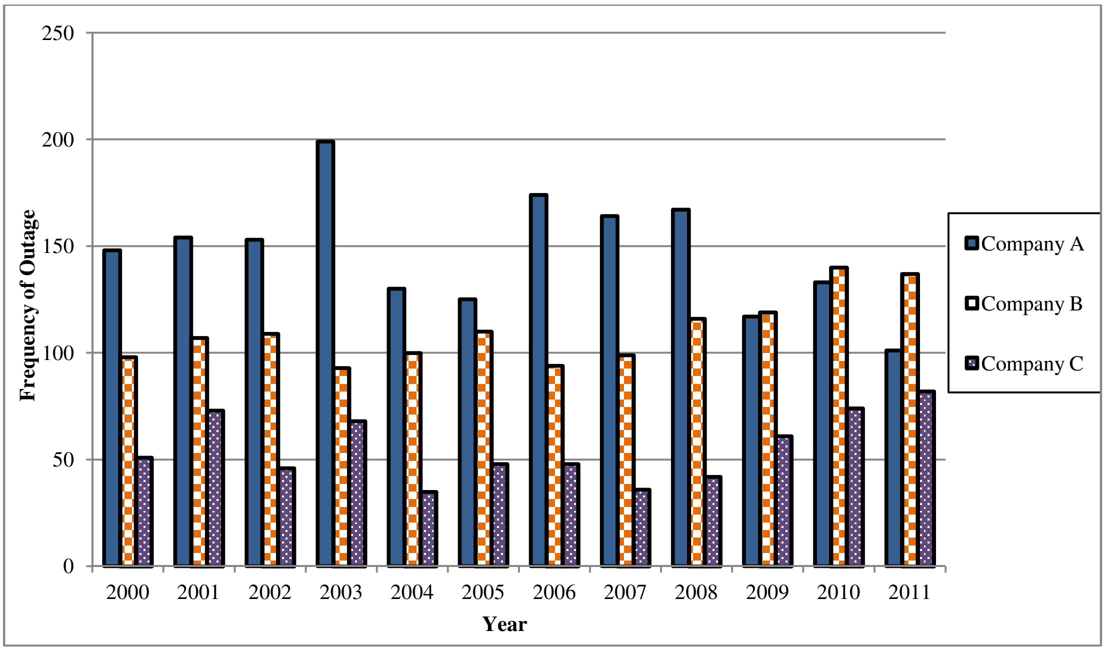


Figure 4-18 - Yearly Non-Weather-Related Outages

Skewness & Kurtosis

Skewness and kurtosis were calculated for non-weather-related outages per year, the results are displayed in Table 4-11. For Company A and C the value of skewness is close to zero showing that the distribution of outages is almost a normal distribution, but the skewness value for Company B is positively skewed, which is unexpected. However, by calculating the kurtosis value and constructing a histogram it is clear to see that all three companies have flat-topped distributions, indicating that they are not peaky and the values tend to be similar each year. When analysing the histograms shown in Figure 4-19 it is clear that companies A and C have a low skewness values, they show distributions with small to non-existent tails. However, company B has a high skewness value; it contains data points to the right of the central peak creating a tail. This indicates that a larger sample size is required to get a more accurate skewness value. It is clear why company C has such a low kurtosis value: it has a flat-topped distribution. Whereas companies A and B have a kurtosis value much closer to zero indicating a more a normal type distribution. These flat-topped distributions back-up an earlier statement that non-weather-related outages tend to be consistent.

Table 4-11 - Non-Weather-Related Outages – Skewness and Kurtosis per Company

Company	Skewness	Kurtosis
Company A	0.16	-0.14
Company B	0.77	-0.10
Company C	0.17	-0.69

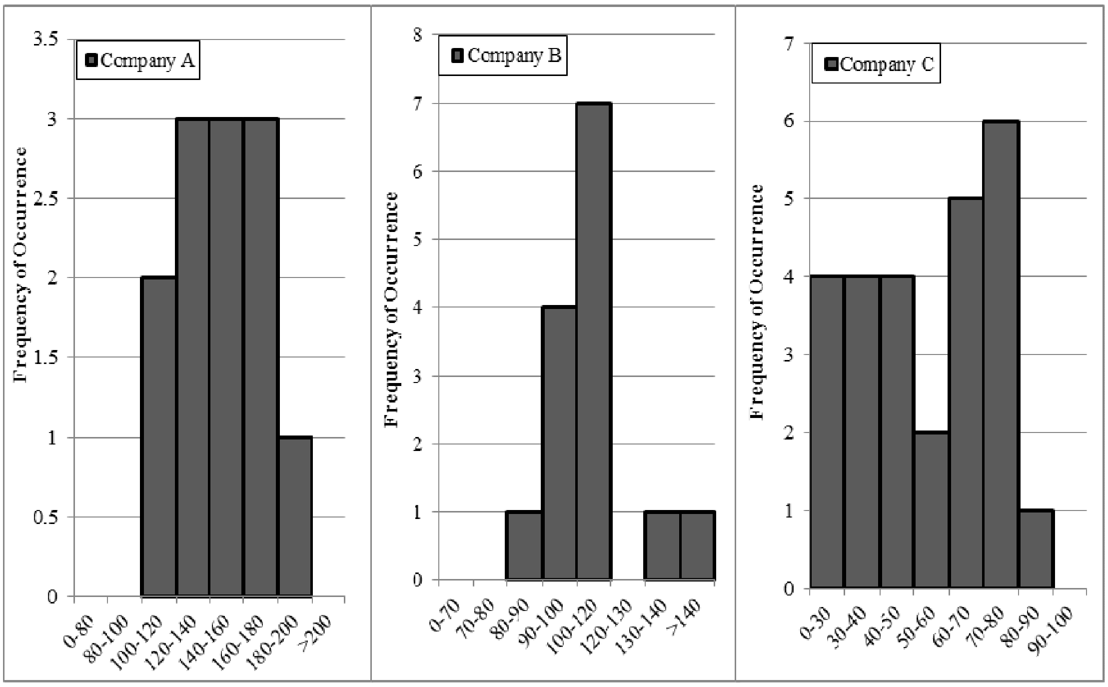


Figure 4-19 - Total Non-Weather-Related Outages per Year per Range

Equipment and Voltage Analysis

The non-weather-related outages were looked at in terms of equipment type and voltage to see if any were more susceptible to non-weather-related outages; the results are shown in Table 4-12 and Table 4-13 respectively. For Company A the equipment type that saw the largest number of non-weather-related outages were Power Transformers, Reactors, etc. and Protection Equipment experiencing 51.9% and 21.3% of non-weather-related outages respectively on Company A’s network. For Company C the equipment types that saw the highest numbers of non-weather-related outages were Protection Equipment at 26.7% and OHLs at 26.56% of non-weather-related outages. Lastly, Company B’s equipment types that experienced the highest numbers of non-weather-related outages were Protection Equipment at 37.09% , Power Transformers, Reactors, etc. at 16.04% and Switchgear, Fusegear and Busbars 15.23%. For all three companies, there is more variation on what equipment type dominates the non-weather-related outages. However, Protection Equipment is affected in equally high proportions in all three regions. Companies C and B experience the most non-weather-related outages on the 132kV network whereas Company A sees the majority of outages on the 400kV network. However, the 275kV network in Company A and B's region does experience 39.32% and 33.77% of non-weather-related outages. Again the differences between the voltage levels that experience outages could be because of the differences between the classification of distribution and transmission as well as the voltage levels that are used on the networks in each region.

Table 4-12 - Equipment Non-Weather-Related Outage Percentages

Equipment/Company	Company A	Company B	Company C
OHL	6.06%	5.48%	26.56%
Cables	3.12%	5.80%	2.80%
Circuit Breaker	9.01%	6.39%	0.00%
Protection Equipment	21.30%	37.09%	26.70%
Power Transformers, Reactors, etc.	51.90%	16.04%	9.92%
Switchgear, Fusegear and Busbars	7.65%	15.32%	18.31%
Miscellaneous	0.96%	0.07%	8.92%
Blank	0.00%	13.82%	6.79%

Table 4-13 - Voltage Non-Weather-Related Outage Percentages

Voltage (kV)	Company A	Company B	Company C
132	10.88%	52.67%	78.76%
275	39.32%	33.77%	16.71%
400	44.36%	12.39%	0.00%
Blank	5.44%	1.17%	4.53%

Statistical Analysis

Figure 4-20 displays the box charts for each company for non-weather-related outages. All three companies' charts show smaller boxes and whiskers indicating that there is little variation in outage spread. The mean and median values for all three companies are also close, again reinforcing the small variation in non-weather-related outages. This observation is backed-up by the values displayed in Table 4-14 which displays the mean, median, the standard deviation, the standard error, the upper and lower confidence limits of these values per company, per year, per 100km. It is clear from the mean and median values for all three companies that there is little variation between the numbers of non-weather-related outages. The values for standard deviation, standard error and confidence limits are also very small, which backs up this assertion. It is also clear that Company B experiences a much larger number of non-weather-related outages per year per 100km compared to Companies A and C. Company A also experiences the least number of non-weather-related outages per year per 100km.

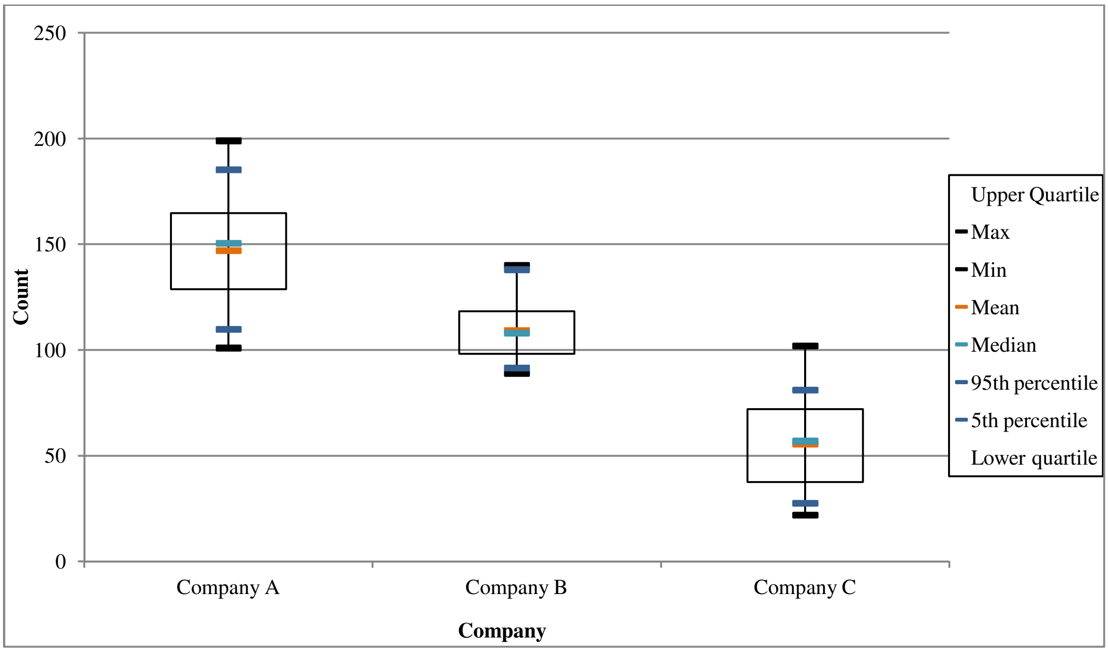


Figure 4-20 - Box Chart: number of Non-Weather-Related Outages per year

Table 4-14 - Basic Statistics per year per 100km of Non-Weather-Related Outages

Company	Mean per year per 100 km	Median per year per 100 km	Std. Dev per year per 100 km	SE per year per 100 km	Upper Confidence limit per year per 100 km	Lower Confidence limit per year per 100 km
A	1.04	1.06	0.18	0.05	1.14	0.93
B	2.86	2.82	0.39	0.11	3.06	2.65
C	1.13	1.16	0.41	0.08	1.29	0.98

4.3.4 Weather Fault and Non-Weather Outage Comparison

While separate analysis of weather and non-weather-related outages has been useful, it is also useful to consider them in comparison with each other. A basic analysis for each company between weather and non-weather-related outages, for all years of data provided, is shown in Table 4-15.

Table 4-15 - Weather vs. Non-Weather Outages Totals

Company	Non-Weather (%)	Weather (%)
A	51.38%	48.62%
B	50.10%	49.90%
C	46.63%	53.37%

From Table 4-15 it can be seen that for each company there is around a 50/50 split between weather and non-weather-related outages. This clearly shows that while research into preventing non-weather-related outages is important, it is equally important to investigate the effects of weather on the transmission system. Figure 4-21 shows the total weather and non-weather-related outages for the year span 2000 till 2011, as this is the years that all companies have provided both weather and non-weather data. It is clear that non-weather outages display a more consistent trend whereas weather-related outages vary greatly year to year, highlighting the difficulty in predicting weather-related outages. This confirms that weather-related outages should be further investigated, as information showing how weather currently affects the system will allow operators to adapt plans and designs for the system both now and in the future with more confidence when considering the effects of weather.

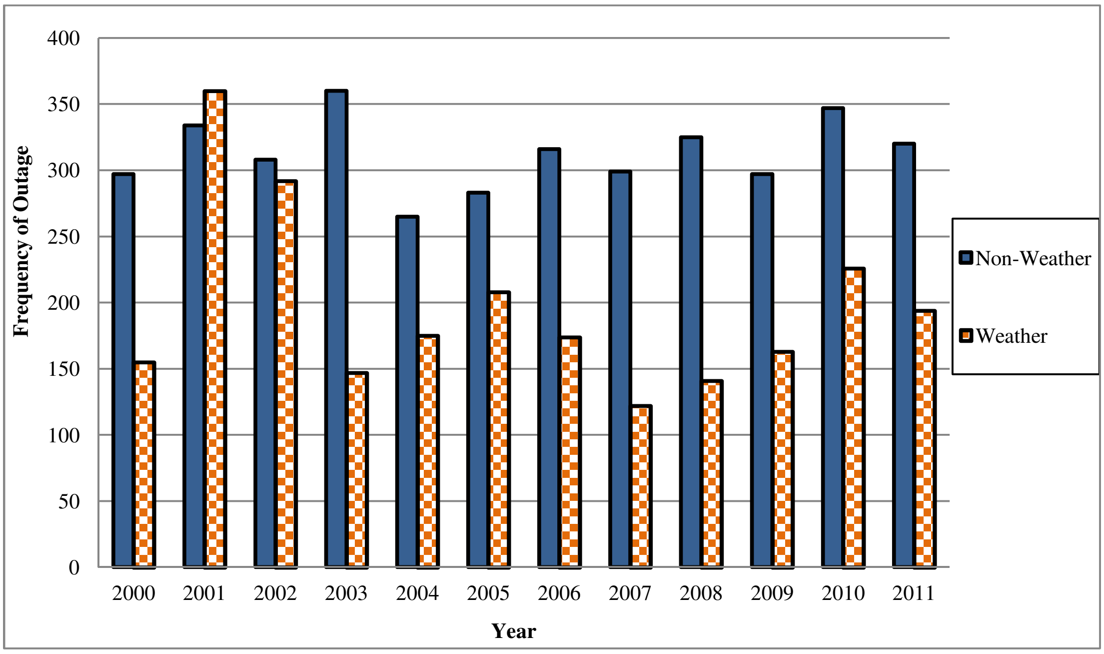


Figure 4-21 - Weather vs. Non-Weather Outages Yearly

It is also important to examine the differences between the seasonal, equipment, and voltage spreads as well as the average outages rates per year per 100km for each company for weather and non-weather-related outages. While weather-related outages experience seasonality, non-weather-related outages do not experience significant seasonality to outages. Weather-related outages are generally very positively skewed but non-weather-related outages while slightly positively skewed are less so in comparison and are much more flat topped. Unlike weather-related outages, which experience the most outages on OHLs, non-weather-related outages see a much greater spread of outages across equipment types. However, there is less of a difference between the spread of voltages for non-weather outages compared to weather outages. For all three companies a similar pattern is followed for each voltage level for both weather and non-weather-related outages. Contrary to non-weather-related outages which has a small box charts and whiskers, weather-related outages are quite spread out, suggesting variation in weather-related outages per year and little variation in non-weather-related outages. This assertion is backed up when comparing the mean and medians of each company's average outage rate per year per 100km. For Company A and B the average outage rate is higher for non-weather-related outages while Company C has a higher outage rate for weather-related outages. However, while Company B experiences a large difference between weather and non-weather-related outages, Company A has a much smaller difference showing that while non-weather-related outage rates are higher than weather there is not a great difference and that weather can still cause a substantial number of outages showing that they are worth further investigation.

4.3.5 Splitting Data into Different regions

As Section 4.3.1 showed, there is a significant difference in the weather types that dominate outages in each licence area therefore; location is an important consideration when modelling weather-related outages. The Scottish network is owned and maintained by two different companies and is a much smaller geographical area than England and Wales but by being owned by different network operators allows the difference in the weather to be analysed. However, England and Wales, which is a larger geographically region, is owned by one company and therefore thus far has been analysed as a whole, making it difficult to see if there is any weather type dominates in a particular area. To better understand if any weather type dominates, England and Wales was split into two (Figure 4-22) and then four sub-regions (Figure 4-23) to look at the percentage split of weather-related faults compared to the total for the whole region. Using the latitudes and longitudes, the sub-regions in which each substation was location were determined. Due to substations being near boundary areas, lines or on boundary lines, using the station that was closest to provide the best area to assign to will lead to a slight margin of error around the boundary areas but this will be minimal. If a line crossed a boundary, it was assigned to the region where the highest proportion of the line was located. For further analysis in the area owned by NG will be split into two areas as a finer grain of spatial delineation would not be practically possible due to the limited available outage data, as errors occur with substations near boundaries and therefore less errors occurs with only one boundary line. However, location is clearly important and therefore required to be taken into account even at a lower resolution due to the weather differences between the north and the south of the country.

Figure 4-22 – GB Four Area Split

Figure 4-23 - GB Six Area Split

Table 4-16 shows the two areas' percentages of the total outages that were caused by each weather type. From this it is clear that the South region of NG sees a much higher percentage of lightning-related outages, almost 30% more than the North whereas the North region experiences over 30 percent more of the wind and snow-related outages. The regional split of outages due to each weather type is also shown in Figure 4-24, where it can be clearly seen that the percentage of lightning-related outages is higher in the South but that the North sees a much higher percentage of outages caused by wind and snow. Again it is also clear that the South has a much higher proportion of the salt-related outages due to a number of lines that are operated on the coast. Overall each area contains a similar number of unclassified weather-related outages and the total of outages experienced in each area is also very similar. Table 4-16 also shows the outages per 100km for each of the two regions. It is discernible that the south region experiences more lightning-related outages that the north region, whereas the north region experiences more snow and wind-related outages that the south.

Table 4-16 – National Grid Two Area Outage Split

Weather Category	**North England and North Wales Region**		**South England and South Wales Region**	
	(%)	Outages per 100km	(%)	Outages per 100km
Lightning	37.89%	5.38	62.11%	5.53
SSB & Ice	69.23%	1.98	30.77%	0.55
Wind, Gales & Windborne Objects	67.58%	3.62	32.42%	1.09
Rain & Flooding	55.32%	0.48	44.68%	0.24
Salt, Condensation & Corrosion	11.11%	0.02	88.89%	0.09
Pollution, Mist & (Freezing) Fog	39.36%	0.68	60.64%	0.65
Fire Not Due to Faults	33.33%	0.05	66.67%	0.07
Other Weather	28.57%	0.22	71.43%	0.34
Blank & Unknowns	46.91%	2.09	53.09%	1.48
Total	**47.51%**	14.52	**52.49%**	10.06

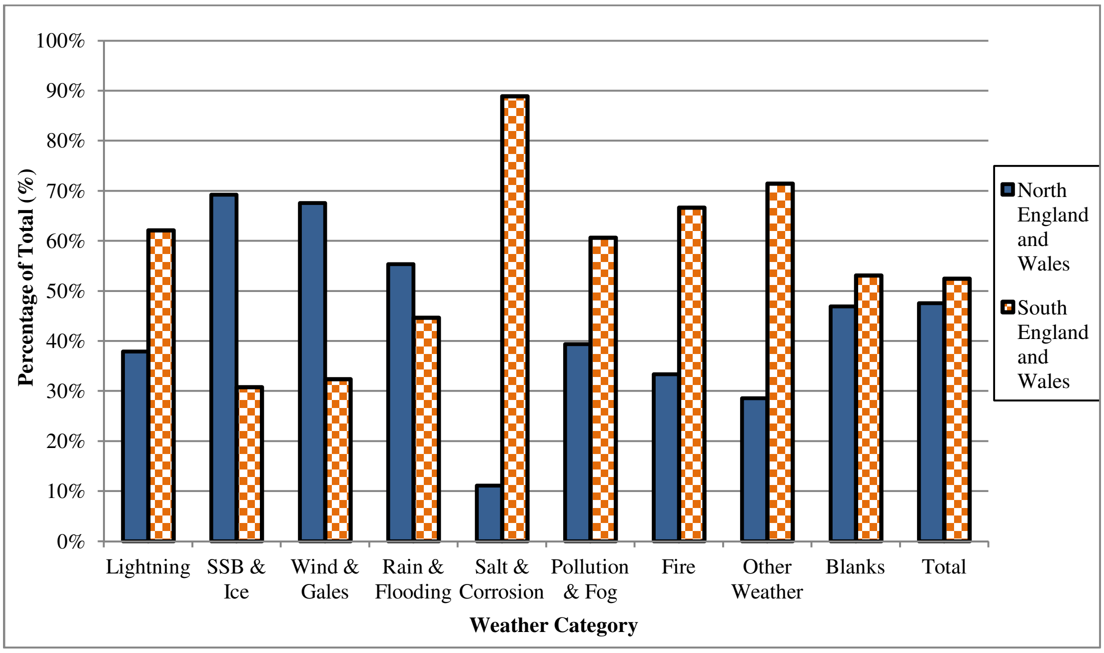


Figure 4-24 - National Grid Two Area Outage Split

4.3.6 Transmission System Reliability

As transmission outages do not always cause a customer outage due to the meshed topology of the system, it is important to consider the effects these outages have on the system in another way as they may increase strain on the system, cause consequential fault outages and reduce system availability. The results for what NG describes as "system availability", in [153] & [208] as discussed in Section 2.1.3 and Equation 2-1, both the calculated, from provided data, and reported, from NG, are shown in Table 4-17. It's also important to remember that no outage data is available for Company A for 2012 and therefore the values for system availability for 2011-12 will be lower than what they are reported.

Table 4-17 - Availability (%) of GB Transmission Network

Availability (%)	2011-12	2010-11	2009-10	2008-09	2007-08	2006-07
Weather Outages	99.98	99.97	99.98	99.99	99.99	99.98
Non-Weather Outages	99.75	99.66	99.67	99.61	99.46	99.51
Total	99.73	99.63	99.65	99.60	99.45	99.50
Reported	93.78	94.47	95.44	94.55	94.91	95.25

The calculated values are higher than the reported values as they do not include planned outages, which were unavailable for this analysis, which are included in the calculation of system availability as shown in Equation 2-1. The NG reports only report overall system unavailability, for the report years that correlate with the outage data. It is not possible to determine the unplanned system availability. As this information is unavailable, it is impossible to determine if there is a correlation between the reported and the annual component failure rates that have been calculated. However, by using the reported value of system availability it is possible to calculate the value of planned system unavailability due to planned outages. These values are displayed in Table 4-18.

Table 4-18 – Unavailability (%) of GB Transmission Network

Unavailability (%)	2011-12	2010-11	2009-10	2008-09	2007-08	2006-07
Weather Outages	0.02	0.03	0.02	0.004	0.01	0.02
Non-Weather Outages	0.25	0.34	0.33	0.39	0.54	0.49
Total	0.27	0.37	0.35	0.40	0.55	0.50
Reported	6.22	5.53	4.56	5.45	5.09	4.75
Assumed Planned Outages	5.95	5.16	4.21	5.05	4.54	4.25

It is clearly seen in Table 4-18 that planned outages cause a much higher percentage of system unavailability, than non-weather-related outages and weather-related outages, which is expected. While it was previously stated that there is a 50/50 split between weather and non-weather outages, weather outages tend to be more transient and non-weather more permanent. This will be further discussed in Section 7.4. As discussed in Section 4.3.1, yearly analysis shows that during 2010 a high number of 'SSB & Ice' outages were experienced across two of the geographically regions. From Table 4-18 it is clear that during the period of 2010-11 the unavailability of the transmission system due to weather-related outages is almost double that of every other year shown. While it is still a small percentage of overall system availability, it shows the effect a major event can have on system availability and that it is important to consider what the future effects on system availability may be if extreme storms increase in frequency or strength. While it is possible to schedule planned outages and place them at times that have the least adverse impact on the system, weather-related outages are uncontrollable and tend to occur in clusters. This will mean that there is a significant chance of more than one circuit being out of service simultaneously in a given area and, hence, greater stress on the remaining network.

4.4 Data Recommendations

As has been discussed there is a large amount of interest with regards to outages on power systems, as well as access to data in order to model and understand these outages, if there are trends and ways to improve the system to cope with outages or predict them before they happen. However, as has been shown in this work the data containing outages information can be somewhat lacking vital information or can be hard to interpret. It is clear from the records that have been analysed within this chapter that there has been a lack of continuity between changes in recording years, as well as between companies within GB. While the networks are owned and maintained by different companies, the network still covers one country and it would be recommended that there is a repository where all outage data for GB should be stored and therefore, a consistency between companies would be achieved. This would allow for the records to be maintained and data gaps be filled allowing for time to be saved when using the data and more accurate investigations on outage data to be conducted. There is a data repository in place for the distribution system within GB but nothing is in place for the transmission system. A similar system to the Transmission Availability Data System (TADS) that exists within the US would be recommended, and include detailed outage causes, locations, time of outage, time of restoration and for weather related outages details on the weather that caused the outage and a weather value.

4.5 Summary

This chapter presented the application of Stage 1 of the proposed methodology to the GB test case for the purposes of demonstrating the effectiveness of this methodology. The first aim of this chapter was to present a comparison between reanalysis weather data and observation weather data, showing that ERA-Interim reanalysis data is an acceptable replication of past observation data. An analysis was also completed investigating if CAPE was a good proxy for lightning strikes. It was found that while there was a trend between these variables - as the value of CAPE increases so does the number of lightning strikes - it was also found that the relationship was more complicated than initially expected. Due to time constraints and being out with the scope of this research it was not investigated further, but it is widely accepted that CAPE is a reasonable proxy for lightning strikes as discussed in Section 4.1.3. The second aim of this chapter was to present a discussion and initial analysis of the current effects of weather on the GB test case by analysing historical outage data. This analysis showed that 'Wind, Gales and Windborne Objects' and 'SSB & Ice' outages are highly dependent on major events which cause high numbers of outages during the winter months whereas 'Lightning' is a more consistent cause of outages during the summer months. Companies B and C experience the highest number of weather-related outages per year per 100km of circuit length in the company's area. It also showed the same analysis for non-weather-related outages which showed that there was no seasonality or yearly trend and Company B sees the highest number of outages per year per 100km. It finally contained a comparison between reported availability of the GB transmission network and the calculated availably, though due to the unavailability of planned outage data, this was an incomplete analysis. This chapter met the research aims three and four that were discussed in Section 1.5.

Chapter 5 - Analysis of Correlations between Weather-Related Outages and Weather

Stage Two of the methodology, as discussed in Chapter 3 -, is presented in this chapter applied to the GB test case. It aims to develop correlations between different weather variables and outage classes in order to build quantifiable relationships. These relationships can then be used in the later stages to determine the risks that weather and climate change could pose to the transmission network. For the purposes of the GB test case the three main weather variables that cause the most outages on the GB transmission network are: “Lightning”, “Wind, Gales and Windborne Objects”, and “SSB & Ice”, as determined in Stage One of the methodology. These three categories will be analysed against different weather variables that could have caused the outages to allow the weather variable with the best correlation to be determined. This chapter will begin with a data refinement section that was required for the GB network outage data to provide more accurate information on what caused the weather-related outage. The subsequent three sections of this chapter will analyse the top three weather-related outage categories against different weather variables to determine the most prevailing weather for each outage class. This chapter will aim to meet research aim five; to develop a correlation analysis between different weather variables and weather-related outages and identify the most useful weather behaviour indicator for the associated outage, as described in Section 1.6.

5.1 Data Refinement

To complete the correlation analysis, it is first necessary to have more detail about the weather that caused each outage. After the data blank filling described in Section 4.2.3, the majority of weather-related outages have a weather type assigned, but a more specific weather value is needed. It is important to remember that data within the outage dataset may contain classification errors. For example, if the outage was mistakenly classed as weather-related when it was not, then it is possible for the outage to be assigned a weather value that would be unlikely to cause an outage. It is also possible that the wrong weather type was assigned to the outage. This may be due to either human error when recording the values, previous damage to equipment, or a malfunction. Analysis of misclassified data will not be part of the correlation analysis but is recommended for future work.

The following process was followed:

- The latitude and longitude of each outage was determined by taking the location of the substations and the length of line that tripped. The distance between the stations is the line length, and half of this value is used as the outage location.
- Each outage was placed in a grid from the ERA-Interim weather dataset.
- Various weather variables were downloaded from the ERA-Interim dataset.
- The outage was assigned weather values from these variables for the matching grid square.

At this stage it is unclear what weather variable is the best indicator of a fault from a specific weather type and so several weather variables were investigated. For ‘Wind, Gales and Windborne Objects’ outages two weather datasets were downloaded: 10m Wind Speed (10m U Wind Direction Component and 10m V Wind Direction Component) & 10m Wind Gusts. For ‘Lightning’ outages, CAPE and finally for ‘SSB & Ice’ outages multiple datasets were required: Snowfall, Snow Depth, Minimum Temperature at 2m and 10m Wind Gusts on Snow days. As there is not enough data, ‘Other Weather’ outages will not be analysed in this section. Once all outages have been assigned weather values, the correlation analysis can be completed. This involves creating the frequency distribution of each weather variable along with the frequency distribution of weather values for each weather-related outage and the cumulative frequency distributions. The next three sections will look at frequency distributions, cumulative frequency distributions and finally correlations for the top weather-related outages classes for the GB transmission network and their aforementioned weather variables. Due to the volume of results for this section of analysis, only North Scotland’s results will be discussed, the rest of the figures shall be displayed in Appendix D.

5.2 Wind, Gales and Windborne Objects

5.2.1 Wind Gusts Frequency Distributions and Cumulative Frequency Distributions

The range of wind gust values was split equally into twenty one bins, and all occurrences within each bin counted. The same process was completed for ‘Wind, Gales and Windborne Objects’ outages. From this a frequency distribution and cumulative frequency distributions for both wind gust occurrences from ERA-Interim and ‘Wind, Gales and Windborne

Objects' outage occurrences in North Scotland were plotted and these can be seen in Figure 5-1 and Figure 5-2 respectively. Figure 5-1 shows that 89% of wind gust occurrences are below 17.5m/s. However, Figure 5-2 indicates that 93% of 'Wind, Gales and Windborne Objects' outages occur above 17.5m/s. This suggests that the transmission system is designed to deal with the lower wind gusts that are more likely to be seen during everyday weather conditions but that it is not designed to deal with the more extreme values that occur above 17.5m/s, and that when these values do occur there is a much higher chance of outages on the system.

The cumulative frequency distributions for both of the data sets are then plotted in Figure 5-3. This figure highlights that 90% of 'Wind, Gales and Windborne Objects' outages occur during the top 11% of wind gust occurrences. It also indicates that 66% of 'Wind, Gales and Windborne Objects' outages coincide with the occurrence of the top 1% of wind gusts.

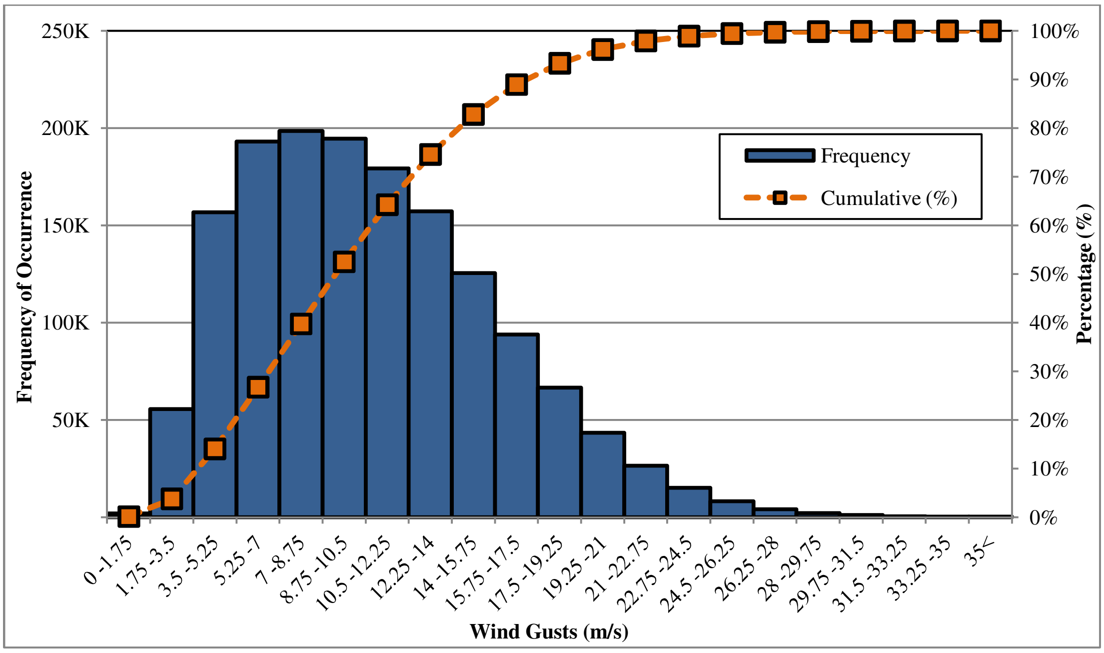


Figure 5-1 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Gust Occurrences, North Scotland

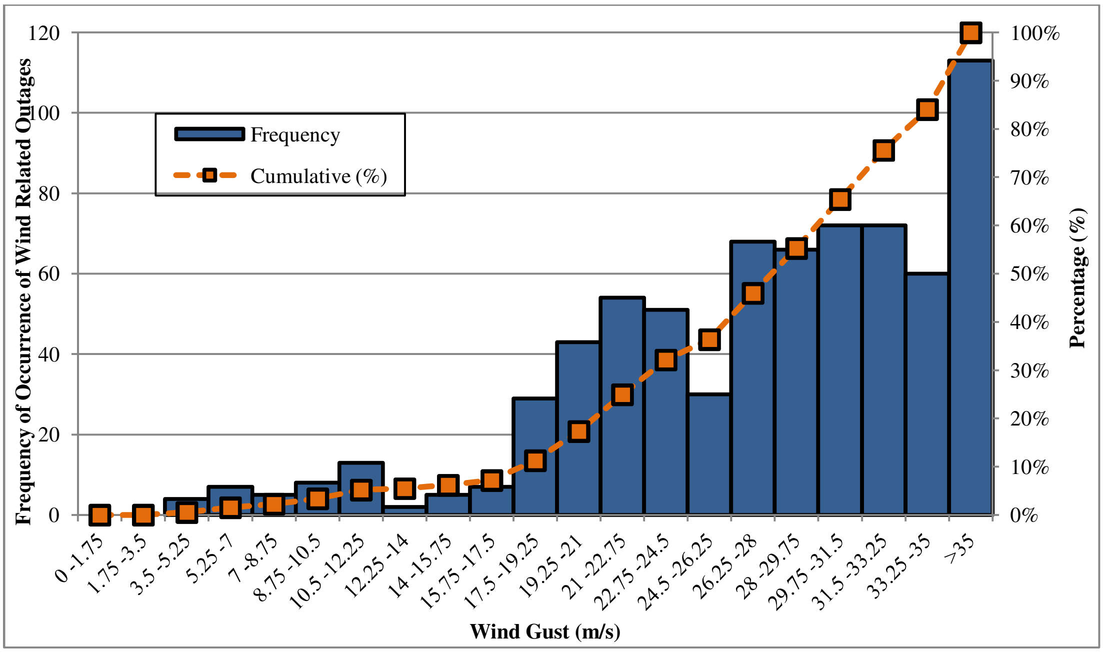


Figure 5-2 – Wind Gust Frequency Distribution and Cumulative Frequency Distribution for Wind-Related Outages, North Scotland

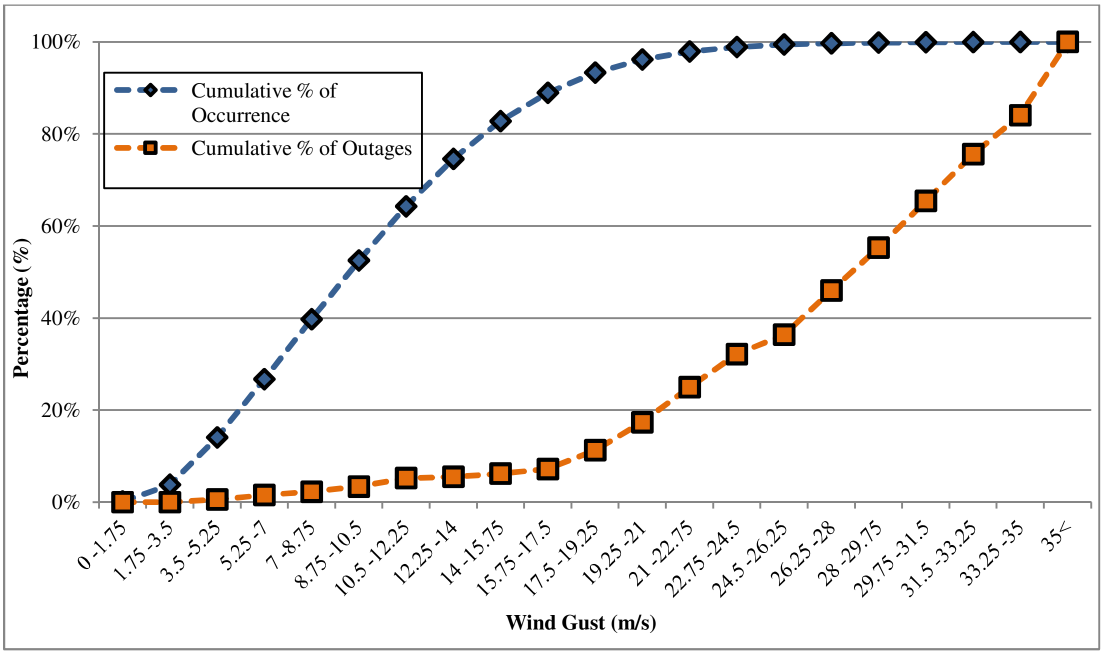


Figure 5-3 - Cumulative Distribution Function for Wind Faults and 10m Wind Gust Occurrences, North Scotland

5.2.2 Wind Gusts Correlation Analysis

Figure 5-4 displays the scatter plot of wind gusts against the frequency of 'Wind, Gales and Windborne Objects' outages. It shows the coefficient of the determination (R^2) for the quadratic curves used.

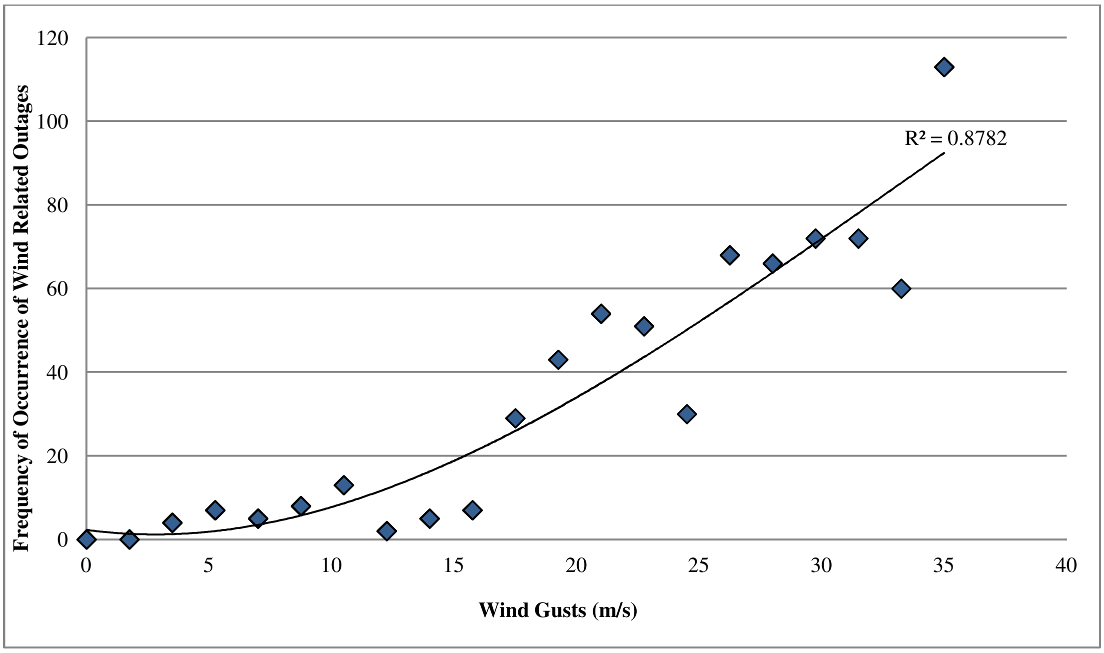


Figure 5-4 - Relationship between Wind-Related Outages and 10meter Wind Gusts, North Scotland

It is clear that there is a strong relationship between wind gust values and ‘Wind, Gales and Windborne Objects’ outages, with an R^2 value of 0.878. This indicates that approximately 88% of variation in ‘Wind, Gales and Windborne Objects’ outages is caused by variation in wind gusts, and 12% of variation of ‘Wind, Gales and Windborne Objects’ outages is unmodelled. Transforming the data, as discussed in Section 2.2.2, does not improve the value of R^2 for these data sets. While wind gusts have a strong relationship with ‘Wind, Gales and Windborne Objects’, it is important to check that a stronger one does not exist with wind speeds. Therefore, the same analysis is completed with wind speed as the weather variable.

5.2.3 Wind Speed Frequency Distributions and Cumulative Frequency Distributions

Frequency distributions and cumulative frequency distributions for both wind speed occurrences and ‘Wind, Gales and Windborne Objects’ outage occurrences were plotted and these can be seen in Figure 5-5 and Figure 5-6 respectively. From Figure 5-5 it is seen that 93% of wind speed occurrences are below 12.25m/s. However, from Figure 5-6 it is clear that above this wind speed the frequency of wind-related outages increases but unlike wind gusts, at a less consistent rate than wind speeds.

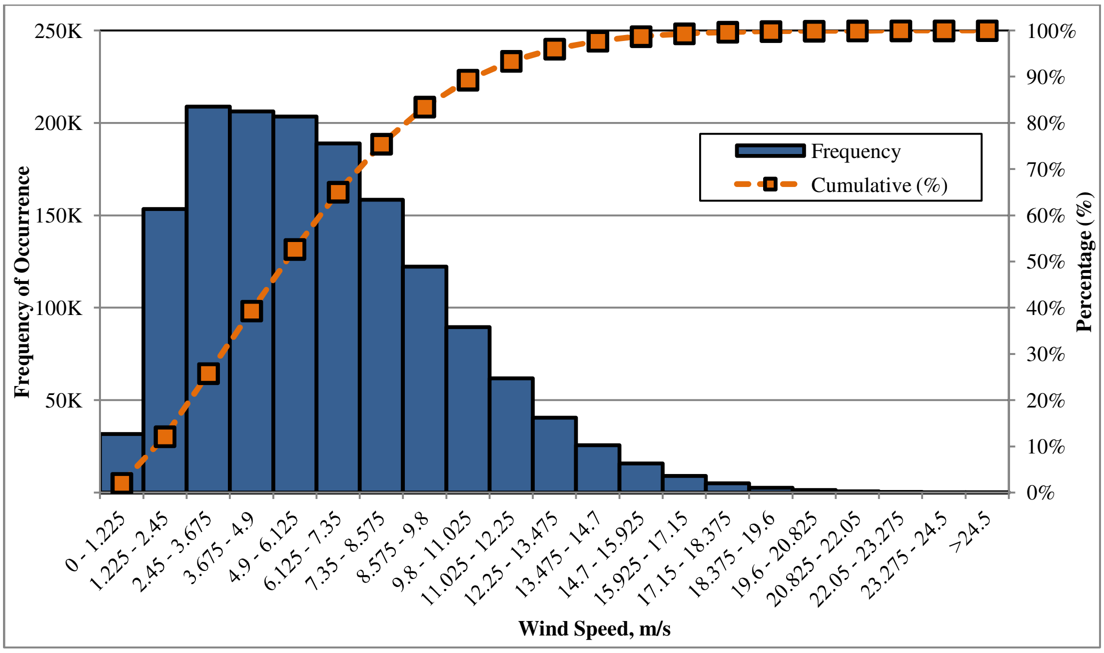


Figure 5-5 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Speed Occurrences, North Scotland

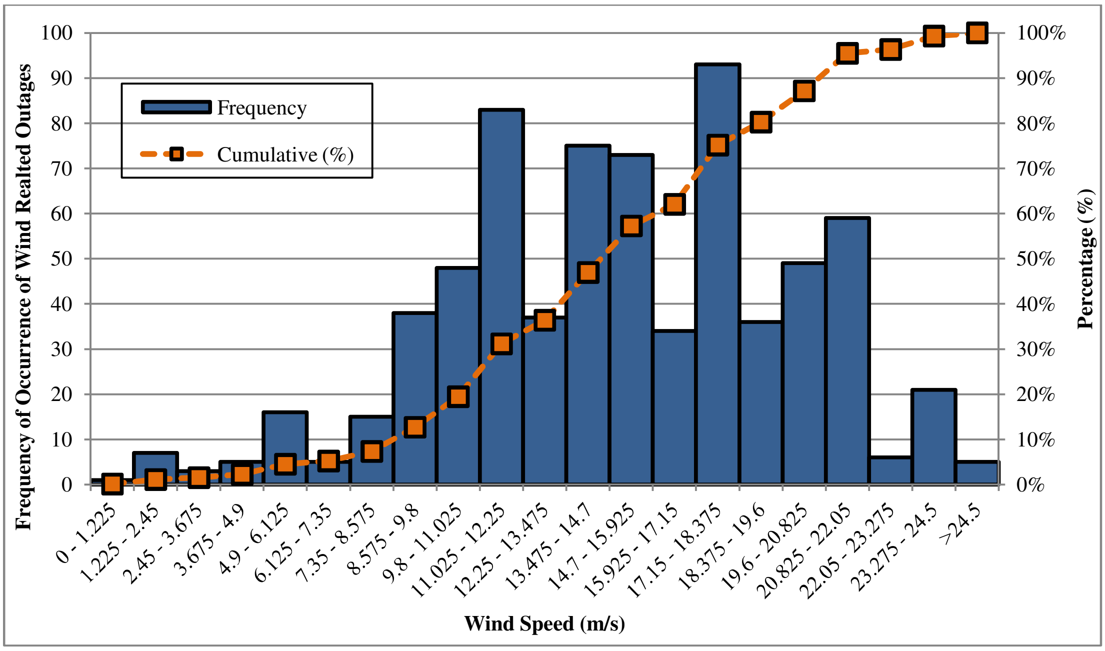


Figure 5-6 – Wind Speed Frequency Distribution and Cumulative Frequency Distribution for Wind-Related Outages, North Scotland

Figure 5-7 shows the cumulative frequency distributions for both wind speed and 'Wind, Gales and Windborne Objects' outages. It show that 70% of 'Wind, Gales and Windborne Objects' outages occur during the top 7% of wind speeds and that in the top 1% of wind speeds, 43% of 'Wind, Gales and Windborne Objects' outages occur.

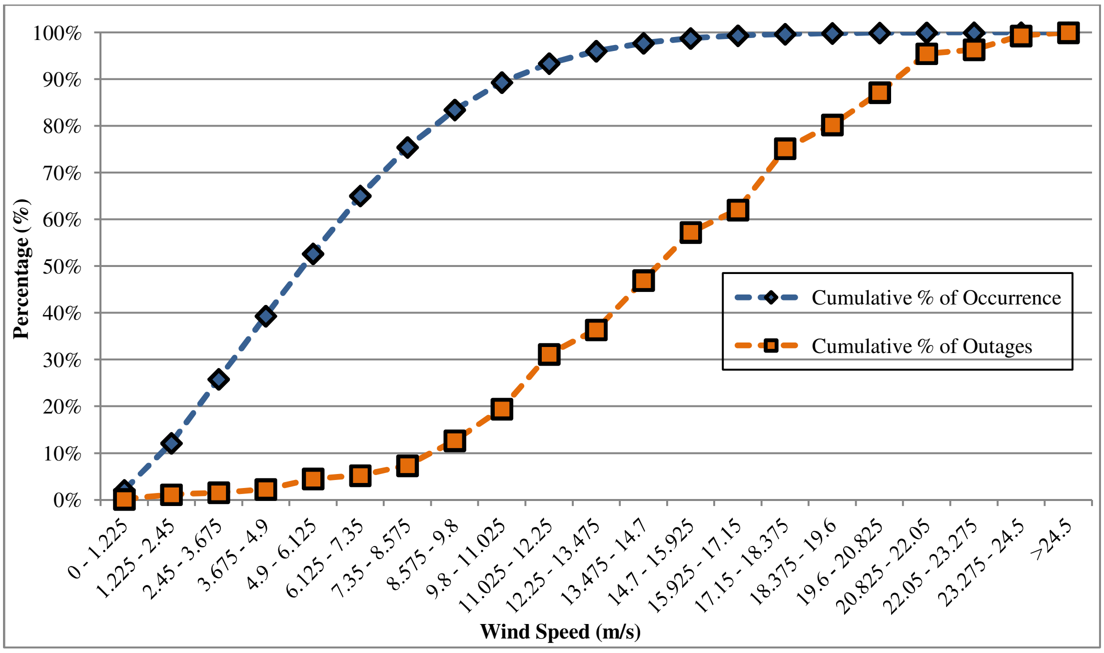


Figure 5-7 - Cumulative Distribution Function for Wind Faults and 10m Wind Speed Occurrences, North Scotland

5.2.4 Wind Speed Correlation Analysis

The scatter plot of wind speed against the log frequency of ‘Wind, Gales and Windborne Objects’ outages is shown in Figure 5-8, this data was log transformed, as discussed in Section 2.2.2. As before the coefficient of the determination is displayed and indicates a good relationship between wind speed and ‘Wind, Gales and Windborne Objects’ outages with a R^2 value of 0.7994. There is a downwards trend at the higher values of wind speed due to a lower number of outages occurring. This could be contributed to the rarity of occurrence at these wind speeds, or they occur after the middle values of wind speed have already caused outages on the system. Wind gusts were used as the measure for wind-related outages as, while both have high values of the coefficient of determination, wind gusts is higher and the correlation has less of a downwards trend at higher values.

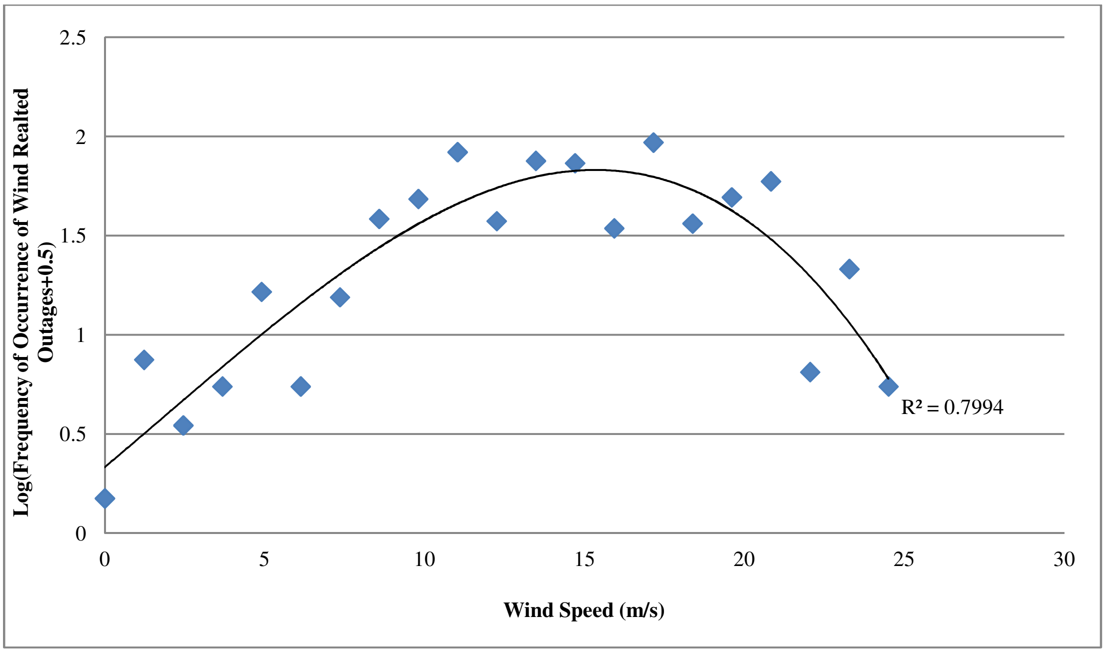


Figure 5-8 - Relationship between Wind-Related Outages and 10meter Wind Speeds, North Scotland

5.3 SSB & Ice

5.3.1 Snowfall Frequency Distributions and Cumulative Frequency Distributions

The first obvious weather variable to investigate for 'SSB & Ice' outages is snowfall, i.e. the snowfall for a particular hour on a particular day. The frequency distribution and cumulative frequency distributions for snowfall and 'SSB & Ice' outages for North Scotland are shown in Figure 5-9 and Figure 5-10 respectively. Figure 5-9, however, excludes days where there was no snowfall as during the time period analysed the majority of days experienced no snowfall. Figure 5-9 shows that on days when snowfall does occur 85% of snowfall occurrences occur in the first 11 bins, showing a similar trend to the wind gusts and wind speed graphs. Figure 5-10 shows that 92% of outages occur in the first 11 bins, however, over 30% of snow related outages occur when there is no snowfall indicating that snowfall may not be the best indicator of snow-related outages as outages can still occur when snow is not falling but is already lying. It can also be seen from this that 'SSB & Ice' outages occur at all values, with no values showing a significant increase in 'SSB & Ice' outages.

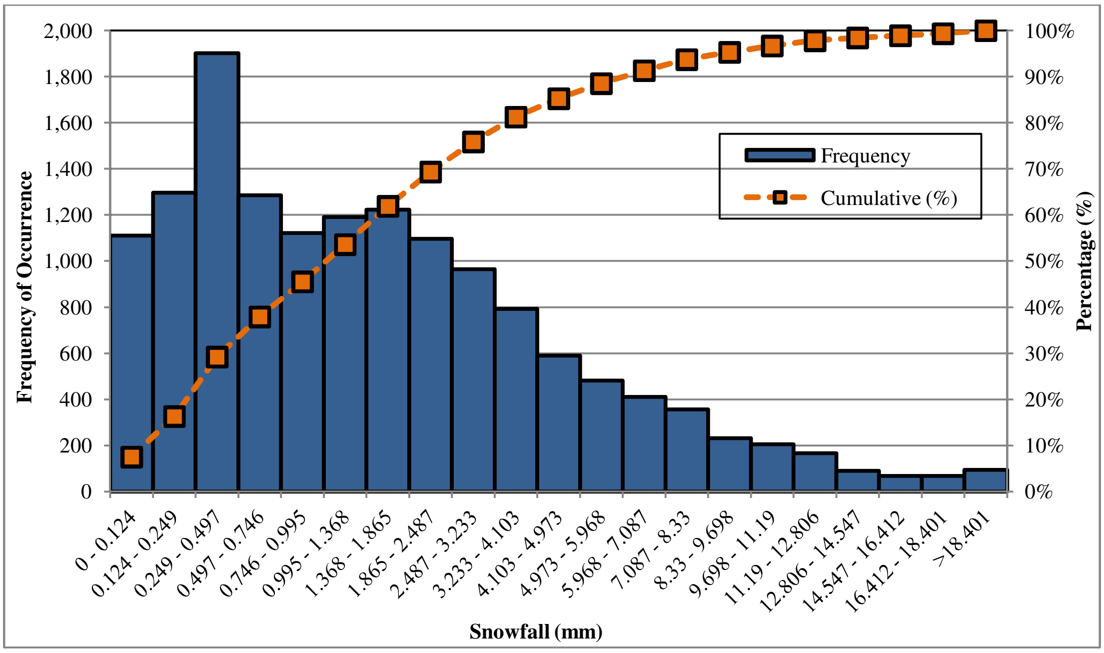


Figure 5-9 - Frequency Distribution and Cumulative Frequency Distribution for Snowfall Occurrences, North Scotland

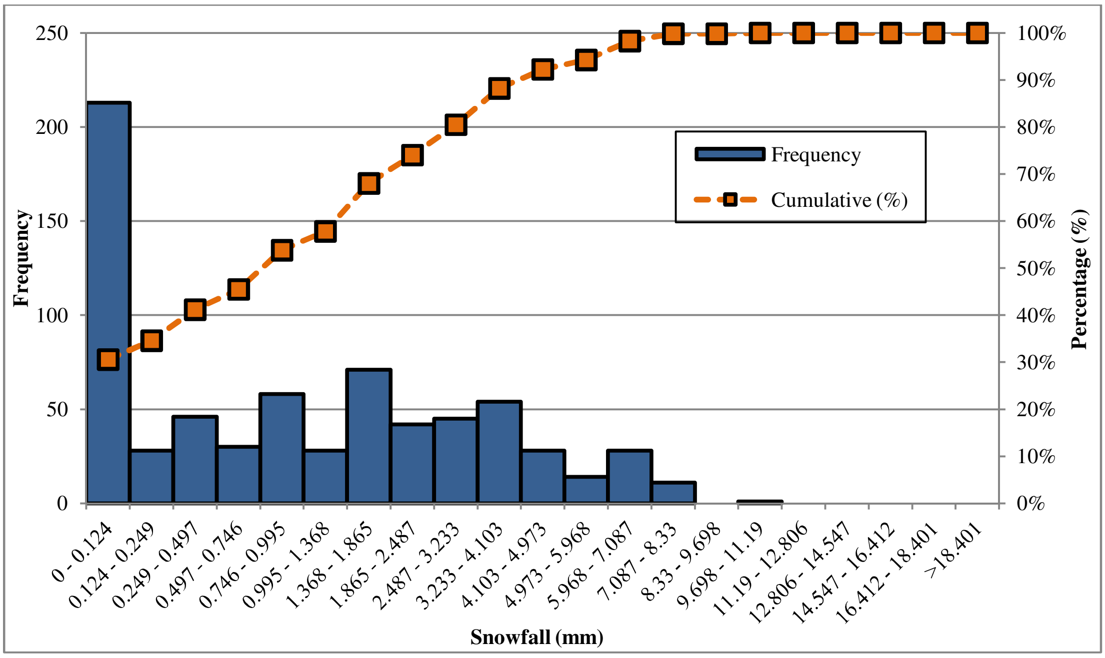


Figure 5-10 – Snowfall Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, North Scotland

The cumulative frequency distributions for both datasets are plotted in Figure 5-11. It clearly shows that the cumulative percentage of snowfall occurrences and snow-related outages follow a similar pattern. But the cumulative of occurrence does not include days where snowfall did not occur but cumulative percentage of outages does, which is over 30% of snow-related outages.

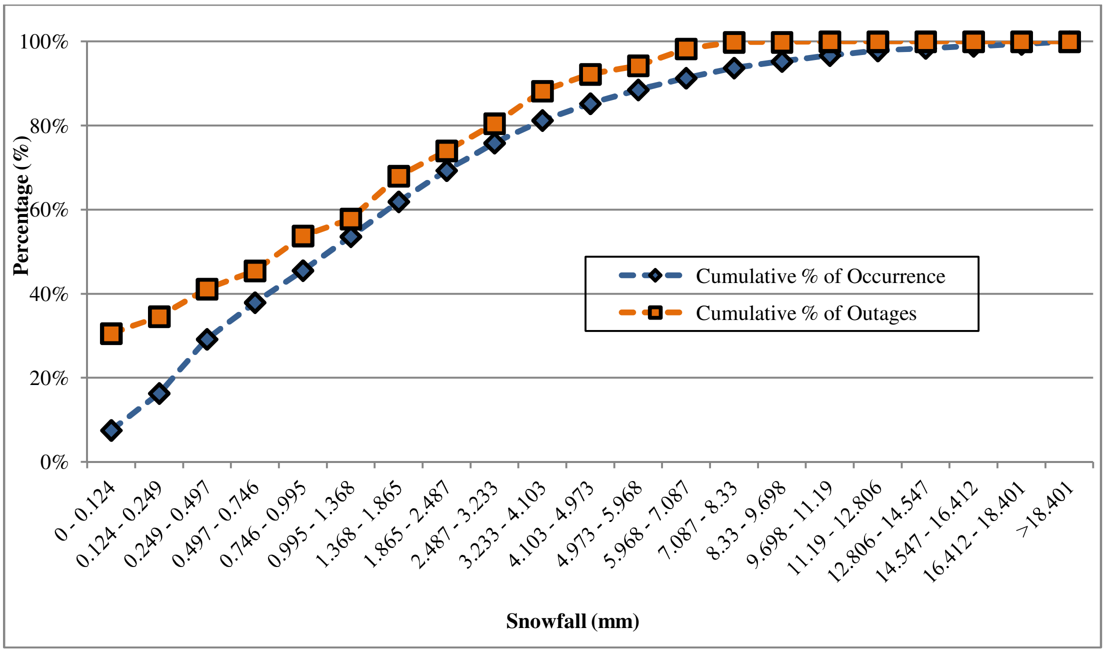


Figure 5-11 - Cumulative Distribution Function for Snow-Related Outages and Snowfall (mm) Occurrences, North Scotland

5.3.2 Snowfall Correlation Analysis

The scatter graph of snowfall against the frequency of ‘SSB & Ice’ outages is shown in Figure 5-12. Figure 5-12 shows that a relationship does exist between snowfall and ‘SSB & Ice’ outages with an R^2 value of 0.62. Figure 5-12 indicates that while snowfall has a relationship with ‘SSB & Ice’ outages it may not be the best weather type to indicate them.

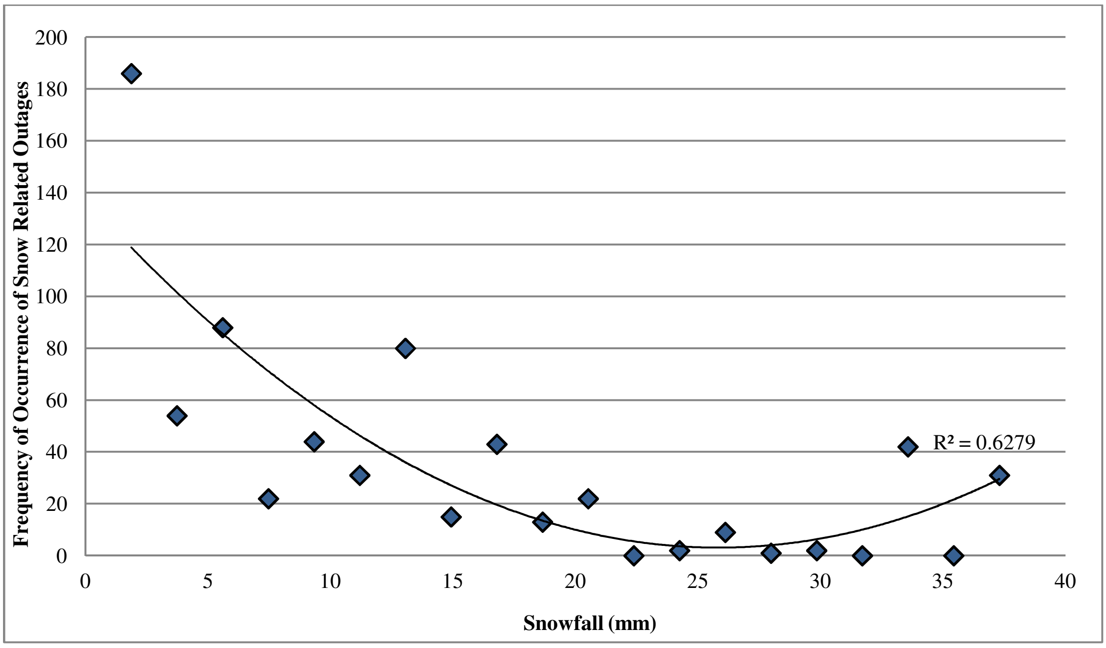


Figure 5-12 - Relationship between Snow-Related Outages and Snowfall (mm), North Scotland

5.3.3 Snow Depth Frequency Distributions and Cumulative Frequency Distributions

Snow depth, is the depth of snow at a point in time, is a possible weather indicator of 'SSB & Ice' outages. The frequency distribution and cumulative frequency distribution for snow depth and 'SSB & Ice' outages for North Scotland are shown in Figure 5-13 and Figure 5-14. Figure 5-13 shows that 92% of occurrences occur in the first 11 bins. From Figure 5-14 this is where around 69% of 'SSB & Ice' outages occur. Similar to snowfall, snow depth for 'SSB & Ice' outages shows a trend where, after a specific value, the numbers of outages do not increase. Figure 5-15 displays the cumulative frequency distributions for both snow depth and 'SSB & Ice' outages. Figure 5-15 highlights that the while the majority of snow depth days occur in the lowest bins, the majority of 'SSB & Ice' outages occur at higher snow depths.

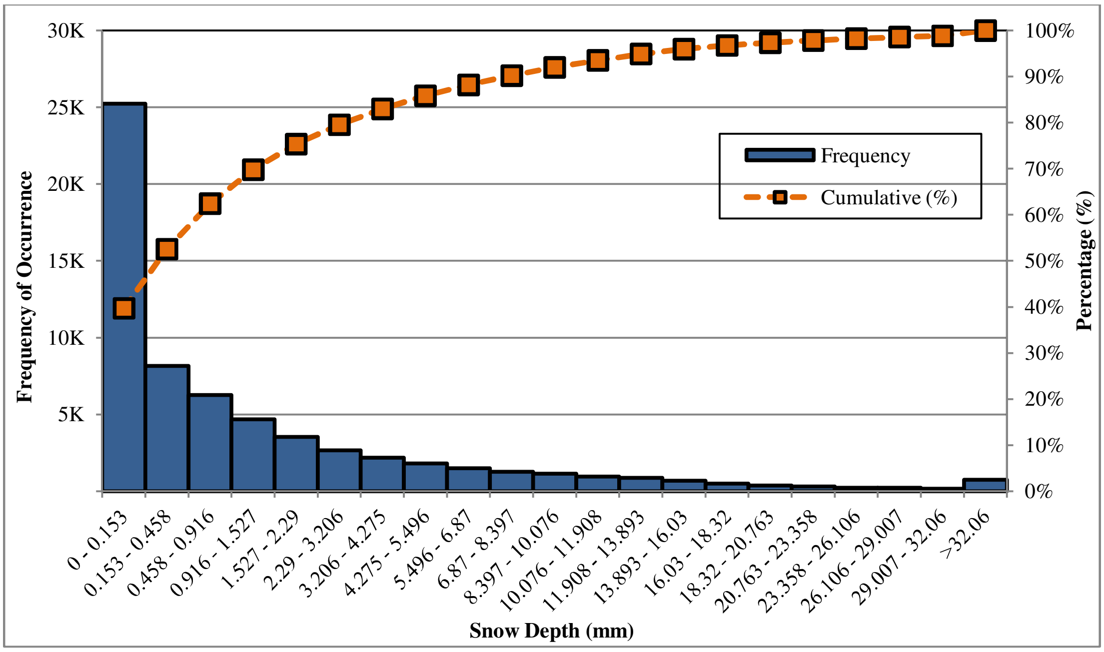


Figure 5-13 - Frequency Distribution and Cumulative Frequency Distribution for Snow Depth Occurrences, North Scotland

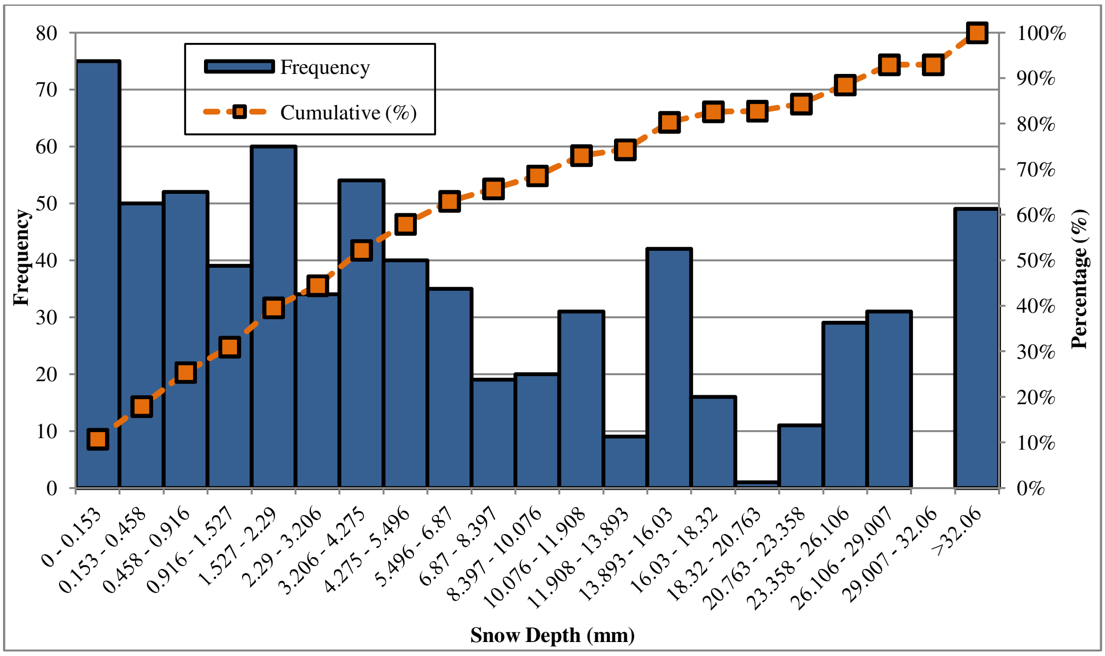


Figure 5-14 – Snow Depth Frequency Distribution and Cumulative Frequency Distribution for Snow Outages, North Scotland

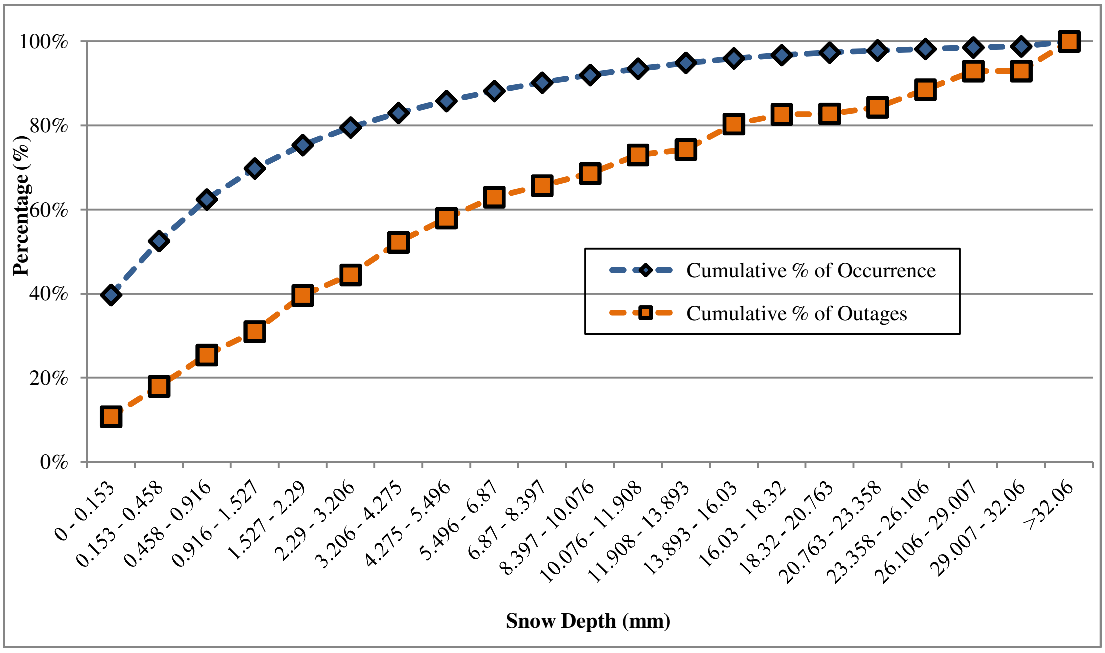


Figure 5-15 - Cumulative Distribution Function for Snow-Related Outages and Snow Depth (mm) Occurrences, North Scotland

5.3.4 Snow Depth Correlation Analysis

To investigate further if snow depth is a good indicator of ‘SSB & Ice’ outages, scatter graphs of snow depth against frequency of ‘SSB & Ice’ outages occurrence are shown in Figure 5-16. This shows a slightly stronger relationship compare to snowfall with an R^2

value of 0.69. Figure 5-16 indicates that snow depth is a better indicator of ‘SSB & Ice’ outages than snowfall.

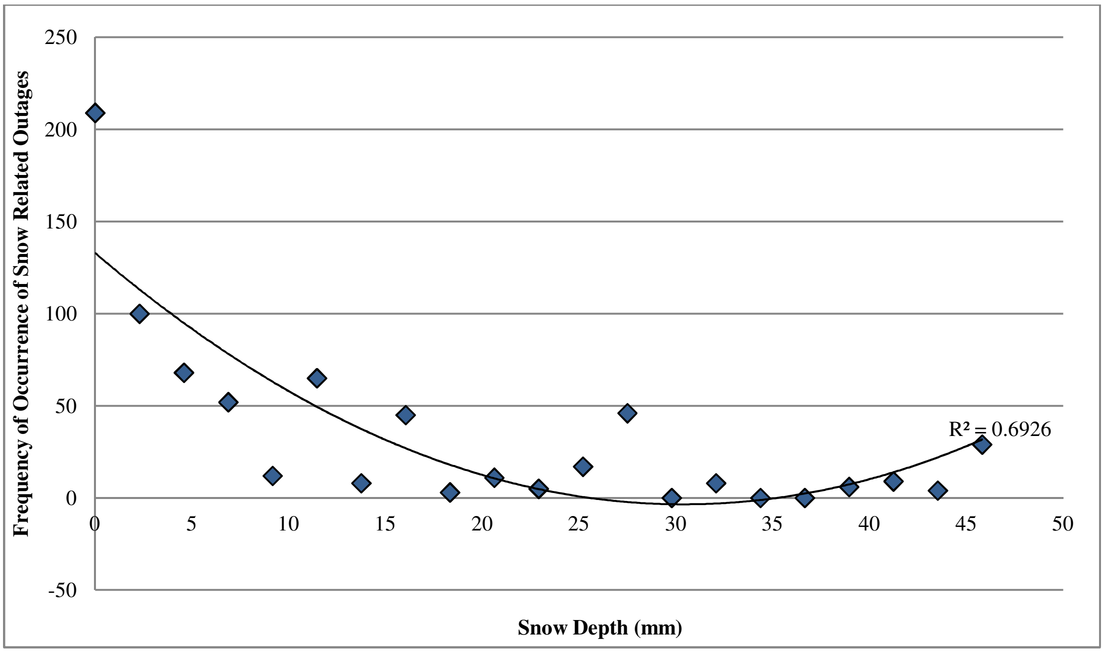


Figure 5-16 - Relationship between Snow-Related Outages and Snow Depth (mm), North Scotland

5.3.5 Minimum Temperature Frequency Distributions and Cumulative Frequency Distributions

Minimum temperature was investigated; Figure 5-17 and Figure 5-18 displays the frequency distribution and cumulative frequency distribution for minimum temperature and snow outages. Figure 5-17 shows that minimum temperature, is negatively skewed, meaning that 50% of occurrences occur in the highest bin rather than the lowest. From Figure 5-18 it is clear that ‘SSB & Ice’ outages occur over a specific range of temperatures; from -4.97°C to 3.98 °C which relates to 31% of minimum temperature occurrences, where 95% of ‘SSB & Ice’ outages occur. Figure 5-19 displays the cumulative frequency distributions for minimum temperature and ‘SSB & Ice’ outages. It shows 98% of snow outages occur during the lower 32% of minimum temperatures

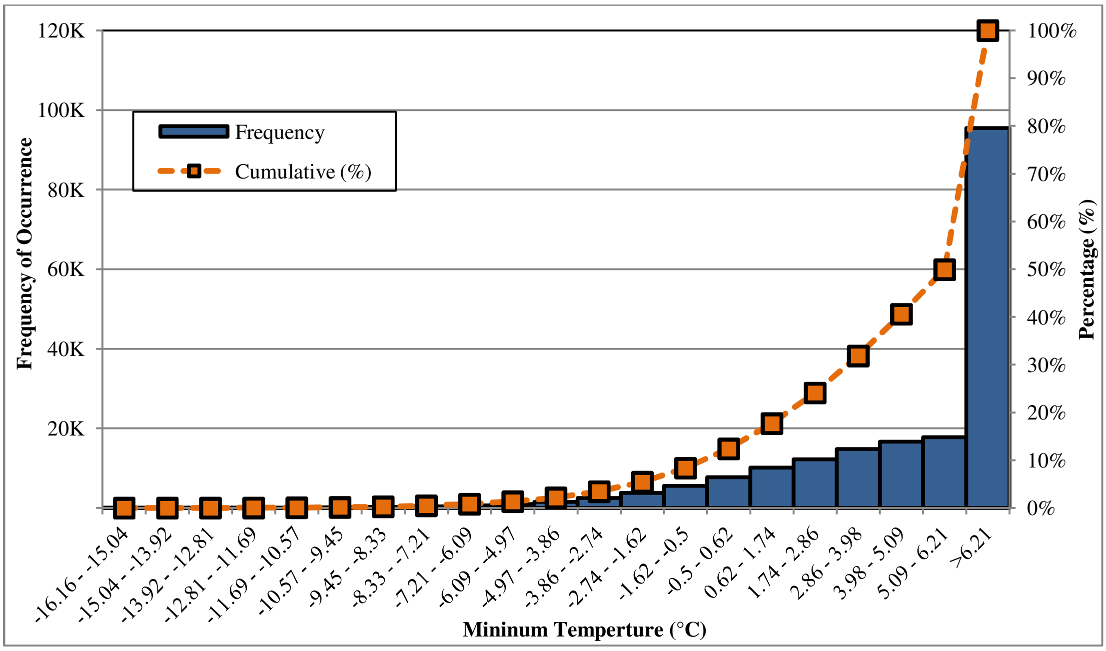


Figure 5-17 - Frequency Distribution and Cumulative Frequency Distribution for Minimum Temperature (°C) Occurrences, North Scotland

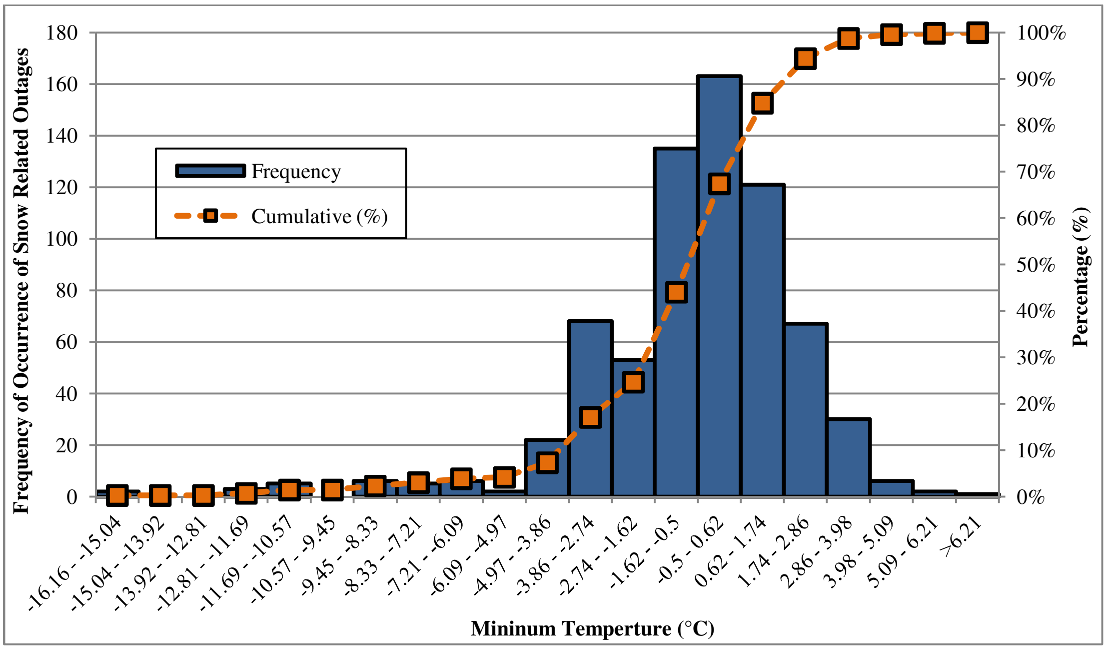


Figure 5-18 – Minimum Temperature Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, North Scotland

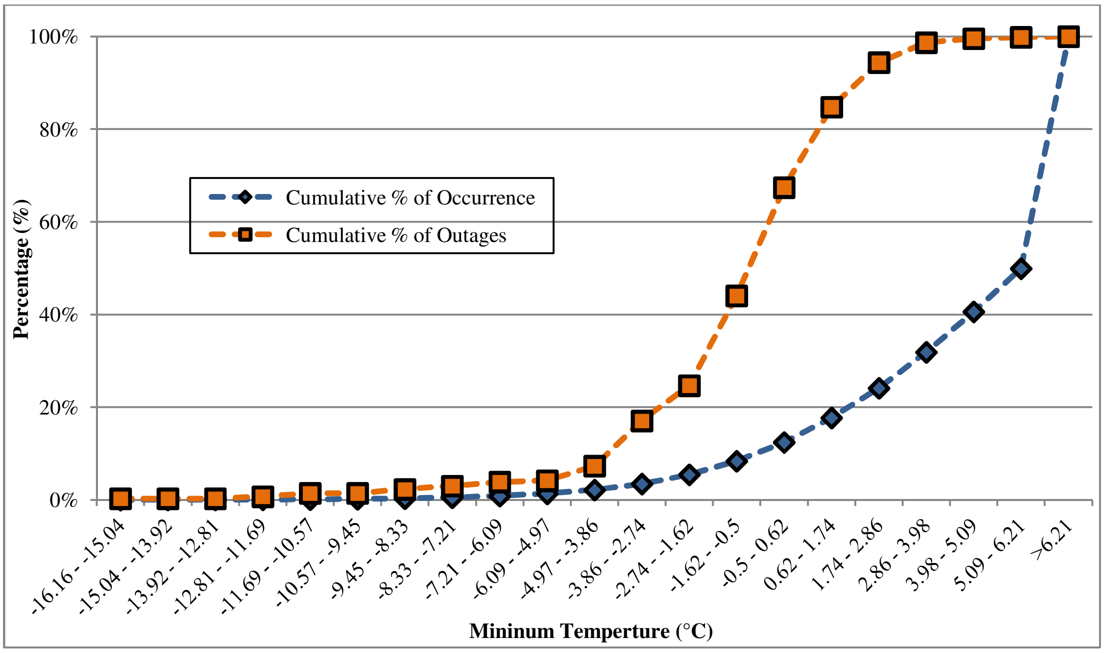


Figure 5-19 - Cumulative Distribution Function for Snow-Related Outages and Minimum Temperature (°C) Occurrences, North Scotland

5.3.6 Minimum Temperature Correlation Analysis

Figure 5-20 shows the scatter graphs of log minimum temperature against frequency of 'SSB & Ice' outages. Figure 5-20 displays a R^2 value of 0.55, showing that while 'SSB & Ice' outages occur over a specific range of temperature, it is a poor indicator and this relationship is more likely related to the temperatures that are suitable for snow to occur.

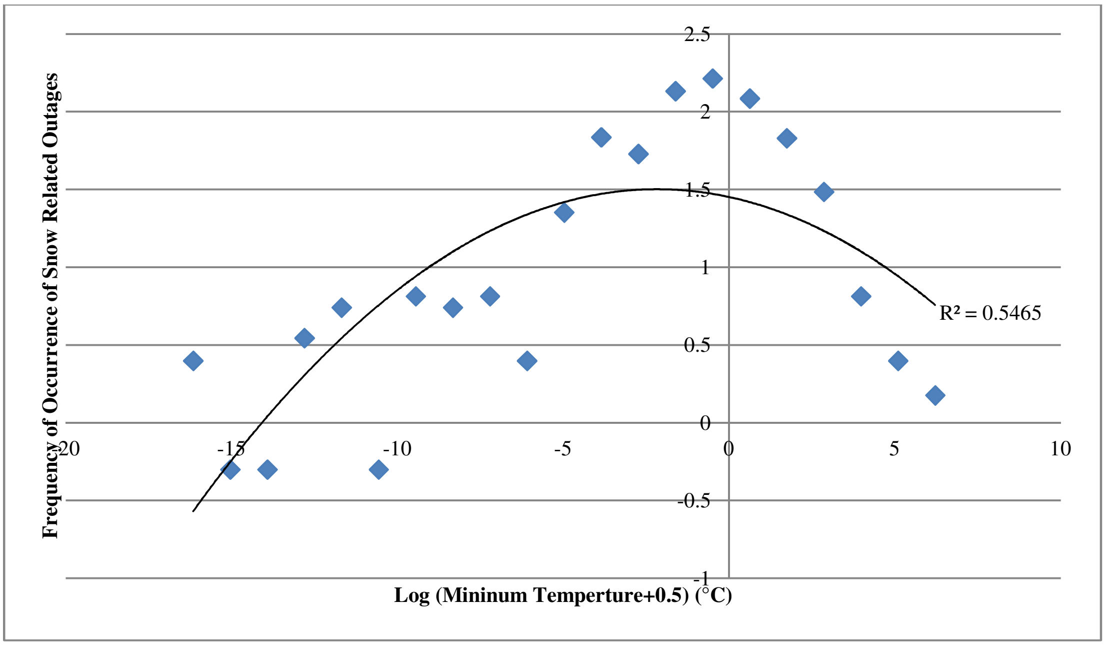


Figure 5-20 - Relationship between Snow-Related Outages and Minimum Temperature (°C), North Scotland

It is therefore possible that any correlation between temperature and snow-related outages is likely a by- product of the correlation between minimum temperature and snow, rather than being directly correlated. Minimum temperature is not a good indicator of 'SSB & Ice' outages, and therefore will not be used. It may be that 'SSB & Ice' outages are not indicated by just one weather type and multiple weather types may be a better indicator.

5.3.7 Wind Gusts on Snow Days Frequency Distributions and Cumulative Frequency Distributions

As analysed in Section 5.3.4 snow depth was a better indicator of 'SSB & Ice' outages compared to snowfall which suggests that on days where snow is not falling but is still lying from previous days can still cause outages. This suggests that looking at the relationship between snow and 'SSB & Ice' outages is not enough and that another weather variable contributes to outages. One possible weather combination that may be a good indicator of 'SSB & Ice' outages is wind gusts on snow days, a day were snow is lying, as the wind gusts may whip up snow causing outages long after the snow has stopped falling. Figure 5-21 and Figure 5-22 display the frequency distributions and the cumulative frequency distributions of wind gusts on snow days and 'SSB & Ice' outages respectively. Figure 5-21 displays a similar relationship to wind gusts over all days, to what is displayed in Figure 5-1, as expected. However, Figure 5-22 shows that 60% of outages occur when there is snow and the wind gusts are above 17.5m/s.

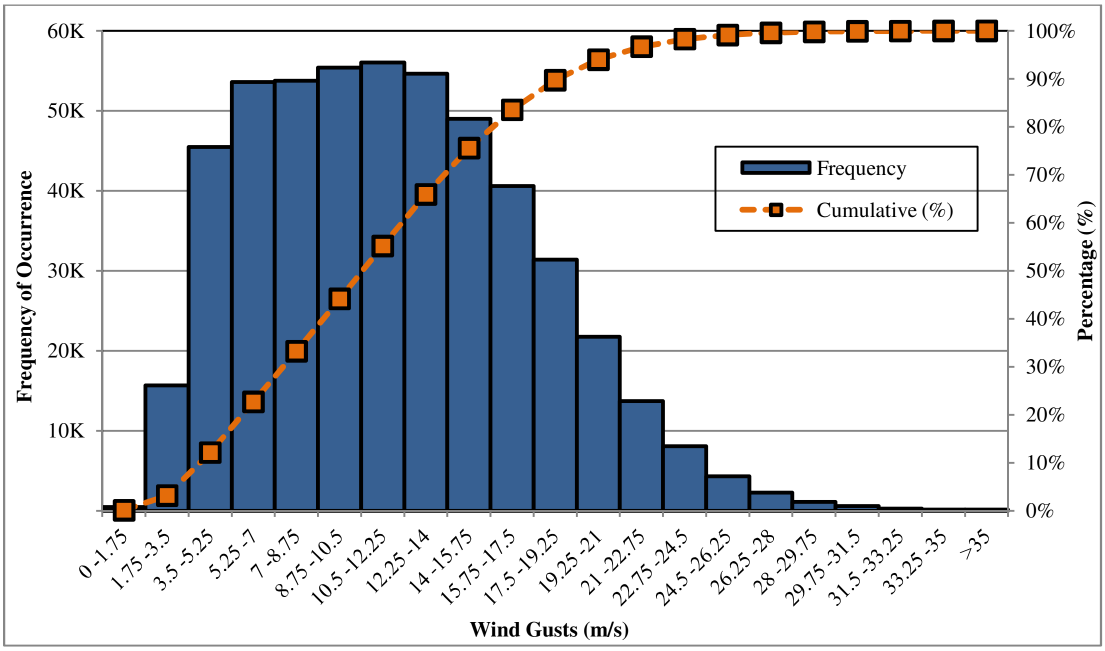


Figure 5-21 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Gusts on Snow Days Occurrences, North Scotland

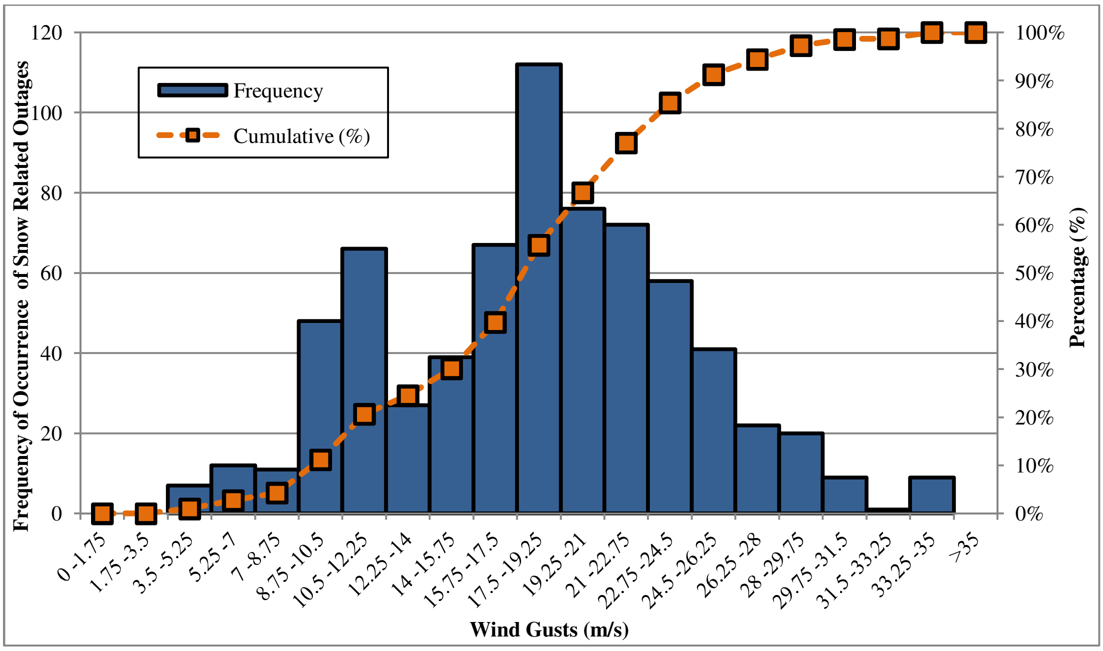


Figure 5-22 – Wind Gusts on Snow Days Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, North Scotland

Figure 5-23 shows the cumulative frequency distributions for wind gusts on snow days and 'SSB & Ice' outages. In the top 16% of wind gusts on snow days 60% of 'SSB & Ice' outages occur.

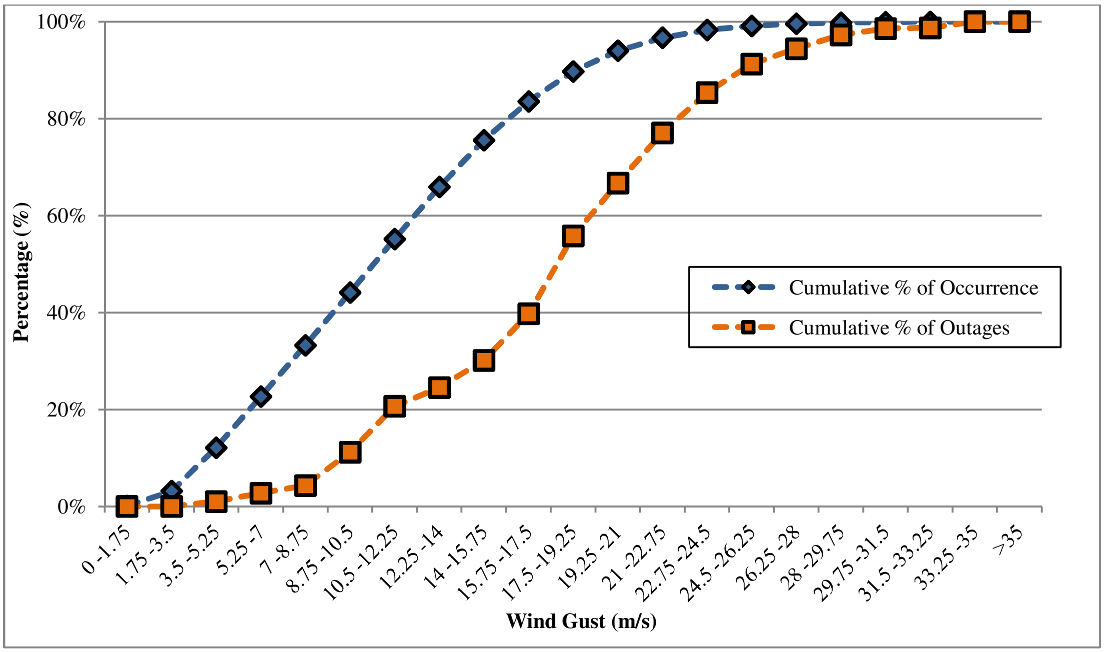


Figure 5-23 - Cumulative Distribution Function for Snow-Related Outages and Wind Gusts on Snow Days (m/s) Occurrences, North Scotland

5.3.8 Wind Gusts on Snow Days Correlation Analysis

Figure 5-24 is the log of wind gusts on snow days against the log frequency of ‘SSB & Ice’ outages.

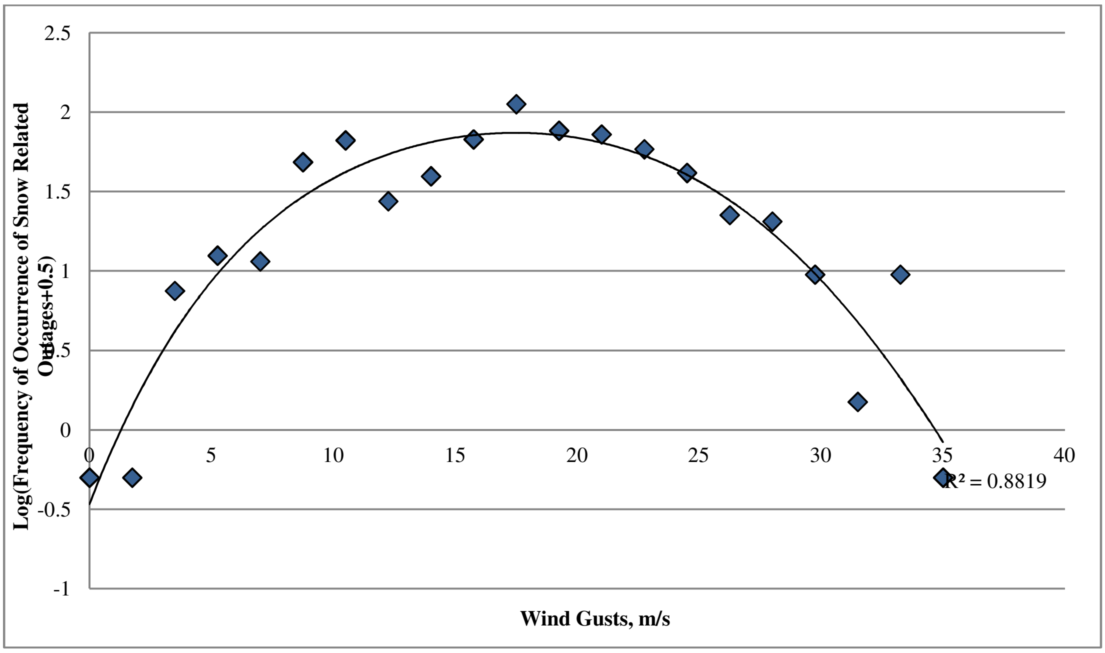


Figure 5-24 - Log Relationship between Snow-Related Outages and 10meter Wind Gusts on Snow Days (m/s), North Scotland

Figure 5-24 displays a R^2 value of 0.88. There is a downwards trend at the higher values of wind gusts due to a lower number of outages occurring at these wind gusts in comparison to the middle wind gusts. This could be contributed to the rarity of occurrence of these wind gusts and, therefore, a lower number of outages have occurred, or due to circuits that might be expected to trip at the highest gusts having already tripped at lower gusts, which could be a possible tangent for future work. Figure 5-24 indicates a strong relationship between ‘SSB & Ice’ outages and wind gusts on snow days. It is clear from the analysis that wind gusts on snow days are the best indicator of ‘SSB & Ice’ outages. While minimum temperature is an important factor when considering ‘SSB & Ice’ outages, there a specific range of temperatures that this type of outages occurs under as shown in Figure 5-25. But by considering wind gusts on snow days only, it takes into account the days where that temperature range is met and therefore is indirectly still considered.

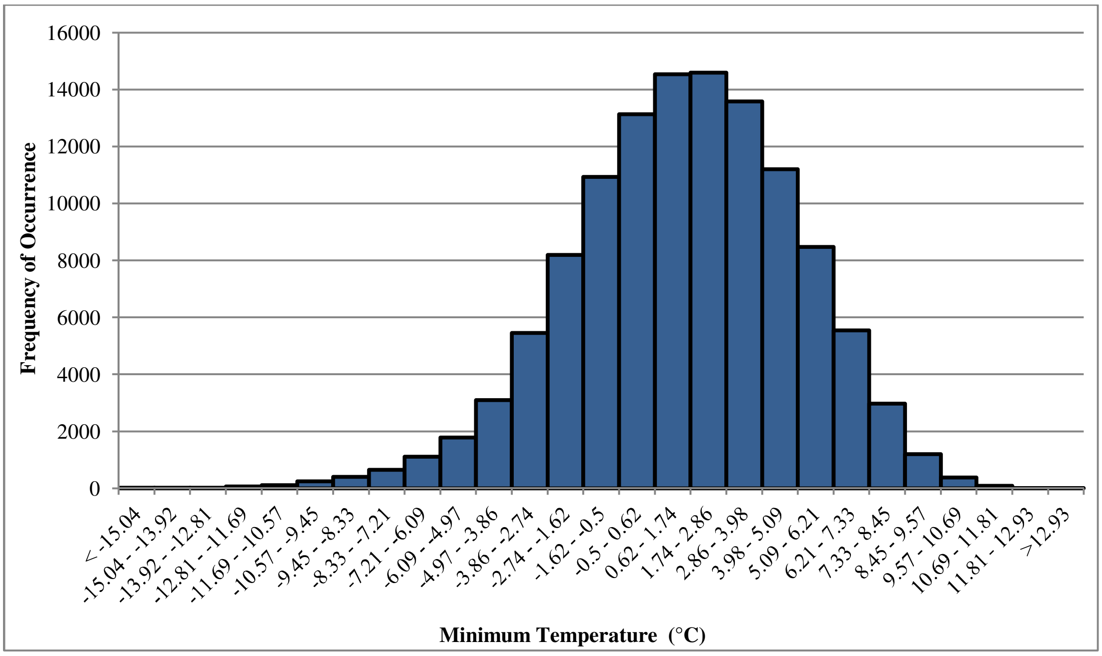


Figure 5-25 - Minimum Temperature on Snow Days

5.4 Lightning

The same process was used for ‘Lightning’ outages. While CAPE has already been identified as a good proxy for lightning strikes, the investigation into the relationship between lightning strikes and ‘Lightning’ outages will still be completed.

5.4.1 Lightning Strike Frequency Distributions and Cumulative Frequency Distributions

The frequency distribution and cumulative frequency distribution for daily lightning strikes and ‘Lightning’ outages are shown in Figure 5-26 and Figure 5-27. 98% of days see fewer than 86 strikes. Figure 5-27 indicates that around 49% of ‘Lightning’ outages occur during this period while 51% of ‘Lightning’ outages occur during the top 2% of lightning strike days. Figure 5-28 shows the cumulative frequency distributions and highlights that 67% of ‘Lightning’ outages occurred during the top 99% of lightning days, while 33% of ‘Lightning’ outages occurred during the top 1% of lightning days.

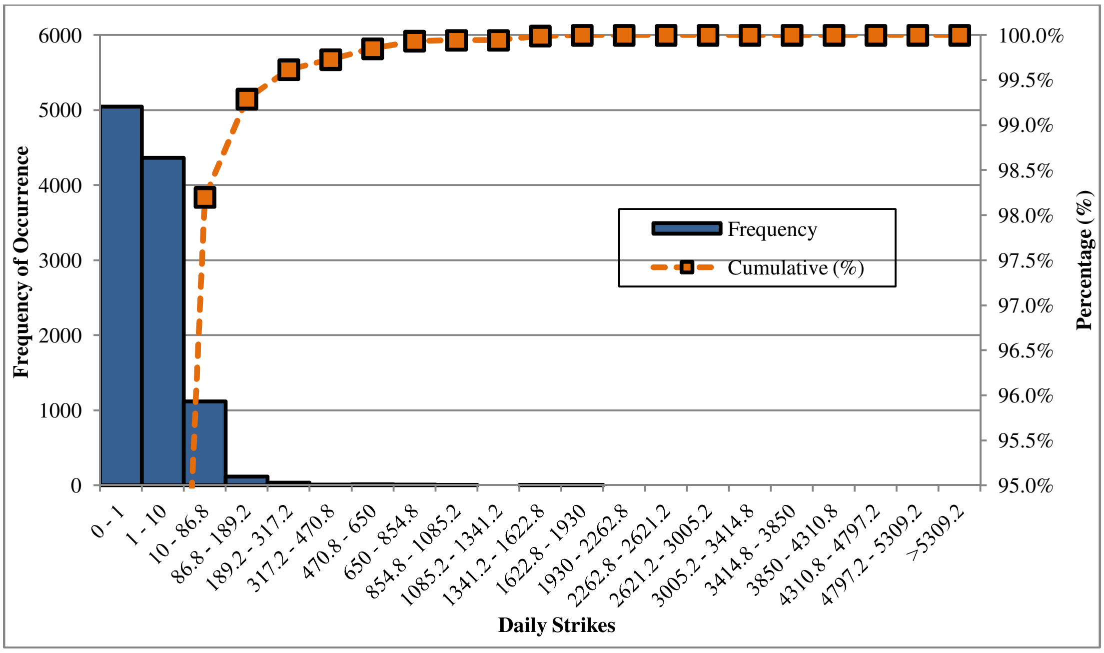


Figure 5-26 - Frequency Distribution and Cumulative Frequency Distribution for Daily Lightning Strikes, North Scotland

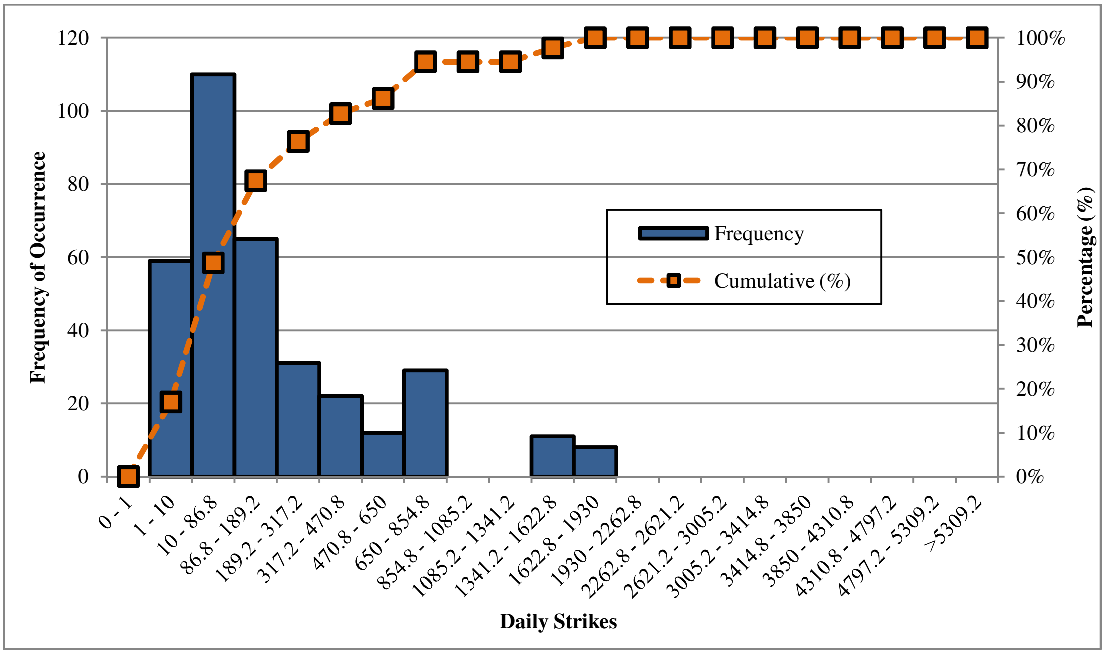


Figure 5-27 - Daily Lightning Strikes Frequency Distribution and Cumulative Frequency Distribution for Lightning-Related Outages, North Scotland

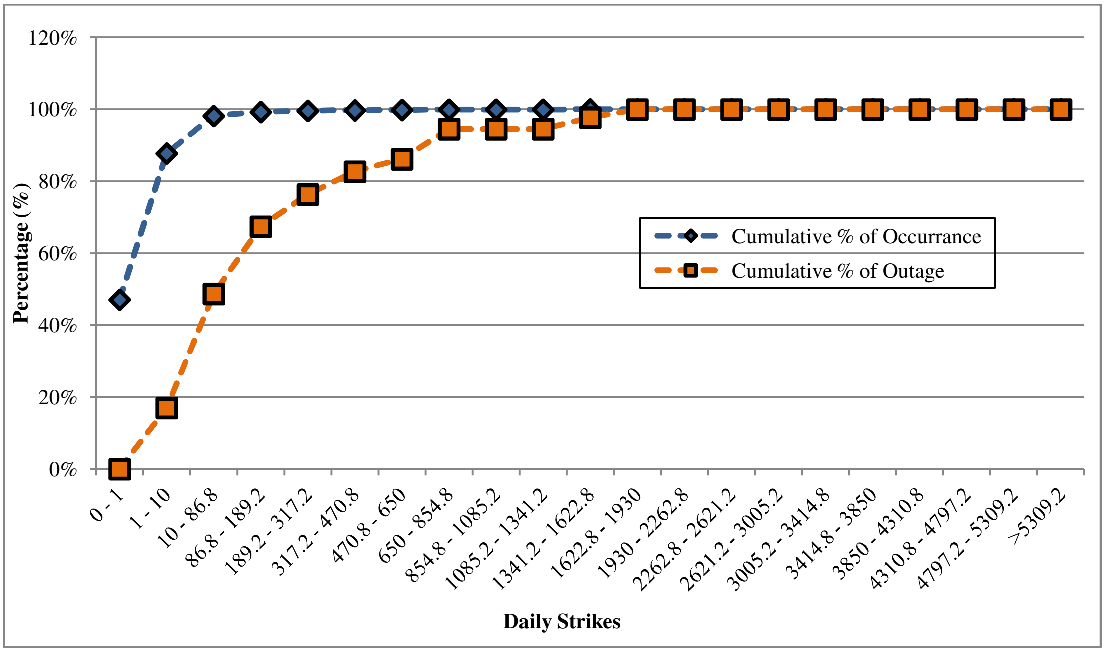


Figure 5-28 - Cumulative Distribution Function for Lightning-Related Outages and Daily Lightning Strikes, North Scotland

5.4.2 Lightning Strike Correlation Analysis

Figure 5-29 and Figure 5-30 show the scatter plots of daily lightning strikes against frequency of ‘Lightning’ outages and log daily lightning strikes against log frequency of ‘Lightning’ outages.

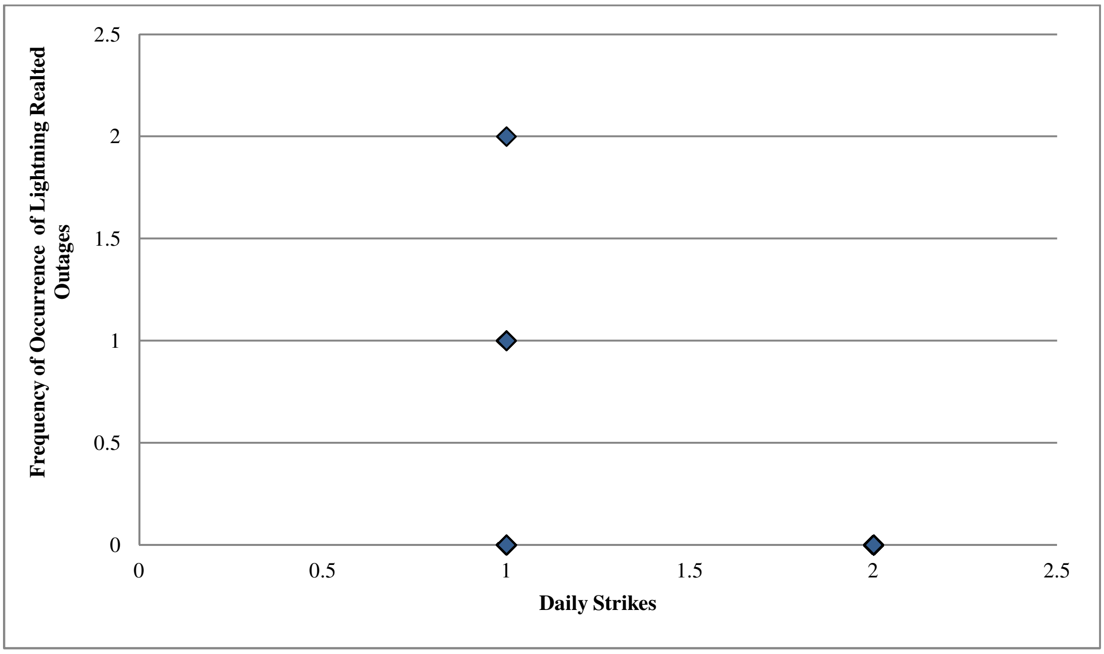


Figure 5-29 - Relationship between Lightning-Related Outages and Daily Lightning Strikes

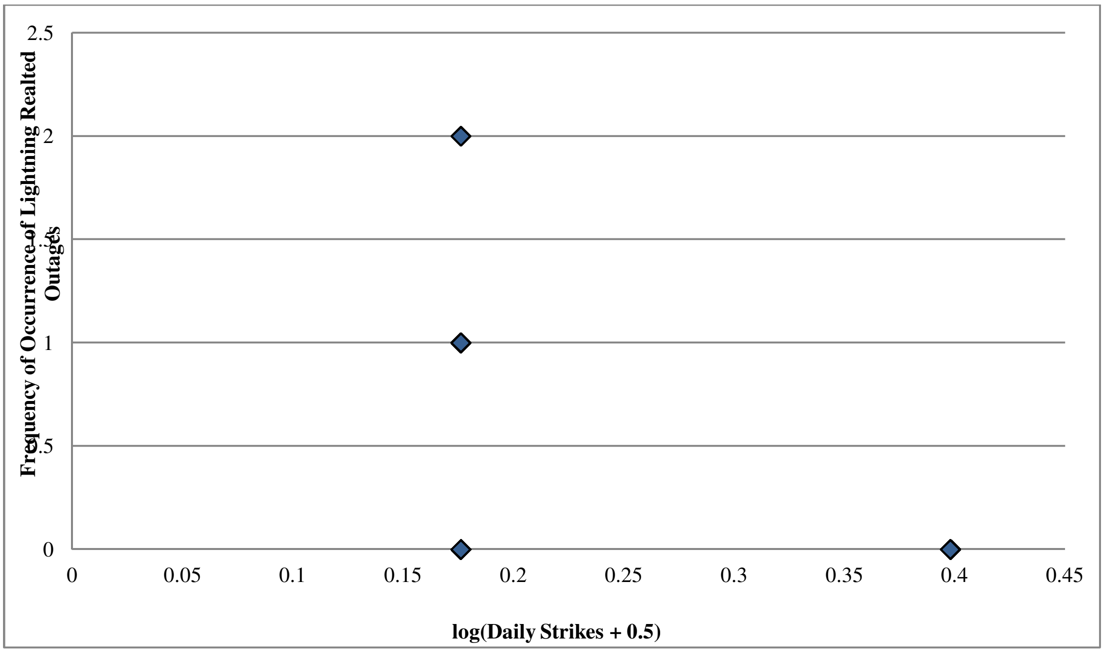


Figure 5-30 - Log Relationship between Lightning-Related Outages and Daily Lightning Strikes

From Figure 5-29 the relationship is difficult to see but when transformed the relationship is clearer: as the number of strikes increases as does the frequency of a ‘Lightning’ outage. A relationship is seen when plotted, but due to the complexity of the relationship, plus high numbers of strikes where no outages occur the R^2 is unable to be reliably determined.

5.4.3 CAPE Frequency Distributions and Cumulative Frequency Distributions

Figure 5-31 and Figure 5-32 show the frequency distribution and cumulative frequency distributions. From Figure 5-31, 60% of recorded values of CAPE occur in the lowest bin but Figure 5-32 shows that only 11% of ‘Lightning’ outages occur, meaning that 89% of ‘Lightning’ outages occur at CAPE values above this, suggesting that high values of CAPE are an indicator for ‘Lightning’ outages. The cumulative frequency distributions are shown in Figure 5-33 and show that in the top 40% of CAPE values, 89% of ‘Lightning’ outages occur and in the top 1% of CAPE values, 27% of outages occur.

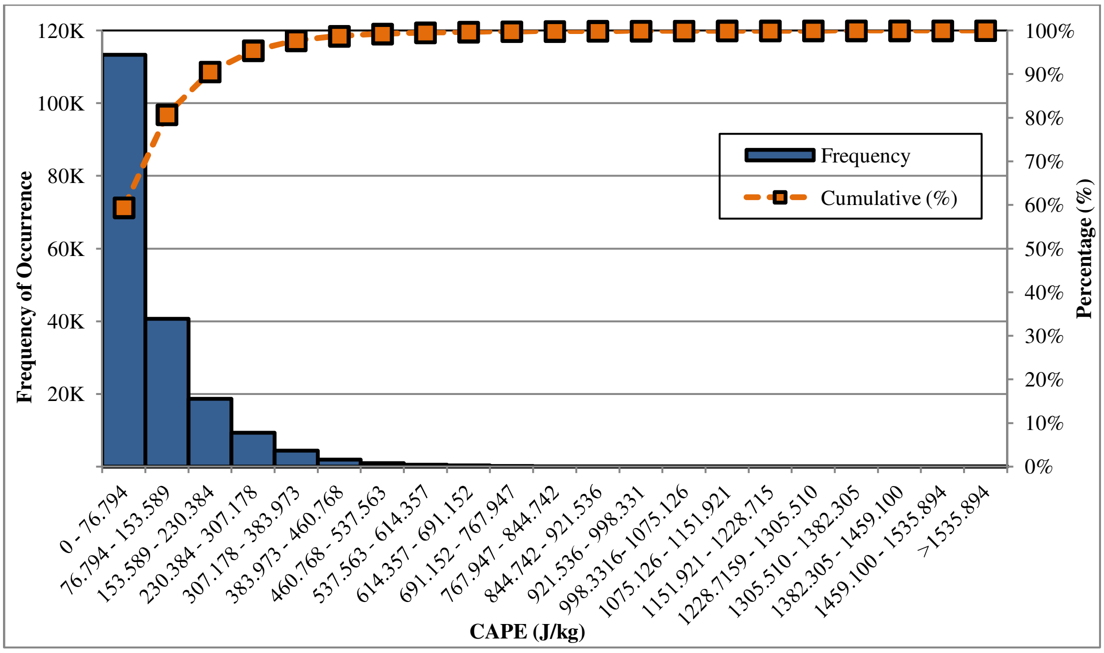


Figure 5-31 - Frequency Distribution and Cumulative Frequency Distribution for CAPE Occurrences, North Scotland

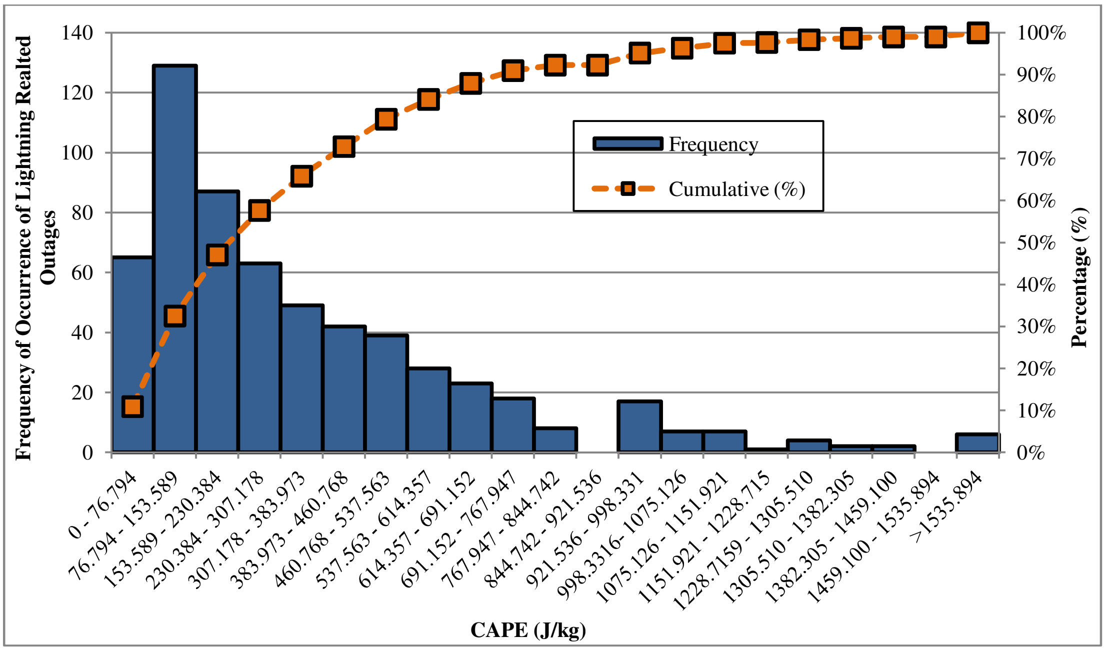


Figure 5-32 - CAPE Frequency Distribution and Cumulative Frequency Distribution for Lightning-Related Outages, North Scotland

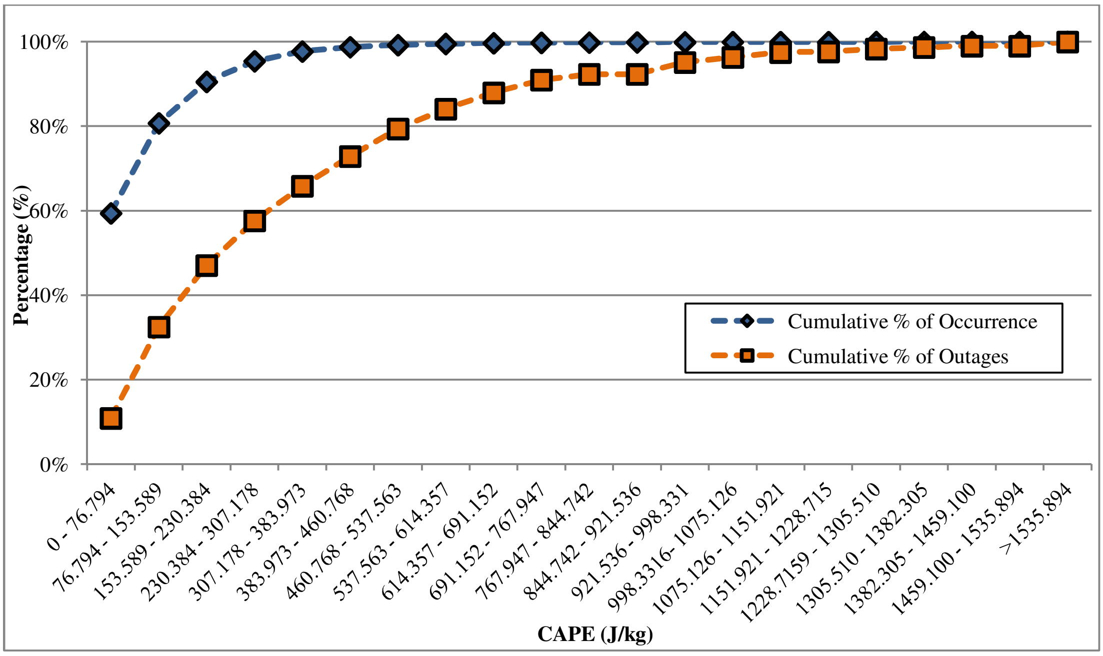


Figure 5-33 - Cumulative Distribution Function for Lightning-Related Outages and CAPE (J/kg) Occurrences, North Scotland

5.4.4 CAPE Correlation Analysis

The scatter plot of CAPE against frequency of 'Lightning' outages is shown in Figure 5-34.

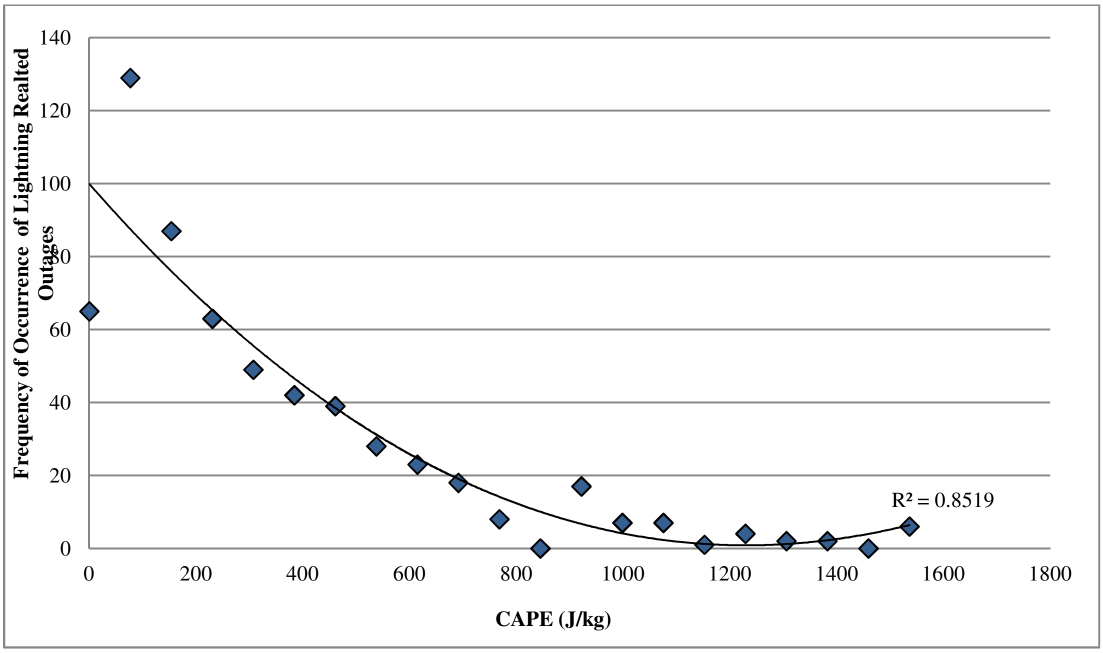


Figure 5-34 - Relationship between Lightning-Related Outages and CAPE (J/kg), North Scotland

Figure 5-34 displays a R^2 value of 0.85 indicating a variation of 85% in 'Lightning' outages is caused by variation in CAPE. It is clear that there an upwards trend towards the higher values of CAPE, this could be contributed to values of CAPE not occurring and therefore no outages have occurred at these values. Figure 5-34 indicates that CAPE is a good indicator for ‘Lightning’ outages. Due to the difficultly in predicting lightning strikes in climate projections it is sensible to use a proxy as a method of analysing the effects of changes in lighting will have on the system. As discussed earlier, CAPE is a good indicator of lightning strikes and is also a good indicator of ‘Lightning’ outages, and therefore CAPE will be used as the indicator for ‘Lightning’ outages for the duration.

5.5 Summary

This chapter has presented Stage Two of the methodology applied to the GB test case. This chapter presented detailed correlation analysis between different weather variables and the frequency of occurrence of outages of different classes to build and define quantifiable relationships. For each outage class different weather variables were tested to determine which provided the highest correlation with outages. Using the information found in Stage One it was possible to determine the three main weather variables that cause the most outages on the GB transmission network: “Lightning”, “Wind, Gales and Windborne Objects”, and “SSB & Ice”. ‘Wind, Gales and Windborne Objects’ outages were found to be highly correlated with wind gusts, indicating a strong relationship between the outage class and that weather variable. Hence, the magnitude of wind gusts will be used as an indicator of likelihood of occurrence of ‘Wind, Gales and Windborne Objects’ outages in the next stage of the methodology. While lightning strikes are correlated with ‘Lightning’ outages, there is difficulty in projecting lightning strikes for future weather and therefore CAPE, which is also highly correlated with the frequency of occurrence of lightning-related outages, will be used as the indicator for them. Finally ‘SSB & Ice’ outages were tested against many different weather variables but due to the complex nature of snow as it can lie for many days after a snow event, a more complex relationship was required to provide a high correlation. The best indicator of ‘SSB & Ice’ outages was determined to be wind gusts on snow days and this will be used for further analysis of ‘SSB & Ice’ outages. The relationships that have been developed within this stage will be used in the following stage. This chapter met research aim five that was described in Section 1.6 to develop a correlation analysis between different weather variables and weather-related outages and identify the most useful weather behaviour indicator for the associated outage.

Chapter 6 - Quantification of Weather Dependent Fragility Curves

This chapter aims to fulfil research aim six that was discussed in Section 1.6 by applying Stage Three of the proposed methodology to the GB test case. Chapter 4 - described analysis of the weather that affects the GB network and Chapter 5 - has shown the defining weather variables for a weather-related outage. Using the information developed it is now possible to develop fragility curves or conditional probabilities for failures of the dominant weather-related outages, as discussed in Section 1.3, this chapter details the process involved. This chapter will conclude with basic probabilities calculations, which will be the probability of a failure occurring which is not dependent on a specific weather, for non-weather and ‘Other Weather’ outages to allow for the full picture of modelling outages on the GB transmission network to be considered.

6.1 Data Refinement

To understand the effects that climate change will have on security and reliability of the transmission system, it is necessary to develop conditional probabilities of weather-related outages. This will allow changes in weather to be postulated and probabilities of failure to be determined. To do this Bayes’ Theorem (Equation 2-4) is used as shown in Equation 6-1 to calculate the conditional probability of failure for the top three weather-related outages given certain weather states:

$$P(O|W) = \frac{P(W|O) \times P(O)}{P(W)} \tag{6-1}$$

where

- P(O|W) is the probability of a weather-related outage occurring based on a weather value within the bin occurring.
- P(W) is the probability of a weather value in each bin occurring based on historical records.
- P(W|O) is the total number of outage occurrences in each bin divided by the total number of occurrences over all bins

- P(O) is the probability of a weather-related outage occurring including misclassified weather-related outages.

When calculating P(O) it is necessary to take into account the number of weather-related outages that occur that were classified as a weather-related outage but do not have an exact cause or non-weather-related outages that were triggered by weather, i.e. the outages that were misreported. As discussed in Section 4.2.2, there are a proportion of outages that are classed as weather-related but the exact weather cause is unknown. These 'Blanks and Unknowns' weather-related outages were split between the other four weather-related outage categories by the ratio that already exists within the historical outage data per area. These historical ratios can be seen in Table 6-1.

Table 6-1 - Historical Outage Ratios per Area

	Area A	**Area B**	**Area C**	**Area D**
Lightning	28.17%	22.00%	40.63%	64.97%
SSB & Ice	32.89%	26.91%	20.03%	6.41%
Wind, Gales & Windborne Objects	33.46%	37.20%	28.27%	12.55%
Other Weather Types	5.47%	13.88%	11.08%	16.08%

However, unlike the weather-related outages caused by 'Lightning', 'SSB & Ice', and 'Wind, Gales and Windborne Objects', 'Other Weather' and non-weather related outages are not dependent on a specific, quantified weather variable therefore, conditional probabilities cannot be developed for these. Nonetheless they do cause a number of outages on the system and to fully understand the effects of weather they must be taken into account. To do this a basic probability will be calculated, the probability of an 'Other Weather' and non-weather related outage occurring, independent of what weather is occurring. The next two sections will discuss conditional probabilities for each area for the top weather types and the probability of failure for 'Other Weather' and non-weather related outages.

6.2 Conditional Outage Probability Calculations

6.2.1 Wind, Gale and Windborne Objects-Related Outages

As discussed in Section 5.1, each weather-related outage was assigned an exact weather value based on where and when it occurred. This was done using the latitude and longitude of the outage and the weather in the grid square it was occurring (Figure 4-1). The reanalysis data gives one weather occurrence for each grid square which represents the maximum value in that square in a given 3-hour period. Weather statistics were assembled for each area as discussed and presented in Section 5.2. Using Bayes' Theorem, the probability of a weather-related outage occurring can be calculated using the above information. For example, in respect of wind-related outages, the probability of a 'Wind, Gales and Windborne Objects' outage occurring based on the wind gust occurring is calculated per area using:

$$P(O|W_{Wind}) = \frac{P(W_{Wind}|O) \times P(O)}{P(W_{Wind})} \qquad \textbf{6-2}$$

where:

- $P(O|W_{Wind})$ is the probability of a wind-related outage occurring given the occurrence of a wind gust value within a particular bin, this is also known as the posterior distribution.
- $P(O)$is the probability of a wind-related outage occurring, including misclassified weather-related outages, no matter what the weather value is. This is calculated by taking the total number of wind-related outages, including unknowns which were re-sampled as being attributable to wind, and dividing it by the total number of weather occurrences within the area. The unknowns are split by the ratio that currently exists within the data so they are not double or triple counted.
- $P(W_{Wind}|O)$ is, based on historical data, the probability of the wind gust value being in the particular bin when a wind-related outage occurs. This is calculated by dividing the total number of occurrences of wind-related outages that occurred when the wind metric was within a particular bin for the area in question, by the total number of outage occurrences over every bin in the area.
- $P(W_{Wind})$ is the probability of a wind gust value in each bin occurring based on historical records. This is calculated by dividing the total occurrences within a particular bin for each area divided by the total number of occurrences over every bin in the full area.

In other words P(an outage occurring in each area, given a certain wind gust in the area) = P(summed wind outages per bin per area divided the total number of wind outage per area) times P(probability of a wind-related outage) all divided by P(summed wind value per bin per area divided the total number of wind values per area). In order to relate the probability of an outage occurring given a certain wind gust to the number of circuit km of overhead line in an area, the P(O| W_{wind}) values for each area are divided by the number of circuit km in each area and multiplied by 100 to give values per 100km of OHL as shown in Equation 6-3. The circuit lengths of transmission system OHL and cables within each of the areas were found using Appendix B of the 2012 Seven Year Statement by National Grid [209] and are shown in Table 6-2.

$$\begin{matrix} Probability\ (\%) of\ Failure\ due\ to\ Wind \\ Gusts\ per\ Area, per\ 100km, per\ Hour \end{matrix} = \left(\frac{\frac{P(W_{Wind}|O) \times P(O)}{P(W_{Wind})}}{Area\ Circuit\ km} \right) x\ 100 \qquad \textbf{6-3}$$

Table 6-2 - Line Lengths per Area

Area	Length (km)
North Scotland	4905.91
South Scotland	3826.46
North England and North Wales	5462.28
South England and South Wales	8711.44

The wind gust values used are continuous as it is assumed that weather conditions in each of the three hours covered by a reanalysis time slice are the same so the same wind gust value can be taken to occur in each of the three hours. Where it is assumed that every grid square in an area has the same wind gust distribution and every 100km of line in an area has the same likelihood of experiencing an outage. The probabilities of ‘Wind, Gales and Windborne Objects’ outage occurring per area, per 100km, per hour are displayed in Table 6-3. It is evident that at lower wind gusts there is a very low probability of a ‘Wind, Gales and Windborne Objects’ outage occurring, whereas at higher values of wind gusts there is a much higher probability of an outage. It is clear that South England and South Wales has a much lower probability of a ‘Wind, Gales and Windborne Objects’ outage occurring, but both South Scotland and North England and North Wales have almost 100% observed probability of failure if wind gusts occur above 33.25m/s. These results from Table 6-3 are also displayed in Figure 6-1. The chart suggests that a given high wind gust is more likely to cause a wind outage in South Scotland and North England and North Wales than it would in the other regions. This could be attributed to most of the population in North Scotland being mainly 132kV with some 275kV whereas both South Scotland and North England and North Wales are mainly 400kV and 275kV.

Table 6-3 - Probability (%) of Failure due to Wind Gusts per Area, per 100km, per Hour

Wind Gusts (m/s)	North Scotland	South Scotland	North England and North Wales	South England and South Wales
0 -1.75	0	0	0	0
1.75 -3.5	0	1.35E-06	4.8E-07	1.91969E-07
3.5 -5.25	5.24E-07	2.61E-06	6.11E-07	7.41314E-08
5.25 -7	7.44E-07	7.83E-07	3.68E-07	1.33037E-07
7 -8.75	5.17E-07	4.99E-07	3.49E-07	1.24764E-07
8.75 -10.5	8.44E-07	1.52E-06	0	1.2946E-07
10.5 -12.25	1.49E-06	4.18E-06	8.13E-07	3.02972E-07
12.25 -14	2.61E-07	2.03E-06	7.65E-07	3.89969E-07
14 -15.75	8.18E-07	2.25E-06	1.3E-05	5.4969E-07
15.75 -17.5	1.53E-06	1.98E-06	4.75E-06	1.03389E-06
17.5 -19.25	8.93E-06	8.96E-06	3.31E-06	1.36024E-06
19.25 -21	2.03E-05	3.33E-05	5.74E-06	1.75351E-06
21 -22.75	4.19E-05	8.75E-05	8.29E-06	6.76894E-06
22.75 -24.5	6.92E-05	0.000241	3.55E-05	3.60254E-05
24.5 -26.25	7.52E-05	0.000368	0.000207	5.28636E-05
26.25 -28	0.000331	0.000674	0.000362	0.00010547
28 -29.75	0.000615	0.002402	0.000473	0.000345195
29.75 -31.5	0.001347	0.003039	0.007145	0.0002611
31.5 -33.25	0.002909	0.004259	0.006703	0.000300265
33.25 -35	0.004562	0.028746	0.034474	0.001066731
>35	0.008344	0.067929	0.075842	0.000614178

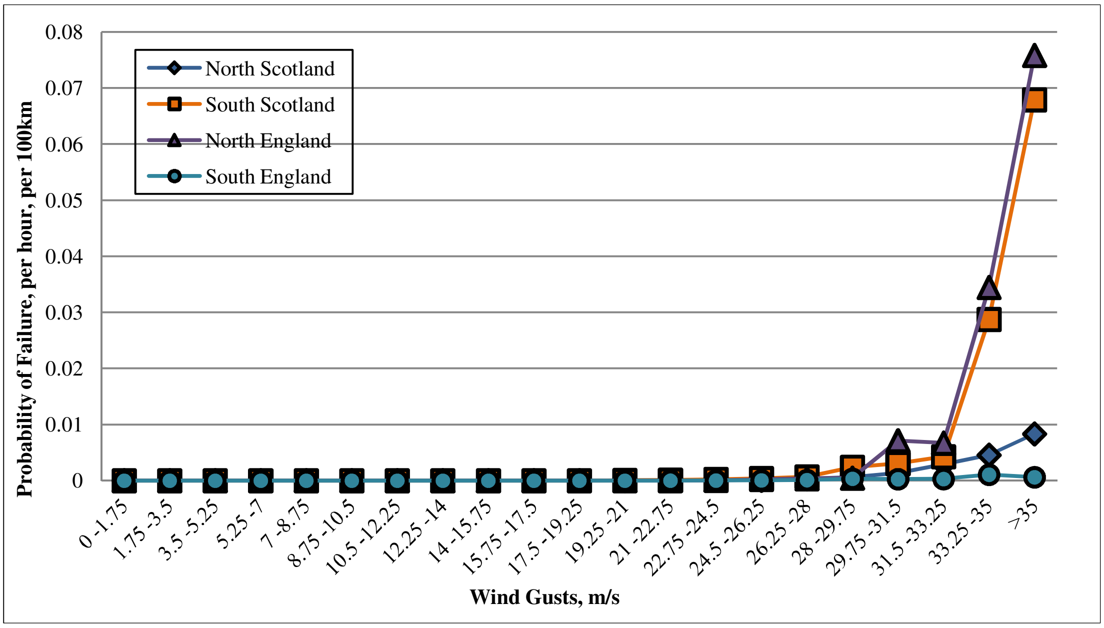


Figure 6-1 - Probability of Failure due to Wind Gusts per Area, per 100km, per Hour

6.2.2 Snow, Sleet, Blizzard and Ice-Related Outages

The same method was used for snow-related outages to assign a weather value to a snow-related outage. Bayes' Theorem is then used in the same manner to calculate the probability of a 'SSB & Ice' outage occurring based on the wind gust on snow days occurring as shown in Equation 6-4:

$$P(O|W_{WindOnSD}) = \frac{P(W_{WindOnSD}|O) \times P(O)}{P(W_{WindOnSD})} \tag{6-4}$$

where:

- $P(O|W_{WindOnSD})$ is the probability of a snow-related outage occurring given the occurrence of a wind gust value on a snow day within a particular bin, this is also known as the posterior distribution.
- $P(O)$is the probability of a snow-related outage occurring, including misclassified weather-related outages, no matter what the weather value is. This is calculated by taking the total number of snow-related outages, including unknowns which were re-sampled as being attributable to wind on snow days, and dividing it by the total number of weather occurrences within the area. The unknowns are split by the ratio that currently exists within the data so they are not double or triple counted.
- $P(W_{WindOnSD}|O)$ is, based on historical data, the probability of the wind gust on a snow day value being in the particular bin when a snow-related outage occurs. This is calculated by dividing the total number of occurrences of snow-related outages that occurred when the wind on a snow day metric was within a particular bin for the area, by the total number of outage occurrences over every bin in the area.
- $P(W_{WindOnSD})$ is the probability of a wind gust value on a snow day in each bin occurring based on historical records. This is calculated by dividing the total occurrences within a particular bin for each area divided by the total number of occurrences over every bin in the full area.

Therefore, P(an outage occurring in each area, given a certain wind gust on a snow day in the area) = P(summed snow outages per bin per area divided the total number of snow outage per area) times P(probability of a snow-related outage) all divided by P(summed wind value on a snow day per bin per area divided the total number of wind gust values on snow days per area). To relate the probability of an outage occurring given a certain wind gust on a snow day to the number of circuit km in an area, the P(O| W_{WindOnSD}) values for each area are divided by the number of circuit km in each area and multiplied by 100 giving the values per

100km per hour as shown in Equation 6-5. The circuit lengths are shown in Table 6-2. The probabilities of ‘SSB & Ice’ outages occurring per area, per 100km, per hour are displayed in Table 6-4. It is evident at the middle to higher wind gusts values North and South Scotland are more likely to have a failure compared to North and South England and South Wales, where the probability of failure is very much lower, though North England and North Wales has a higher probability of failure at higher wind gust values. These results are also displayed in Figure 6-2. This clearly shows that South England and South Wales has very low probability of failure, with North Scotland and North England and North Wales being the most affected at the highest wind gust values and South Scotland is the most affected during the middle to high wind gust values. This indicates that each area is vulnerable under different conditions, which could be contributed to different tower heights, and different geography of the land in the three areas.

$$\begin{matrix} Probability\ (\%) of\ Failure\ due\ to\ Wind\ Gusts \\ on\ Snow\ Days\ per\ Area, per\ 100km, per\ Hour \end{matrix} = \left(\frac{\frac{P(W_{WindOnSD}|O) \times P(O)}{P(W_{WindOnSD})}}{Area\ Circuit\ km} \right) x\ 100 \qquad \textbf{6-5}$$

Table 6-4 - Probability (%) of Failure due to Wind Gusts on Snow Day per Area, per 100km, per Hour

Wind Gusts (m/s)	North Scotland	South Scotland	North England and North Wales	South England and South Wales
0 -1.75	0	0	0	0
1.75 -3.5	0	3.11E-06	0	0
3.5 -5.25	3.16E-06	5.36E-06	0	0
5.25 -7	4.6E-06	1.6E-05	3.85E-05	0
7 -8.75	4.2E-06	1.01E-05	1.7E-05	0
8.75 -10.5	1.78E-05	1.34E-05	7.12E-06	0
10.5 -12.25	2.42E-05	7.26E-06	7.61E-06	0
12.25 -14	1.01E-05	9.01E-06	2.94E-05	2.33E-05
14 -15.75	1.63E-05	1.32E-05	8.79E-06	1.1E-05
15.75 -17.5	3.39E-05	3.83E-05	9.39E-05	0
17.5 -19.25	7.32E-05	7.94E-05	2.23E-05	2.74E-05
19.25 -21	7.18E-05	0.000115	9.91E-05	2.52E-05
21 -22.75	0.000108	0.000381	5.62E-05	0.000151
22.75 -24.5	0.000148	0.000901	5.48E-05	0
24.5 -26.25	0.000196	0.000496	0.000795	9.92E-05
26.25 -28	0.000198	0.000278	0	0
28 -29.75	0.000375	0	0.001335	0
29.75 -31.5	0.000328	0	0	0
31.5 -33.25	8.11E-05	0	0	0
33.25 -35	0.001369	0	0	0
35<	0	0	0	0

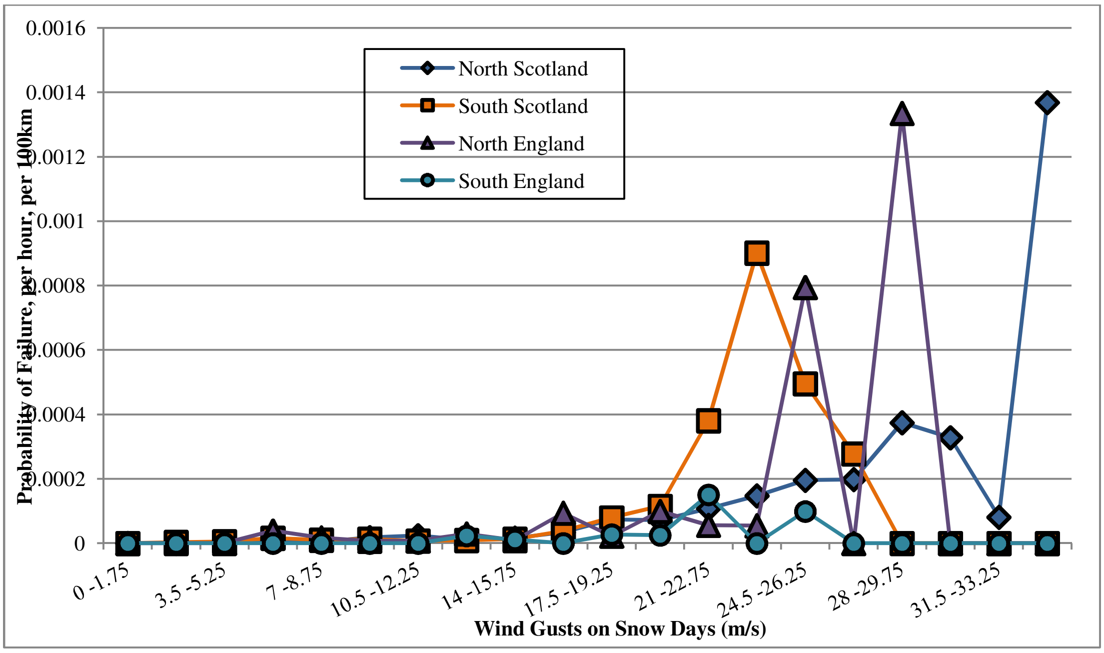


Figure 6-2 - Probability of Failure due to Wind Gusts per Area, per 100km, per Hour

6.2.3 Lightning-Related Outages

The same method that was used previously for both snow-related outages and wind-related outages was applied to lightning-related outages, as discussed in Section 6.2.1**,** to assign a weather value to a lightning-related outage. Bayes' Theorem is then used in the same manner to calculate the probability of a 'Lightning' outage occurring based on the CAPE occurring as shown in Equation 6-6:

$$P(O|W_{CAPE}) = \frac{P(W_{CAPE}|O) \times P(O)}{P(W_{CAPE})} \tag{6-6}$$

where:

- $P(O|W_{CAPE})$ is the probability of a lightning-related outage occurring given the occurrence of a CAPE value within a particular bin, this is also known as the posterior distribution.
- $P(O)$is the probability of a lightning-related outage occurring, including misclassified weather-related outages, no matter what the weather value is. This is calculated by taking the total number of lightning-related outages, including unknowns which were re-sampled as being attributable to CAPE, and dividing it by the total number of weather occurrences within the area. The unknowns are split by the ratio that currently exists within the data so they are not double or triple counted.

- $P(W_{CAPE}|O)$ is, based on historical data, the probability of the CAPE value being in the particular bin when a lightning-related outage occurs. This is calculated by dividing the total number of occurrences of lightning-related outages that occurred when the CAPE metric was within a particular bin for the area in question, by the total number of outage occurrences over every bin in the area.
- $P(W_{CAPE})$ is the probability of a CAPE value in each bin occurring based on historical records. This is calculated by dividing the total occurrences within a particular bin for each area divided by the total number of occurrences over every bin in the full area.

In other words P(an outage occurring in each area, given a certain CAPE value in the area) = P(summed lightning outages per bin per area divided the total number of lightning outage per area) times P(probability of a lightning-related outage) all divided by P(summed CAPE value per bin per area divided the total number of CAPE values per area). To relate the probability of an outage occurring given a certain CAPE value to the circuit km of overhead line in an area, the $P(O|W_{CAPE})$ values for each area are divided by the number of circuit km in each area and multiplied by 100 to give values per 100km as shown in Equation 6-5. The circuit lengths are shown in Table 6-2. The probability of a 'Lightning' outages occurring per area, per 100km, per hour are displayed in Table 6-5. This emphasises that North Scotland and South England and South Wales transmission networks are more susceptible to 'Lightning' outages at higher values of CAPE. These results are also displayed in Figure 6-3, it shows the vulnerability of South Scotland's network at a very high specific value of CAPE – this value of CAPE occurred once causing multiple faults, showing the data sensitivity to extremes and highlighting that a larger sample size would be beneficial. Apart from this value, North Scotland and South England and South Wales have the highest probability of a 'Lightning' outage occurring.

$$\begin{matrix} Probability\ (\%) of\ Failure\ due\ to\ CAPE \\ per\ Area, per\ 100km, per\ Hour \end{matrix} = \left(\frac{\dfrac{P(W_{CAPE}|O) \times P(O)}{P(W_{CAPE})}}{Area\ Circuit\ km} \right) x\ 100 \qquad \textbf{6-7}$$

Table 6-5 - Probability (%) of Failure due to CAPE per Area, per 100km, per Hour

CAPE (J/kg)	North Scotland	South Scotland	North England and North Wales	South England and South Wales
0 - 76.794	0.0000118	0.0000166	0.0000118	0.0000065
76.794 - 153.589	0.0000651	0.0000458	0.0000545	0.0000372
153.589 - 230.384	0.0000955	0.0001233	0.0001215	0.0000753
230.384 - 307.178	0.0001391	0.0001778	0.0001753	0.0001206
307.178 - 383.973	0.0002303	0.0002993	0.0002988	0.0002744
383.973 - 460.768	0.0004357	0.0002047	0.0005645	0.0001633
460.768 - 537.563	0.0008478	0.0009993	0.0006733	0.0004841
537.563 - 614.357	0.0010820	0.0010447	0.0007041	0.0002051
614.357 - 691.152	0.0014888	0.0021949	0.0013588	0.0007056
691.152 - 767.947	0.0019238	0.0035708	0.0011418	0.0004679
767.947 - 844.742	0.0014924	0.0016614	0.0021124	0.0006434
844.742 - 921.536	0.0000000	0.0031273	0.0021430	0.0003350
921.536 - 998.331	0.0054507	0.0016614	0.0004062	0.0014761
998.3316- 1075.126	0.0034200	0.0048332	0.0015457	0.0008552
1075.126 - 1151.921	0.0042247	0.0000000	0.0023471	0.0017779
1151.921 - 1228.715	0.0009327	0.0000000	0.0028165	0.0009008
1228.7159 - 1305.510	0.0048283	0.0000000	0.0019204	0.0010394
1305.510 - 1382.305	0.0025650	0.0000000	0.0000000	0.0024567
1382.305 - 1459.100	0.0029315	0.0000000	0.0000000	0.0019302
1459.100 - 1535.894	0.0000000	0.0000000	0.0000000	0.0045039
1535.894<	0.0064800	0.0531649	0.0000000	0.0023844

From Figure 6-1, Figure 6-2 and Figure 6-3 it is clear that from the top three weather categories that cause failures, ‘Wind, Gales and Windborne Objects’ have the highest probability of occurring, then ‘Lightning’ and finally ‘SSB & Ice’ outages. This makes it possible to analyse future changes to weather and determine what risk these pose to the GB transmission network.

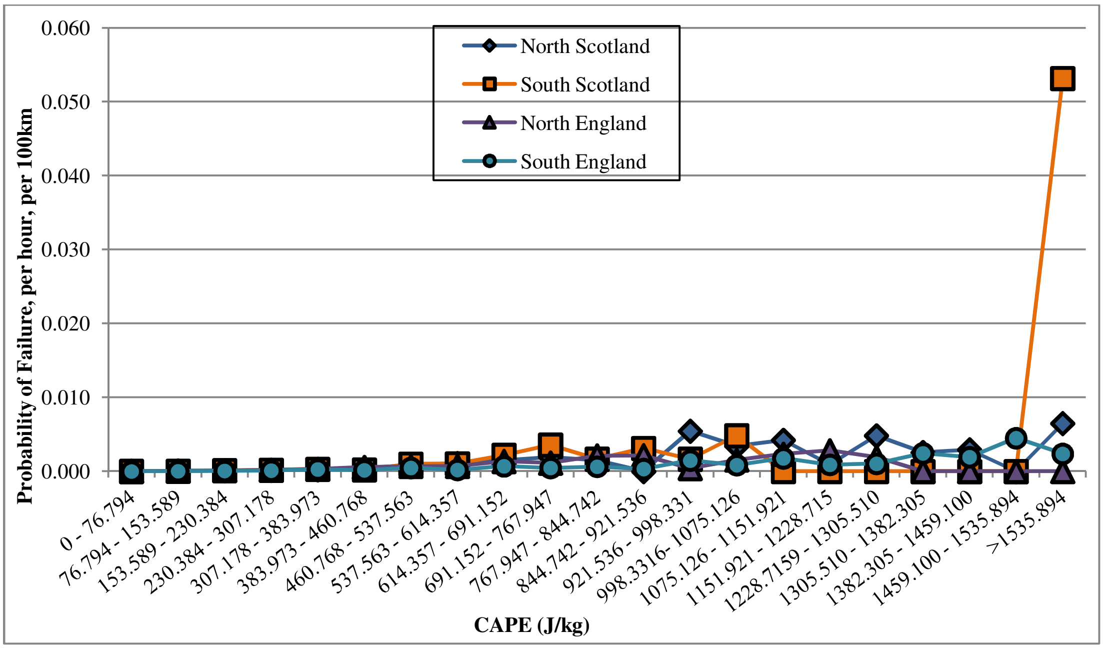


Figure 6-3 - Probability of Failure due to CAPE per Area, per 100km, per Hour

6.3 Outage Probability Calculations

6.3.1 Other Weather Outages

Unlike 'Wind, Gales and Windborne Objects', 'SSB & Ice' and 'Lightning' outages, the 'Other Weather' outage probability can't be determined using Bayes' Theorem, as they are not dependent on specific weather conditions. But to fully understand the effects of weather they must be considered. To do this standard probabilities are developed using the likelihood of an 'Other Weather' outage on any particular day. This required the number of days that the data provided covered, and then the number of outages in each area classed as 'Other Weather' was divided by the number of days, allowing the probability of an 'Other Weather' outage occurring per area, per day. The results are shown in Table 6-6. It is clear to see that South England and South Wales is the worst affected by these 'Other Weather' outages. Again to be able to correctly compare these results they need to be on equal terms, Table 6-7 displays the probability of an 'Other Weather' outages occurring per area, per hour, per 100km. While from Table 6-6 it seems like South England and South Wales is the worst affected, Table 6-7, however, shows this is not the case. Due to having a large transmission network 'Other Weather' outages are spread across more network, meaning that South Scotland is actually the worst affected area and North Scotland is the least. While these numbers are small they are still important in the investigation of transmission system security and reliability.

Table 6-6 - Probability (%) of 'Other Weather' Failure per Area

Area	Probability of an 'Other Weather' Outage per day
North Scotland	1.23%
South Scotland	1.46%
North England and North Wales	1.64%
South England and South Wales	2.63%

Table 6-7 - Probability of 'Other Weather' Failure per Area, per 100km, per Hour

Area	Probability of an 'Other Weather' Outage per hour, per 100km
North Scotland	0.00001047
South Scotland	0.00001588
North England and North Wales	0.00001254
South England and South Wales	0.00001258

6.3.2 Non-Weather-Related Outages

A similar process was undertaken for non-weather-related outages, a standard probability for non-weather-related outages was developed per area per day. Again the number of days that the data is provided for is required; the results are shown in Table 6-8. It is clear that South Scotland and South England and South Wales appear to be the worst affect, with almost double what North Scotland and North England and North Wales experiences. Again to compare these probabilities properly, they must be on a comparable scale, these probabilities are transformed into per area, per 100km, per hour and the results are shown in Table 6-9. It is now clear that South Scotland is the worst affected area with over double the probability of a non-weather-related failure occurring compared to the other areas, with North England and North Wales having the lowest probability. Again these numbers are small but are still an important consideration when modelling the effect of weather-related outages as they cause system disturbances and can affect system reliability before a weather outage occurs.

Table 6-8 - Probability (%) of Non-Weather Failure per Area

Area	Probability of a Non-Weather-Related Outage per day
North Scotland	15.83%
South Scotland	32.33%
North England and North Wales	13.23%
South England and South Wales	30.73%

Table 6-9 - Probability of Non-Weather Failure per Area, per 100km, per Hour

Area	Probability of a Non-Weather Outage per hour, per 100km
North Scotland	0.000134423
South Scotland	0.000352031
North England and North Wales	0.000100884
South England and South Wales	0.000147004

6.4 Summary

This chapter has presented the analysis and the development of fragility curves or conditional probabilities for ‘SSB & Ice’, ‘Lightning’ and ‘Wind, Gales and Windborne Objects’ outages and probabilities for non-weather and ‘Other Weather’ outages. These probabilities were initially developed per area, and then further developed to be per area per 100km per hour, to allow for comparison between areas and for easier modelling at later stages. At higher wind gust values there is a much higher probability of failure for both ‘Wind, Gales and Windborne Objects’ and ‘SSB & Ice’ outages with the two areas in Scotland having the highest probability of failure. For ‘Lightning’ outages at higher values of CAPE there is a higher probability of failure with South Scotland having the highest probability of failure due to the rarest value of CAPE causing multiple outages. South Scotland also has the highest probability of failure due to ‘Other Weather’ outages and non-weather-related outages. This chapter fulfils research aim six that was discussed in Section 1.6 by applying Stage Three of the proposed methodology to the GB test case.

Chapter 7 - Weather & Outage Sampling

This chapter will examine the set up required for the final two stages of the developed methodology applied to the test case. It will discuss the differences between the state and sequential sampling methods and their inputs, as well as an investigation of outage durations, weather extremes and the development of weather test cases using the climate projections. This chapter meets research aims 7, to develop weather test cases, and 8, investigate if a relationship exists between outage duration and weather cause, as presented in Section 1.6. Finally there will be a discussion of the simplified GB network model that will be used to simulate outages and the set up for generation and load profiles.

7.1 Monte Carlo Development

7.1.1 State Sampling Methodology

Figure 7-1 shows the code flow chart for the implementation of the Monte Carlo state sampling model. The majority of 'Wind, Gales and Windborne Objects' and 'SSB & Ice' outages occur during extreme events but these are rare. Therefore, the extreme events ratios, discussed in Section 7.3, are used which could be altered if climate projections suggested there would be an increase. The weather values per area are established for snow, wind and CAPE based on historical values discussed in Chapter 6 -, then using the branch lengths the probability of failure per branch is determined. State sampling does not take into account what occurred in the previous time step. When considering the probability of failure it is necessary to include the longevity of a failure. To do this a new value, P(broken), is created within the state sampling model that considers both the probability of failure and the probability that there has been a failure in previous time steps. Because all the time steps are independent, no information is available about what the weather and the failure rate, P(breaks), was in the past. It is suggested as a point of future work to consider the past values but here it is assumed that P(breaks) is constant in time. Therefore;

$$P(broken) = P(breaks) + P(breaks) * P(fix \geq 1\ hour) + P(breaks) * P(fix \geq 2\ hour) \ldots + P(breaks) * P(fix \geq 10\ hour) \tag{7-1}$$

$$P(broken) = P(breaks) * [1 + P(fix \geq 1\ hour) + P(fix \geq 2\ hour) \ldots + P(fix \geq 10\ hour)] \tag{7-2}$$

Once P(broken) has been determined the MC sampling will determine if the branch is operational or not, thus building up the network. Once this is complete, an OPF can be conducted for every time step. For every run of a case there will be 8760 time steps, where 1 hour is equal to one time-step. 115 trials will take place and thus providing the outputs averaged over 115 years.

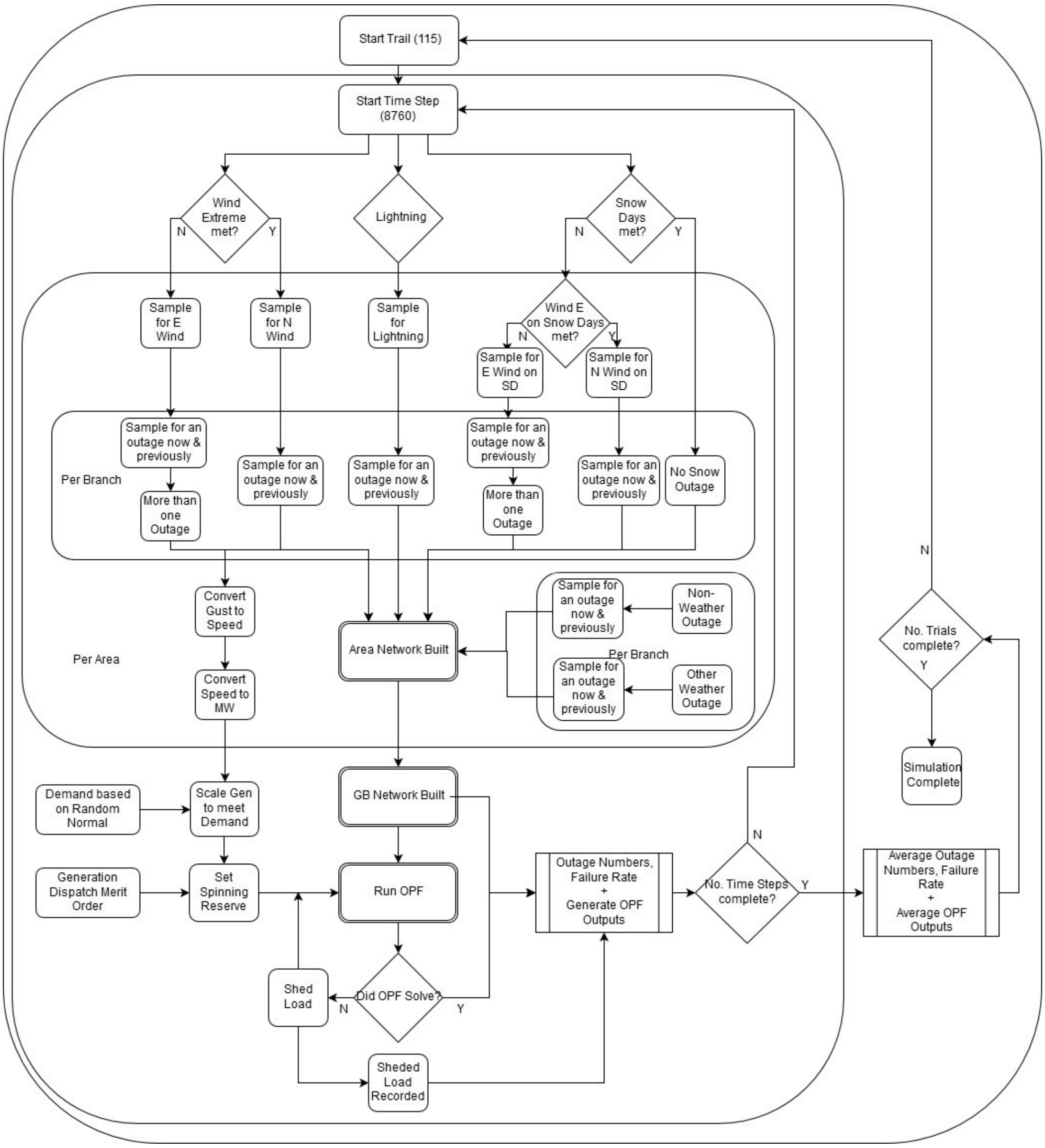


Figure 7-1 - State Sampling Code Flow

7.1.2 Sequential Sampling Methodology

Figure 7-2 shows the code flow chart for the sequential sampling methodology. It is necessary to now consider what the next weather value is based on the previous and also apply durations to not only outages but also to extreme weather events.

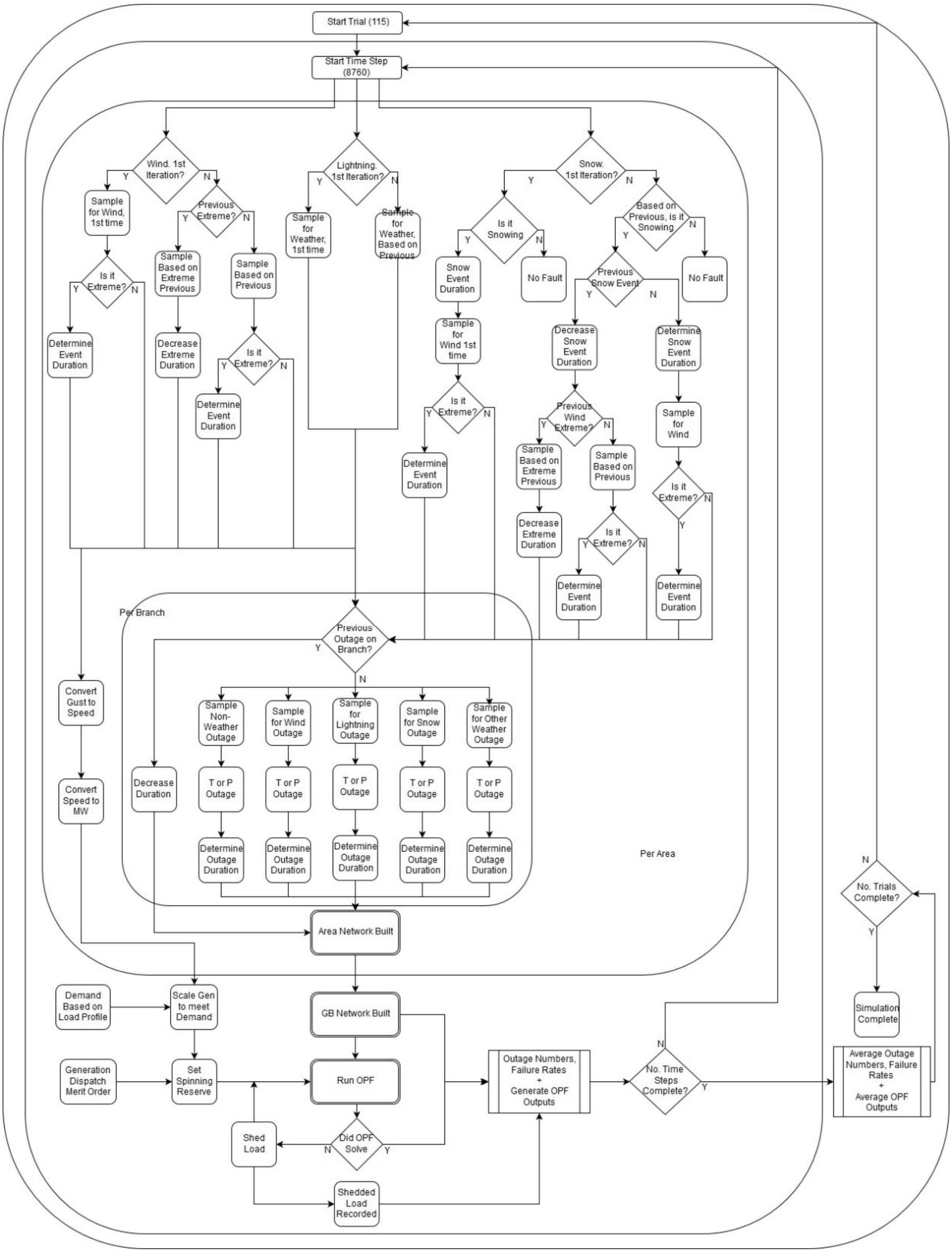


Figure 7-2 - Sequential Sampling Code Flow

The weather is determined per area but after the first iteration the weather value is dependent on the previous value. This was developed using the historical data, by determining if the weather value is X what is the probability of it being Y or Z in the next time step, an example is shown in Table 7-1. This could be further developed to look at more than one previous weather value. The sequential sampling will have 8760 time steps per case and since 8760 time steps are equal to a standard year, the 115 trials to be run will provide the outputs averaged over 115 years.

Table 7-1 – 3.5-5.25m/s Wind Gust Next Value Probability Example

Bins	Probability of Next Value (%)	Cumulative Probability of Next Value (%)
0 -1.75	0.14	0.14
1.75 -3.5	12.86	12.99
3.5 -5.25	53.48	66.48
5.25 -7	26.68	93.16
7 -8.75	5.64	98.80
8.75 -10.5	1.02	99.81
10.5 -12.25	0.15	99.96
12.25 -14	0.02	99.99
14 -15.75	0.01	99.99
15.75 -17.5	0.00	100.00
17.5 -19.25	0.00	100.00
19.25 -21	0.00	100.00
21 -22.75	0.00	100.00
22.75 -24.5	0.00	100.00
24.5 -26.25	0.00	100.00
26.25 -28	0.00	100.00
28 -29.75	0.00	100.00
29.75 -31.5	0.00	100.00
31.5 -33.25	0.00	100.00
33.25 -35	0.00	100.00
35 -More	0.00	100.00

Sequential Sampling Extreme Events Durations

For sequential sampling it is necessary to consider the duration of extreme events for both snow and wind and the duration of weather-related outages. As will be shown in Section 7.2.2 there was no strong correlation between weather values and outage duration. Therefore, to include durations of outages the cumulative frequency distributions were used instead. The results are shown in Table 7-2 to Table 7-6 for ‘Wind, Gales and Windborne Objects’, ‘Lightning’, ‘SSB & Ice’, ‘Other Weather’ and non-weather-related outages respectively.

Table 7-2 – Wind-Related Outages Cumulative Frequency Distribution

Duration (hr)	North Scotland	South Scotland	North England and North Wales	South England and South Wales
0	0.803	0.602	0.069	0.000
1	0.849	0.675	0.335	0.365
2	0.906	0.764	0.697	0.729
4	0.932	0.780	0.814	0.885
6	0.943	0.806	0.851	0.927
8	0.948	0.827	0.878	0.958
10+	1	1	1	1

Table 7-3 – Lightning-Related Outages Cumulative Frequency Distribution

Duration (hr)	North Scotland	South Scotland	North England and North Wales	South England and South Wales
0	0.381	0.379	0.379	0.379
1	0.597	0.677	0.677	0.677
2	0.842	0.831	0.831	0.831
4	0.932	0.895	0.895	0.895
6	0.958	0.911	0.911	0.911
8	0.961	0.911	0.911	0.911
10+	1.000	1.000	1.000	1.000

Table 7-4 – Snow-Related Outages Cumulative Frequency Distribution

Duration (hr)	North Scotland	South Scotland	North England and North Wales	South England and South Wales
0	0.703	0.439	0.439	0.000
1	0.724	0.581	0.581	0.163
2	0.810	0.709	0.709	0.367
4	0.862	0.791	0.791	0.571
6	0.886	0.851	0.851	0.653
8	0.900	0.892	0.892	0.673
10+	1.000	1.000	1.000	1.000

Table 7-5 – Other Weather-Related Outages Cumulative Frequency Distribution

Duration (hr)	North Scotland	South Scotland	North England and North Wales	South England and South Wales
0	0.159	0.082	0.333	0.119
1	0.280	0.230	0.500	0.248
2	0.500	0.434	0.648	0.446
4	0.622	0.541	0.741	0.554
6	0.683	0.648	0.741	0.574
8	0.744	0.713	0.759	0.653
10+	1.000	1.000	1.000	1.000

Table 7-6 – Non-Weather-Related Outages Cumulative Frequency Distribution

Duration (hr)	North Scotland	South Scotland	North England and North Wales	South England and South Wales
0	0.346	0.188	0.051	0.053
1	0.476	0.283	0.095	0.088
2	0.619	0.431	0.171	0.131
4	0.692	0.521	0.202	0.160
6	0.726	0.563	0.255	0.183
8	0.749	0.603	0.283	0.209
10+	1.000	1.000	1.000	1.000

7.2 Outage Duration Relationship Investigation

An issue with studying outages on transmission network is the difficulty to quantify the impact on the system. One possible method considered of quantifying the impact would be to consider a relationship between weather type and duration of weather-related outages by assessing changes in the durations.

7.2.1 Statistical Analysis of Outage Durations

The first step in this process was to analyse the difference in transient and permanent outages per outage type, per area. A transient outage is defined here as an outage with a duration of less than one hour and a permanent outage is one lasting longer than an hour. This definition comes from the data records provided by the transmission companies rather than a standard definition of a transient outage. A statistical analysis of durations per outage type, per area was undertaken. Finally this was then further developed to analyse if specific values of weather types was a factor in durations, for both weather and non-weather-related outages.

Transient and Permanent Ratios

The transient and permanent ratios were analysed for each area for 'Wind, Gales and Windborne Objects', 'Lightning', 'SSB & Ice', 'Other Weather', and non-weather-related outages. The results are shown in Table 7-7, Table 7-8, Table 7-9, Table 7-10, and Table 7-11 respectively. From Table 7-7 it is clear that due to 'Wind, Gales and Windborne Objects' outages, Scotland has a much higher number of transient outages, whereas England and Wales there is a higher ratio of permanent outages. The underlying cause of this could be that there are higher wind gusts in Scotland which leads to more outages, when these occur in England and Wales more damage is caused as the system is not designed to deal with them. The difference in transmission classification for could also contribute to the difference as 132kV outages for England and Wales are not included in this analysis.

Table 7-7 – Wind-Related Outage Ratios between Transient and Permanent

Area	Transient Ratio	Permanent Ratio
North Scotland	0.893	0.107
South Scotland	0.807	0.193
North England and North Wales	0.121	0.879
South England and South Wales	0.000	1.000

Table 7-8 indicates that 'Lightning' outages for all four areas are mostly transient. Most lightning-related outages are caused by strikes hitting OHLs, causing a surge or flash over. Once the protection operates the strike will have passed and the system is restored. The permanent outages will be from strikes that hit more sensitive equipment or that cause broken insulators or dropped lines.

Table 7-8 – Lightning-Related Outage Ratios between Transient and Permanent

Area	Transient Ratio	Permanent Ratio
North Scotland	0.678	0.322
South Scotland	0.670	0.330
North England and North Wales	0.612	0.388
South England and South Wales	0.634	0.366

Table 7-9 shows a similar relationship between transient and permanent outages for 'SSB & Ice' outages that were found for 'Wind, Gales and Windborne Objects'. Scotland experiences more transient outages and England and Wales experiences more permanent outages. This again could be attributed to the differences between transmission system classification between England and Wales and Scotland. It could also be attributed to Scotland experiencing more snow compared to England and Wales and therefore has a high probability of outage due to snow. From Table 7-10 it is clear that for all four areas 'Other Weather' outages tend to cause more permanent outages. This could be due to 'Other Weather' outages containing weather that causes serious damage; flooding, fire and corrosion for example and may require asset replacement. From Table 7-11, as would be expected for non-weather outages there are a higher number of permanent outages. Unlike weather outages, non-weather outages tend to be more serious equipment failures, requiring longer restoration times.

Table 7-9 – Snow-Related Outage Ratios between Transient and Permanent

Area	Transient Ratio	Permanent Ratio
North Scotland	0.877	0.123
South Scotland	0.709	0.291
North England and North Wales	0.248	0.752
South England and South Wales	0.000	1.000

Table 7-10 – Other Weather Outage Ratios between Transient and Permanent

Area	Transient Ratio	Permanent Ratio
North Scotland	0.405	0.595
South Scotland	0.238	0.762
North England and North Wales	0.538	0.462
South England and South Wales	0.276	0.724

Table 7-11 – Non-Weather Outage Ratios between Transient and Permanent

Area	Transient Ratio	Permanent Ratio
North Scotland	0.419	0.581
South Scotland	0.243	0.757
North England and North Wales	0.060	0.940
South England and South Wales	0.054	0.946

An investigation was conducted to see if there was a trend between the weather value and transient and permanent outages. This was done for 'Wind, Gales and Windborne Objects', 'Lightning', and 'SSB & Ice' outages for North Scotland with the results being displayed in Figure 7-3, Figure 7-4, and Figure 7-5. The rest of the results are displayed in Appendix E. Figure 7-3 shows there tends to be transient outages for all wind gust values, as expected as they tend to cause more transient outages and only more serious damage would cause a permanent outage, which is a rarer occurrence. Figure 7-4 indicates that at the highest and lowest values of CAPE transient outages dominate, whereas permanent outages tend to dominate at middle values, suggesting that a relationship may exist, however, at certain values of CAPE there has been no outages, due to no outages or values ever occurring.

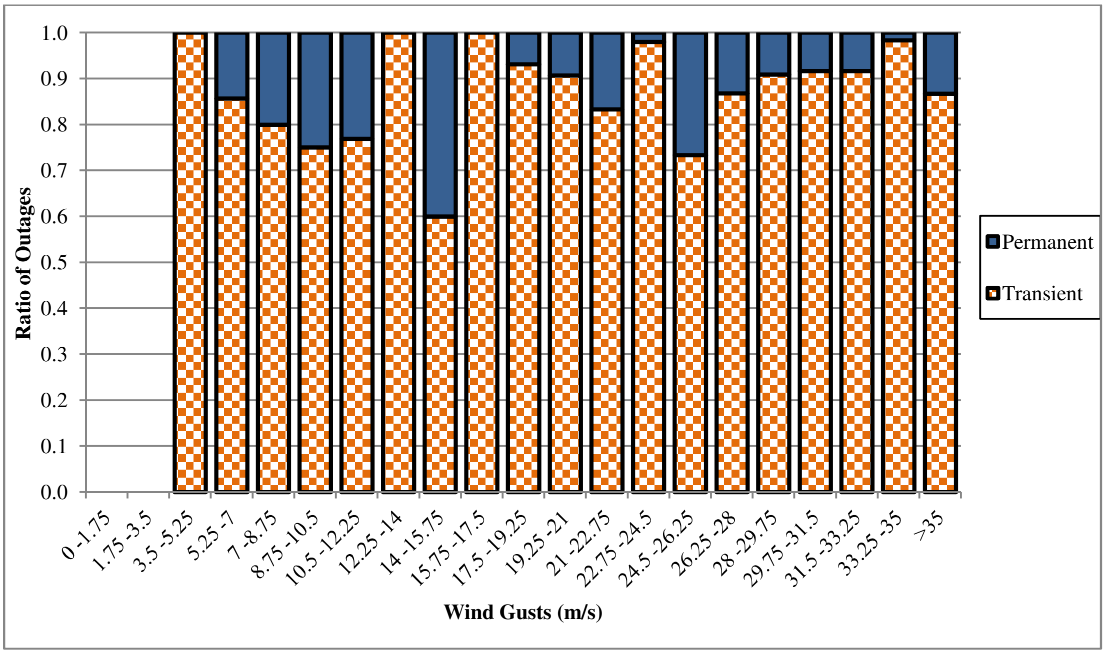


Figure 7-3 – Wind-Related Outage Ratios between Transient and Permanent – North Scotland

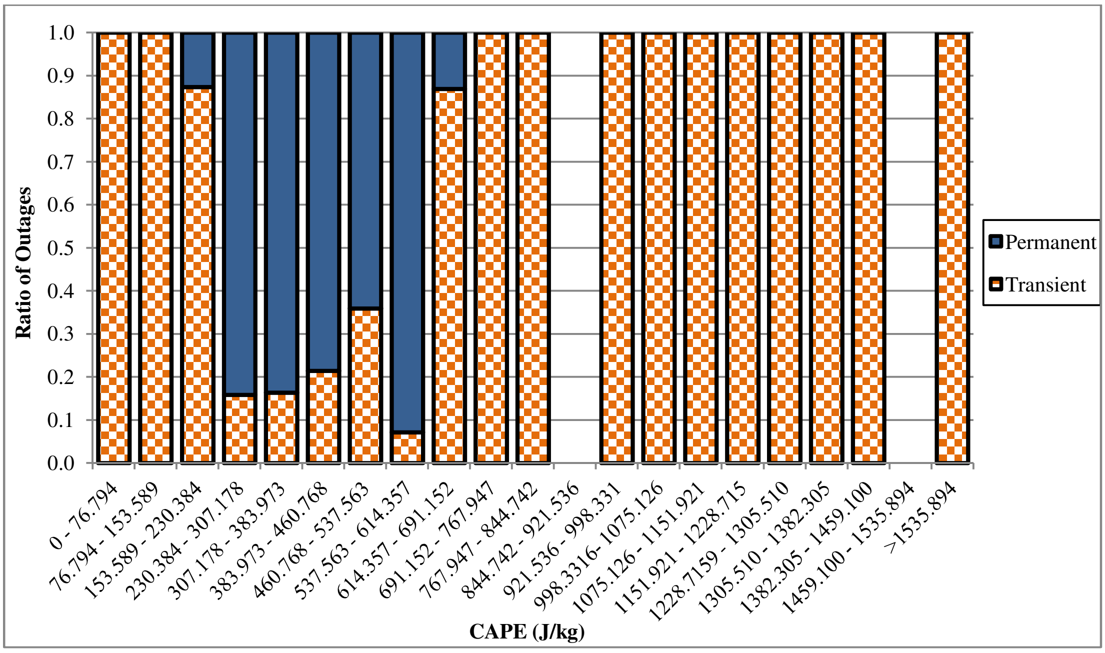


Figure 7-4 – Lightning-Related Outage Ratios between Transient and Permanent – North Scotland

For ‘SSB & Ice’ outages most tend to be transient outages, as shown in Figure 7-5, indicating again that the wind and snow will cause galloping and flashovers which will be restored by protection settings suggesting that no strong relationship exists.

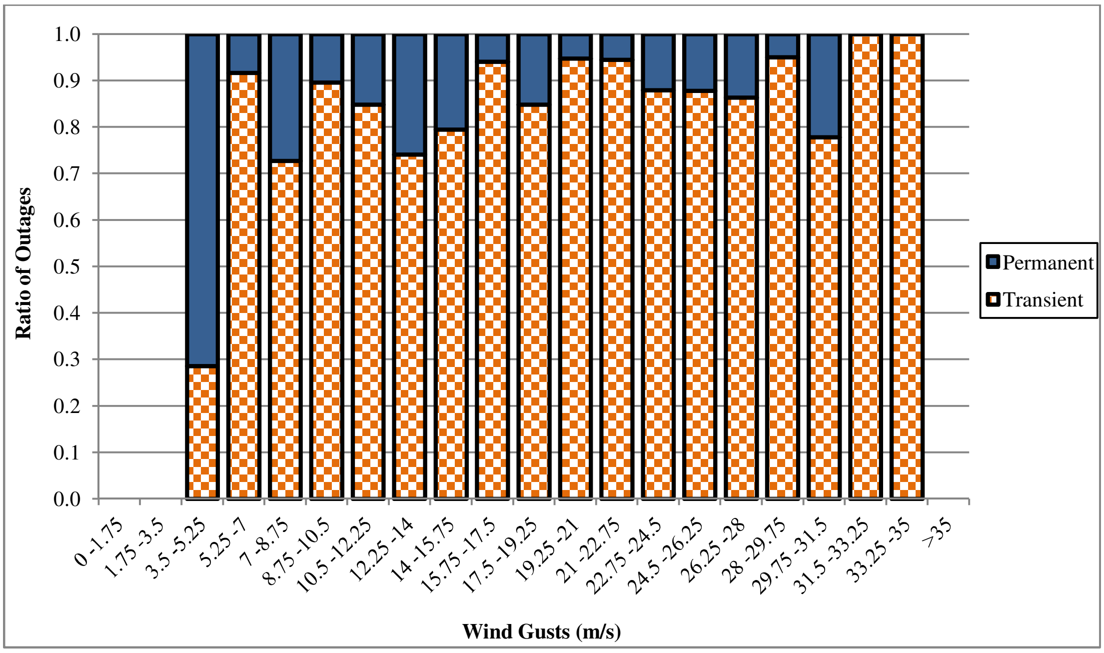


Figure 7-5 – Snow-Related Outage Ratios between Transient and Permanent – North Scotland

Mean and Median Comparison

The next stage analysed the mean and median of outage durations. Mean values and variance are heavily distorted by extreme values and so non-parametric statistics such as quartiles and percentiles can also be informative. Table 7-12, Table 7-14, Table 7-16, Table 7-18 and Table 7-20 show the statistical analysis for weather and non-weather-related transient outages. Table 7-13, Table 7-15, Table 7-17, Table 7-19 and Table 7-21 show the statistical analysis for weather and non-weather-related permanent outages.

Table 7-12 indicates that for transient outages caused by wind there is a small difference between the mean and median for all four areas. This indicates that there tends to be few extreme values to skew the data. Table 7-13 shows that there is a difference between the mean and median values for permanent outages indicating a spread within the data. It is clear that these extreme durations occur more than 5% of the time as there is a large spread between the maximum value, 95th percentile and the upper quartile. It is clear from the maximum duration that these extreme durations can be for a significant amount of time. The only area that is exempt from this pattern is South England and South Wales, where the values are relatively close indicating that not many extreme duration outages occur.

Table 7-12 – Wind-Related Outages Statistical Analysis of Transient Durations (hrs)

Area	North Scotland	South Scotland	North England and North Wales	South England and South Wales
Max	0.95	0.99	0.71	0.00
95th percentile	0.68	0.76	0.21	0.00
Upper Quartile	0.12	0.24	0.24	0.00
Mean	0.12	0.17	0.06	0.00
Median	0.00	0.02	0.00	0.00
Lower quartile	0.00	0.00	0.00	0.00
5th percentile	0.00	0.00	0.00	0.00
Min	0.00	0.00	0.00	0.00

Table 7-13 – Wind-Related Outages Statistical Analysis of Permanent Durations (hrs)

Area	North Scotland	South Scotland	North England and North Wales	South England and South Wales
Max	362.28	219.98	576.00	16.23
95th percentile	100.90	173.68	30.91	8.50
Upper Quartile	10.17	22.07	4.81	4.04
Mean	22.99	31.10	9.95	3.43
Median	3.78	7.68	2.76	2.57
Lower quartile	2.20	2.24	1.85	1.73
5th percentile	1.29	1.27	1.21	1.17
Min	1.00	1.00	1.02	1.09

From Table 7-14 there is small difference between the mean and median for all four areas, indicating that there tends to be no extreme values to skew the data for transient durations.

Table 7-14 – Lightning-Related Outages Statistical Analysis of Transient Durations (hrs)

Area	North Scotland	South Scotland	North England and North Wales	South England and South Wales
Max	0.99	0.99	0.98	1.00
95th percentile	0.84	0.78	0.86	0.85
Upper Quartile	0.36	0.30	0.30	0.43
Mean	0.20	0.19	0.20	0.23
Median	0.02	0.02	0.03	0.07
Lower quartile	0.00	0.00	0.00	0.00
5th percentile	0.00	0.00	0.00	0.00
Min	0.00	0.00	0.00	0.00

From Table 7-15, it is clear that extreme durations exist as there is a spread between the 95th percentile and the maximum value; these extreme values of duration are considerable.

Table 7-15 – Lightning-Related Outages Statistical Analysis of Permanent Durations (hrs)

Area	North Scotland	South Scotland	North England and North Wales	South England and South Wales
Max	1201.50	3808.93	524.85	1872.71
95th percentile	16.14	109.51	17.66	36.17
Upper Quartile	4.02	4.19	4.09	4.45
Mean	14.38	71.56	9.84	21.45
Median	2.56	2.11	2.45	2.73
Lower quartile	1.67	1.51	1.70	1.66
5th percentile	1.12	1.07	1.24	1.14
Min	1.02	1.02	1.07	1.01

Similar results are shown for the transient outages for snow-related outages. However, the permanent outage analysis indicates that North Scotland, South Scotland and North England and North Wales, while they experience extreme durations they are rarer than what South England and South Wales has experienced. This is evident when analysing the 95th percentile and maximum duration which are both high for South England and South Wales, confirming that when snow events do occur the South England and South Wales network is the most vulnerable to extreme durations.

Table 7-16 – Snow-Related Outages Statistical Analysis of Transient Durations (hrs)

Area	North Scotland	South Scotland	North England and North Wales	South England and South Wales
Max	0.97	0.97	0.98	0.00
95th percentile	0.60	0.50	0.46	0.00
Upper Quartile	0.10	0.02	0.02	0.00
Mean	0.10	0.08	0.10	0.00
Median	0.00	0.02	0.02	0.00
Lower quartile	0.00	0.00	0.02	0.00
5th percentile	0.00	0.00	0.02	0.00
Min	0.00	0.00	0.02	0.00

Table 7-17 – Snow-Related Outages Statistical Analysis of Permanent Durations (hrs)

Area	North Scotland	South Scotland	North England and North Wales	South England and South Wales
Max	147.75	128.47	177.05	1210.68
95th percentile	69.60	70.57	21.63	147.48
Upper Quartile	18.91	8.04	5.81	12.98
Mean	17.15	13.18	8.45	46.90
Median	4.90	4.15	3.25	5.02
Lower quartile	2.97	2.12	1.80	2.33
5th percentile	1.84	1.13	1.12	1.57
Min	1.03	1.07	1.03	1.15

The transient analysis for 'Other Weather' shows a similar trend. Whereas, the permanent outages have a much greater spread between mean and median as well as a large gap between the 95th percentile and the maximum values indicating extreme occurrences, as would be expected for the types of weather that are included in this category.

Table 7-18 – Other Weather Outages Statistical Analysis of Transient Durations (hrs)

Area	North Scotland	South Scotland	North England and North Wales	South England and South Wales
Max	0.96	0.95	1.00	0.96
95th percentile	0.93	0.88	0.90	0.84
Upper Quartile	0.55	0.41	0.46	0.54
Mean	0.29	0.26	0.28	0.35
Median	0.13	0.20	0.18	0.42
Lower quartile	0.00	0.00	0.02	0.01
5th percentile	0.00	0.00	0.00	0.00
Min	0.00	0.00	0.00	0.00

Table 7-19 – Other Weather Outages Statistical Analysis of Permanent Durations (hrs)

Area	North Scotland	South Scotland	North England and North Wales	South England and South Wales
Max	145.60	2299.42	782.12	1060.45
95th percentile	104.82	245.46	94.33	187.45
Upper Quartile	12.47	13.15	11.72	23.32
Mean	18.15	67.34	33.57	51.05
Median	5.50	5.96	4.06	6.09
Lower quartile	2.75	2.59	2.02	3.02
5th percentile	1.35	1.22	1.34	1.40
Min	1.01	1.00	1.05	1.12

Table 7-20 for Non-Weather outages indicates that there is not a great spread between the maximum value and the 95th percentile, indicating that there are no extreme values of transient outage durations. Meanwhile, the spread for permanent non-weather-related outages is considerable. For both Scottish areas, the mean is greater than the upper quartile indicating that there a few extreme values skewing the mean.

Table 7-20 – Non-Weather Outages Statistical Analysis of Transient Durations (hrs)

Area	North Scotland	South Scotland	North England and North Wales	South England and South Wales
Max	0.98	1.00	0.96	0.98
95th percentile	0.84	0.87	0.94	0.91
Upper Quartile	0.33	0.50	0.66	0.55
Mean	0.20	0.30	0.35	0.33
Median	0.07	0.23	0.25	0.25
Lower quartile	0.00	0.02	0.00	0.11
5th percentile	0.00	0.00	0.00	0.00
Min	0.00	0.00	0.00	0.00

Table 7-21 – Non-Weather Outages Statistical Analysis of Permanent Durations (hrs)

Area	North Scotland	South Scotland	North England and North Wales	South England and South Wales
Max	5112.00	11059.42	1736.69	2954.80
95th percentile	272.50	525.00	435.82	470.88
Upper Quartile	25.73	46.90	107.38	161.74
Mean	70.96	147.54	99.06	126.19
Median	5.27	9.62	36.73	62.09
Lower quartile	2.42	3.30	10.31	17.88
5th percentile	1.15	1.37	2.06	2.39
Min	1.00	1.00	0.00	1.05

For the final stage of this investigation, the mean and median durations were investigated at specific weather values. Table 7-22, Table 7-23, and Table 7-24 display the results for ‘Wind, Gales and Windborne Objects’, ‘Lightning’ and ‘SSB & Ice’ transient and permanent outages respectively for North Scotland. The results for the other areas can be found in Appendix E. Table 7-22 shows that the transient mean and medians durations are close, though a few do display higher gaps indicating a greater spread of duration values. Whereas the mean permanent outage durations are quite varied from the value of the median for wind outages at higher wind speeds confirming the spread of values that was previously discovered. Overall, for permanent outages at higher wind gusts there are higher values of durations than are seen at the lower values, indicating a possible relationship between wind gusts values and outage durations.

Table 7-22 – Wind-Related Outage Mean and Median Durations – North Scotland (hrs)

Wind Gusts (m/s)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 -1.75	N/A	N/A	N/A	N/A
1.75 -3.5	N/A	N/A	N/A	N/A
3.5 -5.25	0.190	0.145	N/A	N/A
5.25 -7	0.003	0.000	1.574	1.574
7 -8.75	0.000	0.000	9.750	9.750
8.75 -10.5	0.080	0.000	4.656	4.656
10.5 -12.25	0.000	0.000	3.920	3.830
12.25 -14	0.360	0.360	N/A	N/A
14 -15.75	0.123	0.120	6.825	6.825
15.75 -17.5	0.079	0.000	N/A	N/A
17.5 -19.25	0.145	0.020	4.555	4.555
19.25 -21	0.095	0.000	51.732	55.500
21 -22.75	0.011	0.000	7.384	3.730
22.75 -24.5	0.153	0.000	1.500	1.500
24.5 -26.25	0.191	0.094	5.784	3.871
26.25 -28	0.074	0.000	13.049	4.300
28 -29.75	0.080	0.000	5.486	2.657
29.75 -31.5	0.068	0.000	124.600	88.710
31.5 -33.25	0.093	0.000	47.737	3.440
33.25 -35	0.084	0.000	2.450	2.450
>35	0.276	0.087	12.272	3.170

Table 7-23 shows that for lightning-related permanent outages there is a spread of durations at low to medium values of CAPE, indicating some extremes, although no permanent outages have occurred above the value of 691.152J/kg in this area. It is also clear that transient outages do not contain many extreme values as the mean and median values are close at all values of CAPE.

Table 7-23 – Lightning-Related Mean and Median Durations – North Scotland (hrs)

CAPE (J/kg)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 - 76.794	0.260	0.107	N/A	N/A
76.794 - 153.589	0.256	0.144	N/A	N/A
153.589 - 230.384	0.224	0.018	2.967	2.283
230.384 - 307.178	0.260	0.300	18.794	2.486
307.178 - 383.973	0.184	0.185	4.340	2.250
383.973 - 460.768	0.516	0.570	5.466	2.570
460.768 - 537.563	0.344	0.263	2.812	2.437
537.563 - 614.357	0.040	0.040	49.850	2.927
614.357 - 691.152	0.041	0.000	2.452	1.620
691.152 - 767.947	0.017	0.000	N/A	N/A
767.947 - 844.742	0.000	0.000	N/A	N/A
844.742 - 921.536	N/A	N/A	N/A	N/A
921.536 - 998.331	0.018	0.000	N/A	N/A
998.3316- 1075.126	0.051	0.000	N/A	N/A
1075.126 - 1151.921	0.000	0.000	N/A	N/A
1151.921 - 1228.715	0.850	0.850	N/A	N/A
1228.7159 - 1305.510	0.000	0.000	N/A	N/A
1305.510 - 1382.305	0.000	0.000	N/A	N/A
1382.305 - 1459.100	0.000	0.000	N/A	N/A
1459.100 - 1535.894	N/A	N/A	N/A	N/A
>1535.894	0.003	0.000	N/A	N/A

Table 7-24 shows a difference between most of the mean and median values of permanent snow-related durations confirming that there are extreme values of duration. The transient outages do not contain a great deal of spread, indicating that few extreme transient outages occur. While no clear relationship has been found, it possible that the relationship between durations and weather types is more complicated and therefore, will require further investigation.

Table 7-24 – Snow-Related Outage Mean and Median Durations – North Scotland (hrs)

Wind Gusts (m/s)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 -1.75	0.000	0.000	0.000	0.000
1.75 -3.5	0.000	0.000	0.000	0.000
3.5 -5.25	0.000	0.000	31.150	6.630
5.25 -7	0.086	0.000	1.030	1.030
7 -8.75	0.130	0.080	31.310	14.450
8.75 -10.5	0.060	0.000	12.576	6.370
10.5 -12.25	0.113	0.000	25.950	22.975
12.25 -14	0.198	0.000	18.524	3.389
14 -15.75	0.050	0.000	28.070	7.655
15.75 -17.5	0.182	0.000	12.470	14.200
17.5 -19.25	0.107	0.000	15.753	4.900
19.25 -21	0.107	0.000	5.352	5.691
21 -22.75	0.065	0.000	2.662	2.290
22.75 -24.5	0.064	0.000	13.157	3.300
24.5 -26.25	0.074	0.000	17.789	5.470
26.25 -28	0.146	0.000	2.822	2.807
28 -29.75	0.091	0.000	4.070	4.070
29.75 -31.5	0.053	0.000	2.100	2.100
31.5 -33.25	0.000	0.000	0.000	0.000
33.25 -35	0.044	0.000	0.000	0.000
>35	0.000	0.000	0.000	0.000

7.2.2 Correlations between Durations and Weather Type

To further investigate if a relationship exists; a correlation analysis was completed for the top weather categories. The results are again shown only for North Scotland, the rest of the results can be found in Appendix E. This analysis cannot be completed for 'Other Weather' outages and non-weather-related outages are they have not been analysed to be dependent on a specific weather variable. This analysis was initially completed with all data but it was found that the extreme values skewed the analysis. Smaller durations skew data due to auto reclose schemes and larger durations skew the data when an asset was damaged and needed a time-consuming repair, replacement or difficult weather conditions prevent access. These values are not the normal durations, and therefore by removing them it could lead to a more obvious relationship emerging. To enable this, durations that were above the 95th and below the 5th percentile duration were removed. Figure 7-6 and Figure 7-7 show the plots for wind gusts against the mean log duration of 'Wind, Gales and Windborne Objects' outages, for both transient and permanent outages and show R^2 values of 0.3497 and 0.3695.

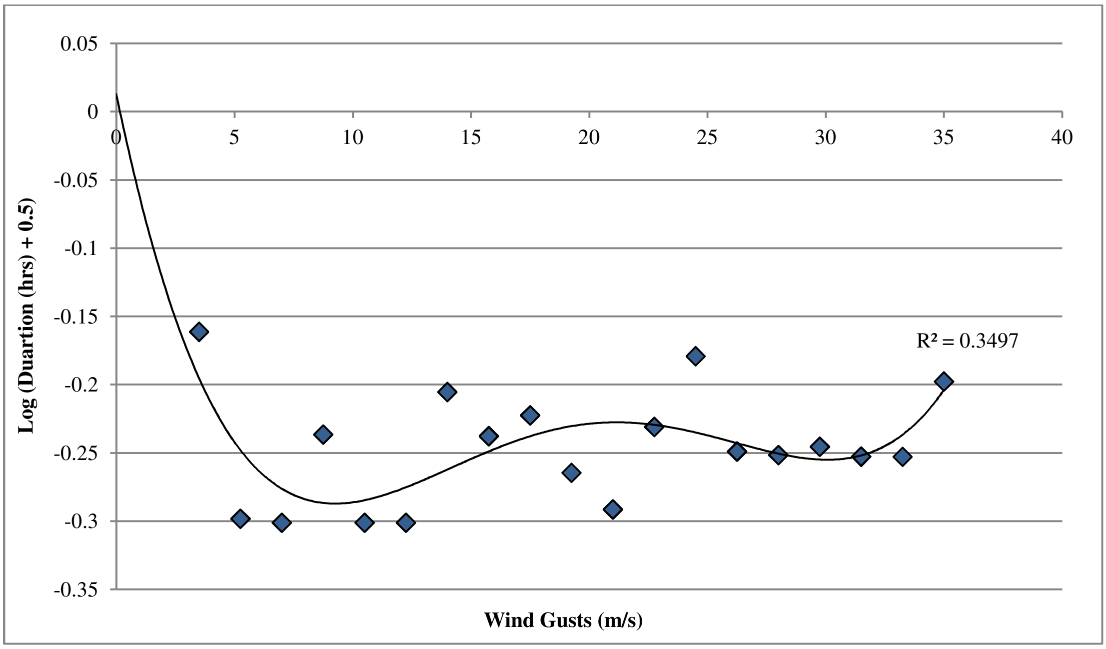


Figure 7-7 – Log Transformed Extremes Removed Mean Duration of Wind-Related Outage at Specific Wind Gust Values – Transient Outages North Scotland

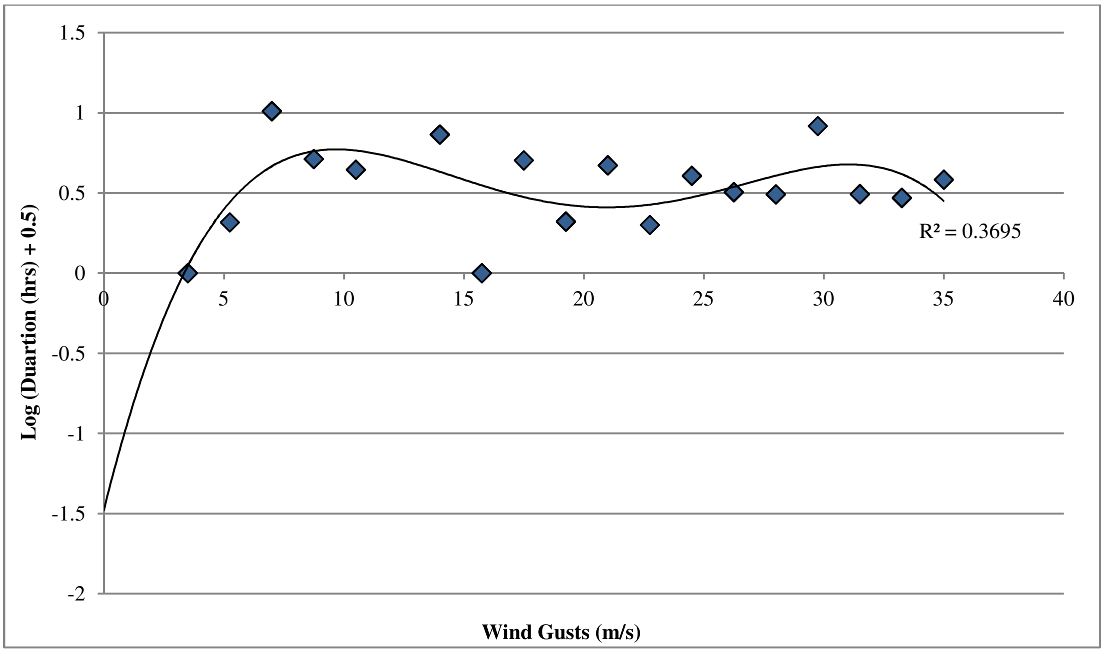


Figure 7-8 – Log Transformed Extremes Removed Mean Duration of Wind-Related Outage at Specific Wind Gust Values – Permanent Outages North Scotland

Figure 7-8 and Figure 7-9 show the plots for CAPE against the mean log duration of 'Lightning' outages for transient outages and the log transform for permanent outages. They show R^2 values of 0.7446 and 0.5063. This indicates that for transient outages there is a strong relationship between the value of CAPE and the outage duration. While the value is lower for permanent outages, it still indicates that there is a possible relationship that is influenced by external factors.

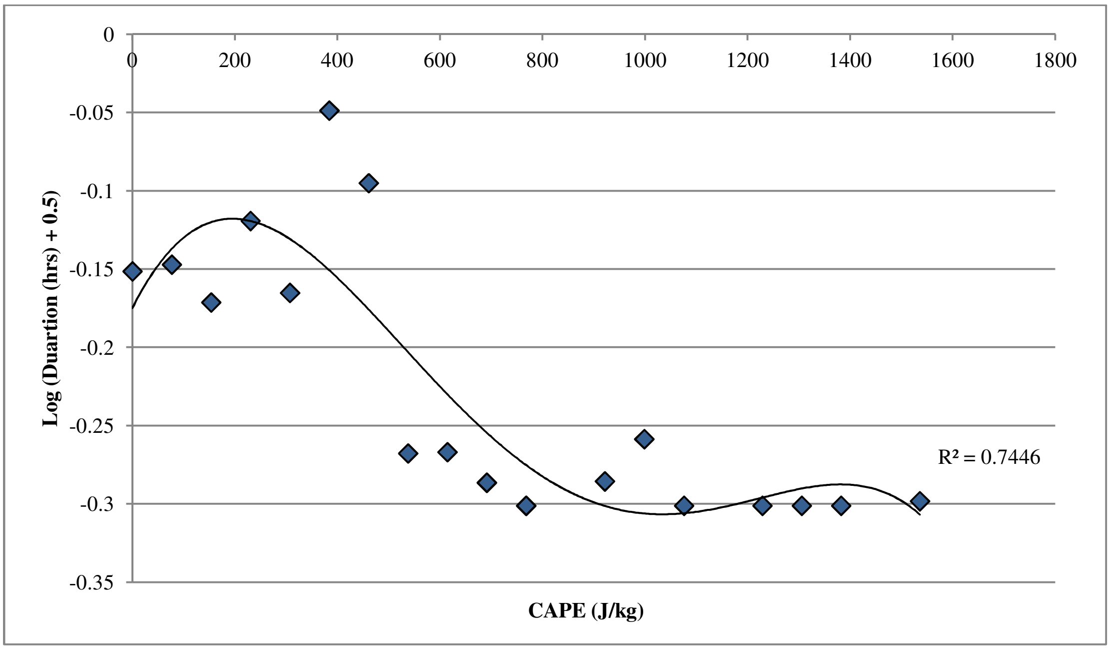


Figure 7-9 – Log Transformed Extremes Removed Mean Duration of Lightning-Related Outage at Specific CAPE Values – Transient Outages North Scotland

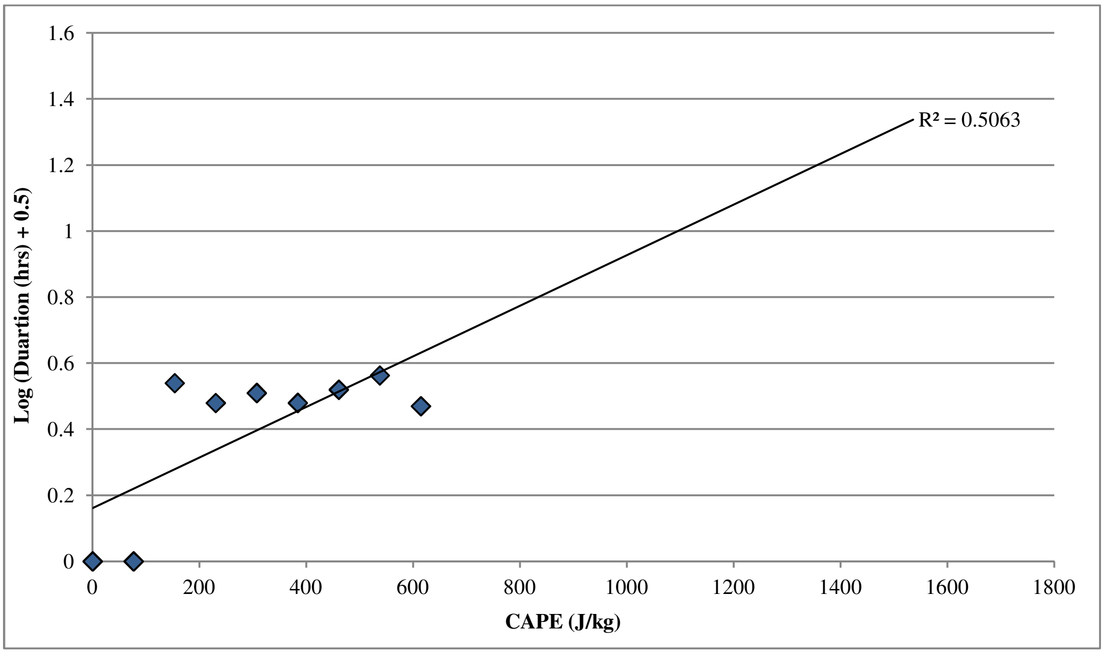


Figure 7-10 - Log Transformed Extremes Removed Mean Duration of Lightning-Related Outage at Specific CAPE Values – Permanent Outages North Scotland

Figure 7-10 and Figure 7-11 show the correlation plots for wind gusts against the log mean duration of 'SSB & Ice' outages. Both figures show R^2 values of 0.3143 and 0.3424. These are relatively low values of R^2 indicting that there is not a strong relationship between duration and wind gusts values on snow days and that other factors exist that affect the duration of a snow-related outage.

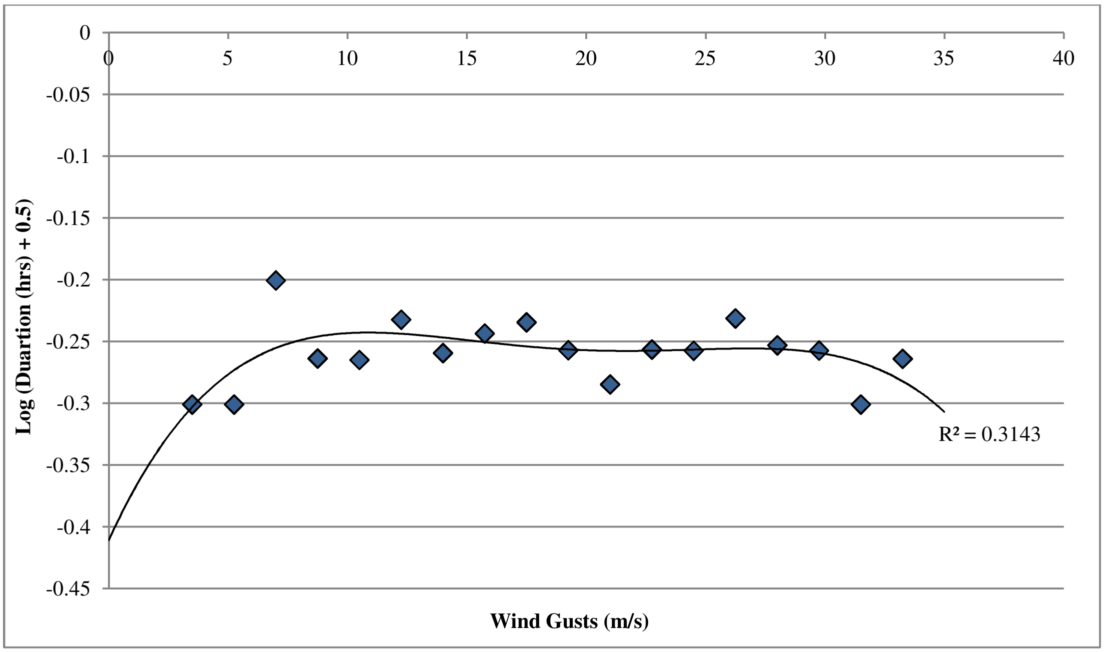


Figure 7-11 – Log Transformed Extremes Removed Mean Duration of Snow-Related Outage at Specific Wind Gust Values – Transient Outages North Scotland

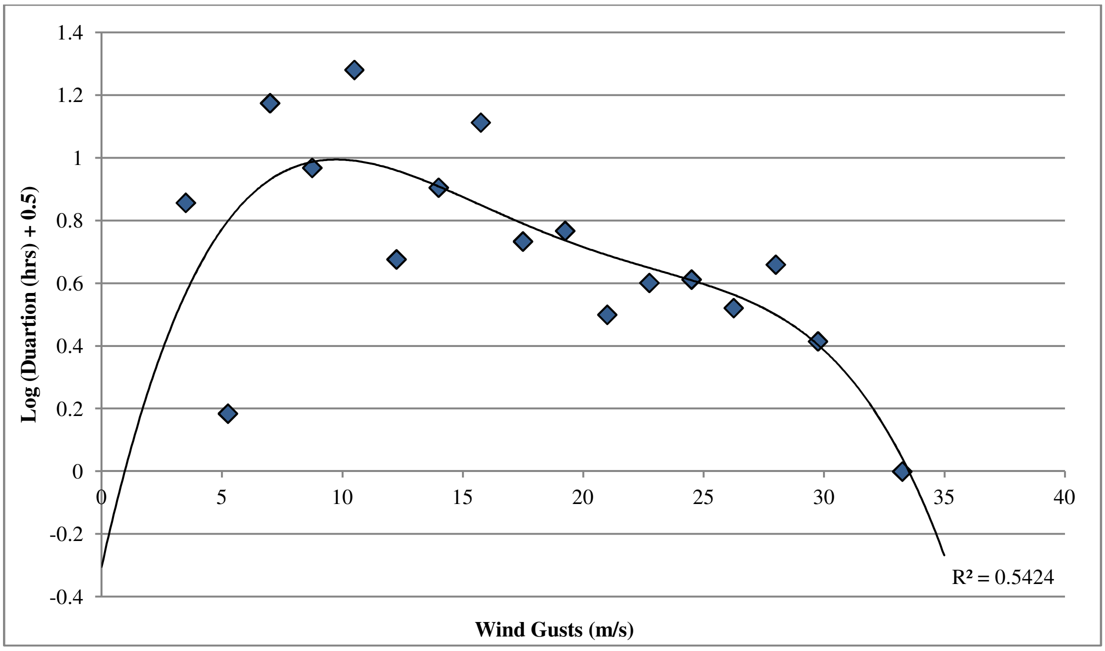


Figure 7-12 – Log Transformed Extremes Removed Mean Duration of Snow-Related Outage at Specific Wind Gust Values – Permanent Outages North Scotland

From the above investigation, it is clear that there may be a complex relationship that exists between outage durations and weather values and will require further investigation. However, it is also important to consider that durations will also be affected by many non-meteorological factors including availability of replacement equipment, and the logistics surrounding physically completing the repair and so may never be suitably modelled without the inclusion of extensive additional data sets; this is an area of research recommended for future work.

7.3 Investigation of Weather Extremes

To understand the differences between the areas and the weather they experience, a basic statistical analysis was completed to evaluate if any area is more susceptible to different weather. By defining the extreme weather for each area it gives an understanding of each area's different weather experiences. These values are used within the sequential sampling simulations to model extreme events.

7.3.1 Analysis of Extreme Wind Gusts

Table 7-25 displays the mean, median, mode, maximum value, minimum value and the standard deviation. It is evident from Table 7-25 that the North of Scotland on average experiences higher wind gusts, and that the South England and South Wales experiences on average the lowest wind gusts.

Table 7-25 - Statistics for Wind Gusts (m/s) over GB

Area	Max	Min	Mean	Median	SD
N Scotland	47.419	0.561	10.793	10.142	5.141
S Scotland	39.380	0.647	10.082	9.540	4.787
N England and N Wales	36.653	0.681	9.797	9.276	4.592
S England and S Wales	38.662	0.392	9.686	9.141	4.509

As indicated in Section 5.2.1 93% of 'Wind, Gales and Windborne Objects' outages occur within the top 11% percent of wind gusts. To analyse this phenomenon, two standard deviations are added to the mean wind gust value. Allowing for the statistically significant wind value to be determined for each area, which can be classed as the value of extreme wind gust [210]. North Scotland sees far higher wind gusts than South England and South Wales meaning that they will have different values for extremes. The results are shown in Table 7-26. As expected the North of Scotland has the highest definition of extreme wind gusts and South England and South Wales see the lowest definition.

Table 7-26 – Definition of an Extreme Wind Gust

Area	Mean	Mean + 2SD
N Scotland	10.793	21.075
S Scotland	10.082	19.656
N England and N Wales	9.797	18.981
S England and S Wales	9.686	18.704

From this it is now possible to look at the ratios of wind gust occurrences above and below the extreme value and the ratio of wind-related outages that occur during normal and extreme conditions. The results are shown in Table 7-27 and Figure 7-12. Normal wind gusts occurred over 90% of the time period analysed, with the proportion of wind-related outages that occurred under these conditions varying from 30.65% to 15.35%, dependent on area. Conversely, extreme wind gusts tended to occur for 3.83% to 6.41% of the time, but the number of wind-related outages that occurred during these times varies from 69.35% to 84.65%. This shows the effect that extreme wind gusts can have.

Table 7-27 - Percentage of Extreme to Normal Wind Gusts and Wind-Related Outages

Area	Extreme Wind Gusts	Normal Wind Gusts	Outages at Extreme Wind Gusts	Outages at Normal Wind Gusts
N Scotland	3.83%	96.17%	82.65%	17.35%
S Scotland	4.27%	95.73%	84.65%	15.35%
N England and N Wales	6.41%	93.59%	69.35%	30.65%
S England and S Wales	5.87%	94.13%	73.96%	26.04%

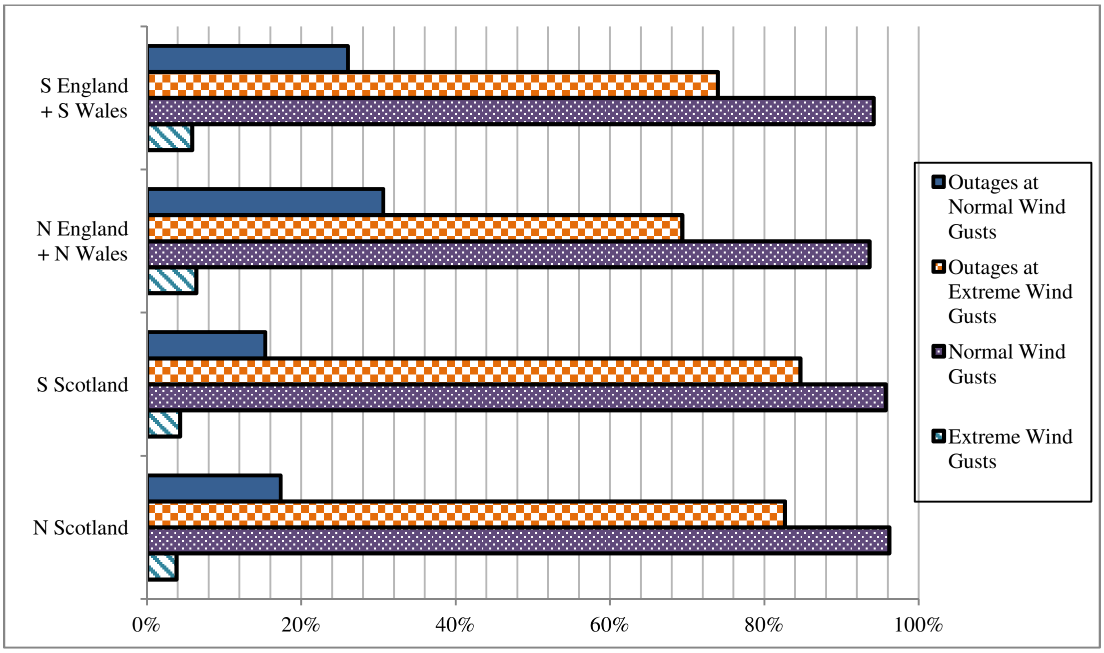


Figure 7-13 - Percentage of Extreme to Normal Wind Gusts and Wind-Related Outages

7.3.2 Analysis of Extreme CAPE

The mean, median, mode, maximum value, minimum value and standard deviation are shown in Table 7-28. North Scotland has the highest average value of CAPE, and South England and South Wales has the lowest. The mean and median values are quite different indicating extreme values of CAPE. This is confirmed with a large standard deviation indicating a spread of data in the value of CAPE.

Table 7-28 - Statistics for CAPE (J/kg) over GB

Area	Max	Min	Mean	Median	SD
N Scotland	2212.22	0.00	93.24	57.25	109.68
S Scotland	1935.94	0.00	80.63	47.33	97.6
N England and N Wales	2129.38	0.00	81.05	43.93	109.52
S England and S Wales	2199.06	0.00	79.32	38.8	119.65

To further investigate the extreme CAPE further analysis was undertaken, the results are shown in Table 7-29. Due to the variation of the standard deviation, South England and South Wales have the highest value of extreme CAPE, and South Scotland has the lowest. The ratios of extreme to normal CAPE and the ratios of ‘Lightning’ outages occurrence have been analysed and are displayed in Table 7-30 and Figure 7-13. As a general rule, 50% of ‘Lightning’ outages occur during normal and 50% occur during extreme conditions.

Table 7-29 – Definition of an Extreme CAPE Event

Area	Mean	Mean + 2SD
N Scotland	93.24	312.595
S Scotland	80.63	275.825
N England and N Wales	81.05	300.078
S England and S Wales	79.32	318.613

Table 7-30 - Percentage of Extreme to Normal CAPE and Lightning-Related Outages

Area	Extreme CAPE	Normal CAPE	Outages at Extreme CAPE	Outages at Normal CAPE
N Scotland	4.58%	95.42%	42.38%	57.62%
S Scotland	7.56%	92.44%	49.36%	50.64%
N England and N Wales	7.73%	92.27%	53.15%	46.85%
S England and S Wales	7.96%	92.04%	57.95%	42.05%

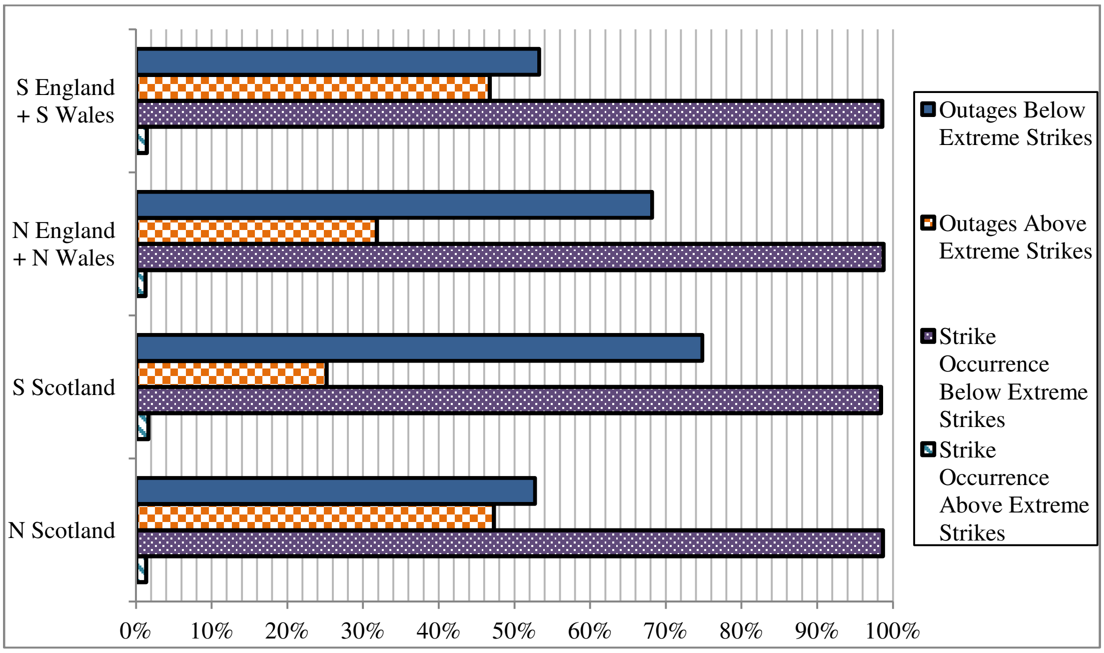


Figure 7-14 - Percentage of Extreme to Normal CAPE and Lightning-Related Outages

7.3.3 Analysis of Wind Gusts on Snow Days Extreme

A statistical analysis of wind gusts on snow days was completed. The results are shown in Table 7-31. This table shows that on average North Scotland experienced the highest wind gusts on snow days, but that there is not a large difference between North Scotland, North England and North Wales and South Scotland. It is also clear that since the mean and median are close in value that there were not many extreme events within the data.

Table 7-31 - Statistics for 10meter Wind Gusts on Snow Days (m/s) over GB

Area	Max	Min	Mean	Median	SD
N Scotland	44.524	0.931	11.847	11.411	5.538
S Scotland	38.685	0.927	11.167	10.785	5.295
N England and N Wales	35.658	0.803	10.302	9.813	4.947
S England and S Wales	33.265	0.849	9.488	9.024	4.362

To analyse the statistically significant values for wind gusts on snow days, the same process as before was followed and the results are shown in Table 7-32. The results are as expected, North Scotland has the highest values of extreme wind on snow days, and South England and South Wales with the lowest value which is similar to the value when analysing all days.

Table 7-32 – Definition of an Extreme Wind Gusts on Snow Days Event

Area	Mean	Mean + 2SD
N Scotland	11.847	22.922
S Scotland	11.167	21.758
N England and N Wales	10.302	20.195
S England and S Wales	9.488	18.212

The ratios between extreme and normal wind gusts on snow days were further analysed. The results are displayed in Table 7-33 and Figure 7-14.

Table 7-33 - Percentage of Extreme to Normal 10meter Wind Gusts on Snow Days and Snow-Related Outages

Area	Extreme Wind Gusts on Snow Days	Normal Wind Gusts on Snow Days	Outages at Extreme Wind Gusts on Snow Days	Outages at Normal Wind Gusts on Snow Days
N Scotland	3.31%	96.69%	22.96%	77.04%
S Scotland	4.10%	95.90%	51.94%	48.06%
N England and N Wales	4.82%	95.18%	25.53%	74.47%
S England and S Wales	4.76%	95.24%	40.82%	59.18%

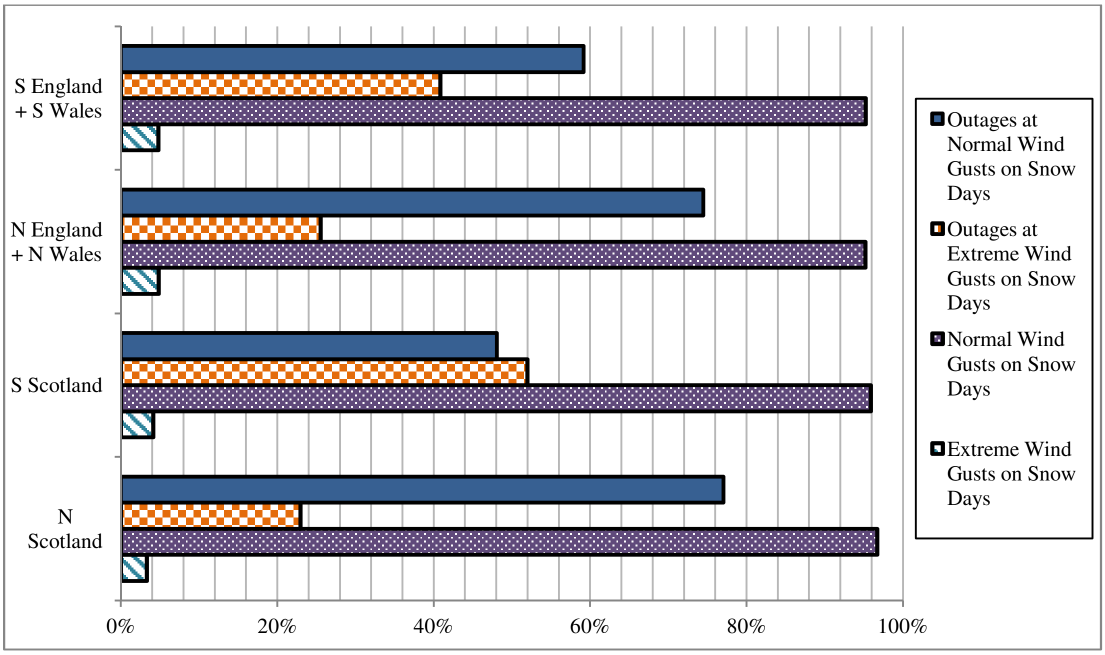


Figure 7-15 - Percentage of Extreme to Normal 10meter Wind Gusts on Snow Days and Snow-Related Outages

They show that the majority of ‘SSB & Ice’ outages occur under normal wind gusts on snow day’s conditions, indicating that the system is susceptible to ‘SSB & Ice’ outages under all conditions. While the extreme conditions cause less outages this could be due to the conditions being rarer.

7.4 GB Weather Test Cases

As discussed in Section 1.2.3 there are many climate projections, however, for this research the UKCP projections will be used as they are specific projections for the UK. To develop these projections into test cases the weather type’s frequency distribution histograms displayed in Chapter 5 - were altered to produce new frequency distribution histograms, where each bin of the frequency of occurrence was altered by the percentage change discussed in the following sections. These will be used to assess the impact of these climate projections. The following sections will show the alterations made and the resultant weather inputs for the model to assess impacts due to climate change. The histograms for South Scotland, North England and North Wales and South England and South Wales can be found in Appendix F.

7.4.1 Wind

The projections in the 11-member RCM are projections are for wind speed, not wind gusts, however, Figure 7-15 shows that there is a linear relationship between then. This indicates if a 10% increase in wind speeds to occur then a 10% increase in wind gusts is also likely to occur. Projected future changes in 30 year averages of surface wind speeds are small according to the RCM ensemble. They indicate seasonal changes at individual locations across the UK mainland within the region of +10% to -15% of 30 year averages of surface wind speed. Since a reduction in wind speed would likely lead to a reduction of wind-related outages, it is not expected to adversely affect the transmission network. Because of this, only test cases related to increased wind speed are developed. Specifically there are test cases developed for a plus 5% and 10% increase in wind gusts as shown in Figure 7-16 for North Scotland.

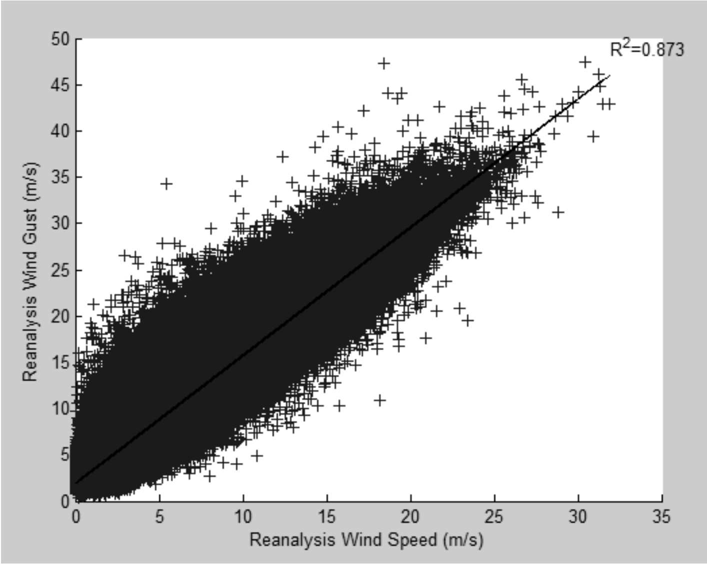


Figure 7-16 - Wind Speed against Wind Gusts

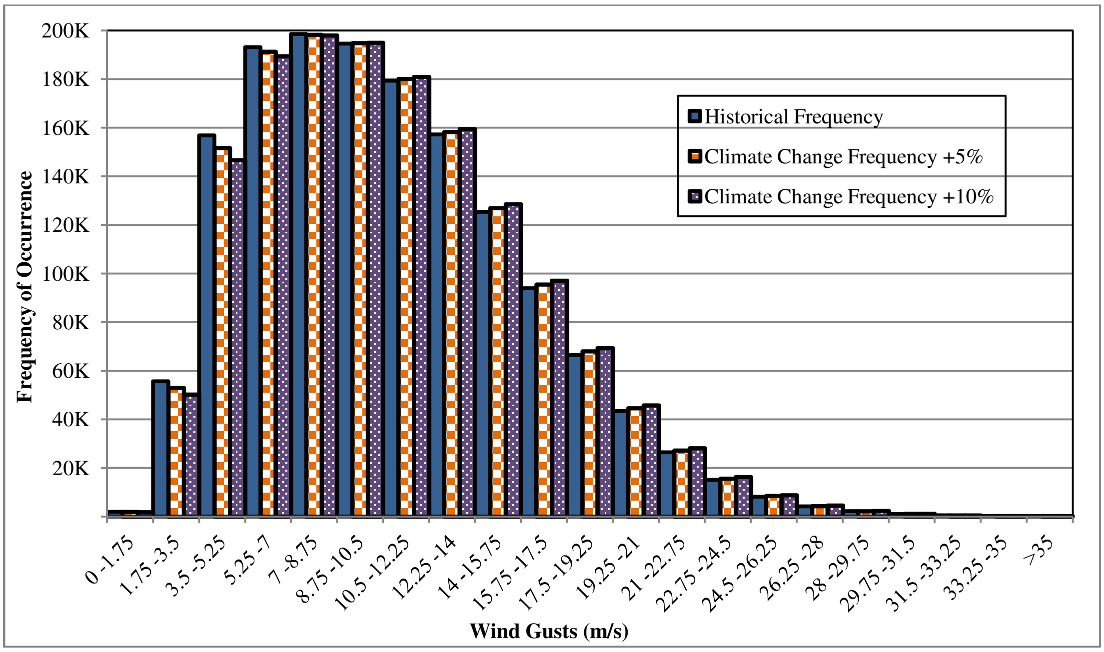


Figure 7-17 - Frequency Distribution for 10m Wind Gust Occurrences, Historical, 5% increase and 10% Increase, North Scotland

Table 7-34 and Table 7-35 show the ratios of occurrences above and below the defined extreme values for a 5% increase and 10% increase respectively, as defined in Section 7.3.1.

Table 7-34 - Wind Gusts Extreme to Normal Ratio with 5% Increase – North Scotland

	Before	After
Occurrences Above Extreme	0.038	0.040
Occurrences Below Extreme	0.962	0.960

Table 7-35 - Wind Gusts Extreme to Normal Ratio with 10% Increase – North Scotland

	Before	After
Occurrences Above Extreme	0.038	0.041
Occurrences Below Extreme	0.962	0.959

Additional Case Studies

In addition to these case studies, two other case studies were developed to look at worst case scenarios. For these additional studies the same process as described above was used where wind was increased by 25% and 50%. While these were not climate projections, there is a large amount of uncertainty around climate projections and it is not 100% certain what will happen.

7.4.2 Lightning

As discussed in Section 4.1.3 lightning is not a quantity that is produced by climate models due to its complexity, instead CAPE is used as a proxy. This is applied in the 11-member RCM projections where the increase in lightning days is inferred from CAPE [211]. Increases in lightning days were projected for all four seasons over the UK, with the largest increase being seen in summer over parts of Scotland and Northern Ireland and Southern England during autumn. During spring and winter there are also small increases in projected number of lightning days in all areas. Due to uncertainties when calculating percentage increase, a percentage increase for lightning is not available for the whole of GB. However, for South East England the changes are projected to be in the range of a 25-50% increase during the summer months, which will provide a worst case scenario for GB. These are shown in Figure 7-17 for North Scotland. Table 7-36 and Table 7-37 show the ratios of occurrences above and below the defined extreme values for a 25% and 50% increase in CAPE, as was defined in Section 7.3.2.

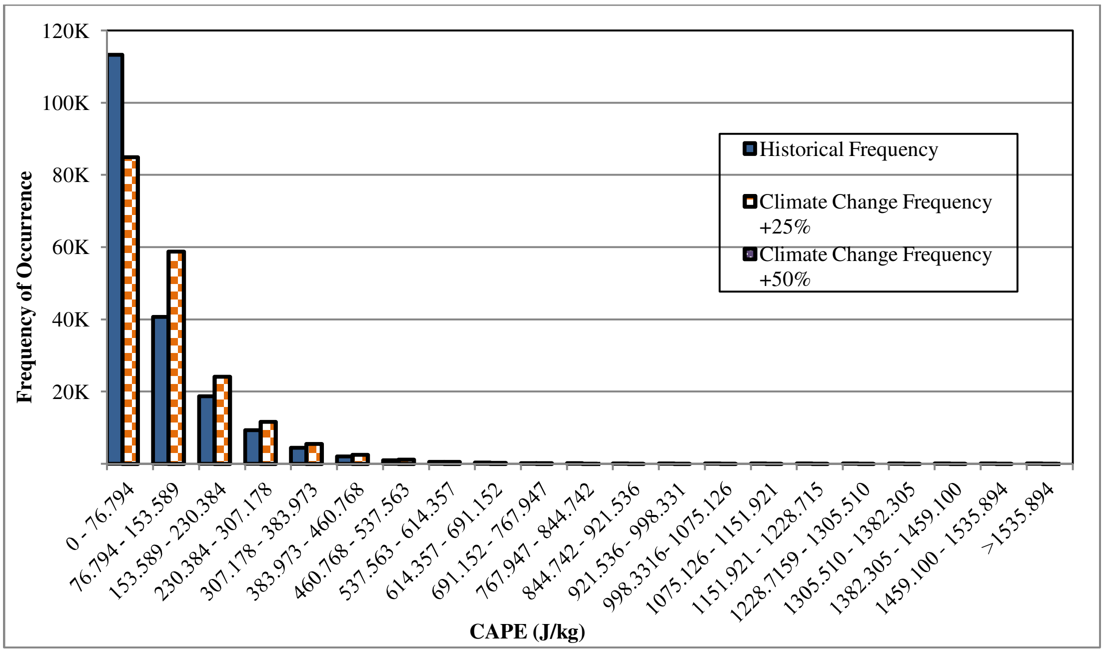


Figure 7-18 - Frequency Distribution for CAPE Occurrences, Historical, 25% increase and 50% Increase, North Scotland

Table 7-36 - CAPE Extreme to Normal Ratio with 25% Increase – North Scotland

	Before	**After**
Occurrences Above Extreme	0.046	0.058
Occurrences Below Extreme	0.954	0.942

Table 7-37 - CAPE Extreme to Normal Ratio with 50% Increase – North Scotland

	Before	**After**
Occurrences Above Extreme	0.046	0.070
Occurrences Below Extreme	0.954	0.930

Additional Case Studies

In addition to the case studies developed using the climate projections, two other case studies were developed to look at worse case scenarios. For these additional studies the same process as described above was used where CAPE was increased by 75% and 100%. While these were not climate projections, there is a large amount of uncertainty around climate projections and it is not 100% certain what will happen.

7.4.3 Snow

Due to warming climates, future snowfall is projected to either never occur or have a drastic decrease in the snow days making it statistically difficult to model. As snow does not occur usually during the summer months the 11 member RCM only considers changes to the spring, autumn and winter seasons. The ensemble-mean projected changes show significant reductions in snow days for all regions in the UK for all 11 scenarios. The reductions are the smallest for North Scotland with a reduction of 40%, 50%, and 70% for winter, spring and autumn respectively with the rest of the UK seeing projected reductions of 70%, 70% and 80% for winter, spring and autumn [212]. As 'SSB & Ice' outages are indicated not only by snow but also by wind gusts, any analysis must also consider the projected changes to wind gusts in the same projections. The two snow test cases developed were reduction of snow (40% in NS and 70% in the rest of GB) and an increase in wind gusts by 5% and 10%. The frequency distributions are shown in Figure 7-17 for North Scotland. Table 7-38 shows the historical snow day to non-snow days ratios compared to the reduction in snow day by 40% for North Scotland and 70% for the rest of GB, where a snow day is defined as any grid square within an area that contains snow, no matter how small.

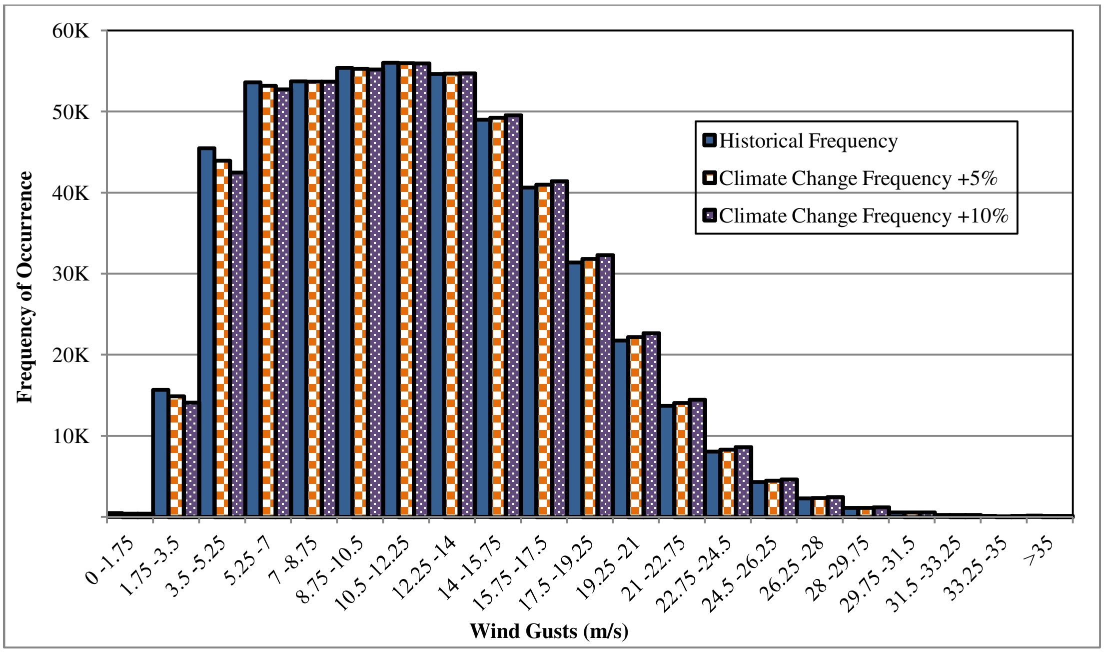


Figure 7-19 - Frequency Distribution for 10m Wind Gust on Snow Days Occurrences, Historical, 5% increase and 10% Increase, North Scotland

Table 7-38 - Snow Days to Non-Snow Days Ratio with 40-70% Reduction

	Snow Days	Non-Snow Days	Snow Days Decrease	Non-Snow Days Increase
North Scotland	0.33	0.67	0.20	0.80
South Scotland	0.24	0.76	0.07	0.93
North England and North Wales	0.14	0.86	0.04	0.96
South England and South Wales	0.09	0.91	0.03	0.97

Although in general there is a reduced likelihood of snow days, indicating a reduction in large snow events, this is still largely uncertain and there remains a possibility that there could be an increase in large snow events. Future work will be required to determine the effects this could have on transmission networks once the climate projections are further developed. Currently, large snow events are what cause a large amount of disruption to the transmission network and since they cannot be ruled out, it is important to investigate, therefore, a weather case study was developed to investigate possible effect of an increase in snow event duration by 10%. This will only be possible to investigate using sequential sampling. Table 7-39 and Table 7-40 show the historical ratios of wind gusts on snow days and wind gusts in snow days with a 5% and 10% increase, respectively, for North Scotland.

Table 7-39 – Wind Gusts on Snow Days Extreme to Normal Ratio with 5% Increase – North Scotland

	Before	After
Occurrences Above Extreme	0.033	0.034
Occurrences Below Extreme	0.967	0.966

Table 7-40 - Wind Gusts on Snow Days Extreme to Normal Ratio with 10% Increase – North Scotland

	Before	After
Occurrences Above Extreme	0.03	0.04
Occurrences Below Extreme	0.97	0.96

Additional Case Studies

In addition to the case studies developed using the climate projections, three other case studies were developed to look at worse case scenarios. For these additional studies the same process as described above was used where wind was increased by 25%, 50% and 50% plus increase snow duration. While these were not climate projections, there is a large amount of uncertainty around climate projections and it is not 100% certain what will happen.

7.4.4 The Worst Case

The final weather case study that will be investigated will consider the worst case possible scenario that could occur based on the 11-member RCM projections. It will consist of a 10% increase to wind gusts, a 50% increase to CAPE and a 40-70% reduction of snow days but a 10% increase to wind gusts on snow days.

7.5 GB Network Model Development

A critical aspect of this methodology is to run an OPF on the affected network, after outage simulation, to determine the risk that the different weather test cases could pose to the transmission network. For the purposes of this research the OPF was performed using MATPOWER's Standard AC OPF. This section aims to describe the simplified GB model that will be used and the setup of the load and generation dispatch for both the state and sequential sampling models.

7.5.1 Simplified GB Model

The network model that was used for this analysis was developed from an older simplified GB model that was developed at the University of Strathclyde [187]. The network diagram schematic is shown in Figure 7-19. The original model was a 29 bus system and was based on the 2009/10 GB transmission network and validated against load flow solutions provided by National Grid. However, this model was lacking within the Scottish transmission network and was updated to include better representation of the Scottish network. The English and Welsh network was largely unchanged from the original model. This network model also includes generator transformers. These are not required for the analysis completed here, and so the model is set up so that they are unable to fail due to weather. The same is also done for the West Coast HVDC link and the series compensation at the Scottish boundary. The representative GB model contains 40 buses, 124 branches and 84 generators. The models parameters per area are shown in Table 7-41. These values will be used in analysing outputs from simulations to allow for comparisons. Appendix G contains network model details.

Table 7-41 - Simplified GB Model Parameters

Area	**Branches**	**Line Lengths (km)**
North Scotland	21	2021.384
South Scotland	23	1647.404
North England and North Wales	40	5361.052
South England and South Wales	40	4220.52
Total	124	13250.36

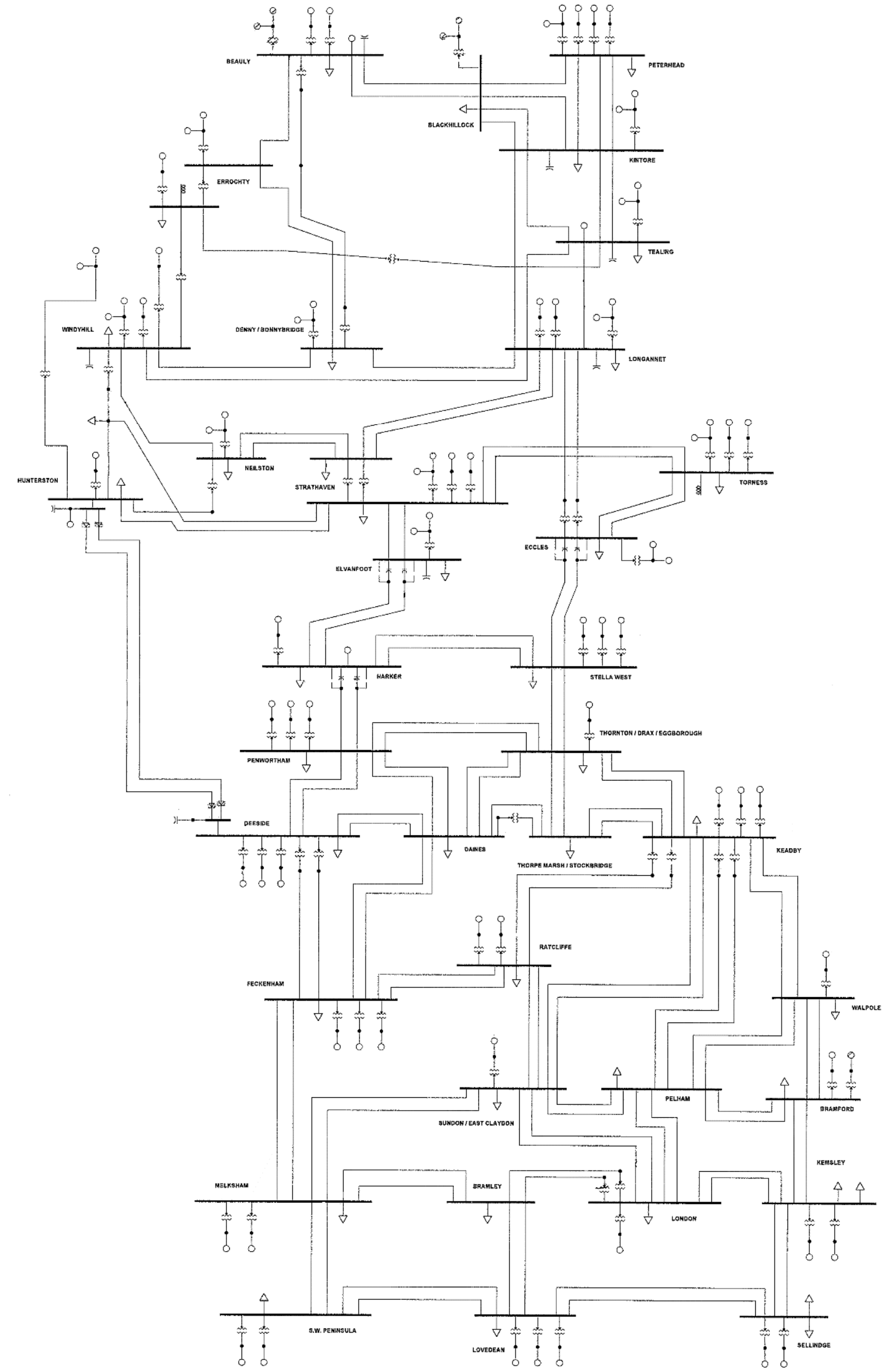


Figure 7-20 - Simplified GB Model

7.5.2 Load Set Up

State Sampling

As state sampling does not have the next iteration dependent on the previous iteration, it is unable to step though a continuous load profile. Therefore, when generating the load for each time step, it will generate a random normal distribution and then will sample from this distribution for each area. This is an accurate way to represent a load profile for a state sampling methodology as when a yearly load profile is turned into a histogram it will produce an almost normal distribution. Figure 7-20 shows a histogram of a yearly load profile for the GB network and the load profile from the state basecase, it is clear to see that this is an almost normal distribution and therefore this is a reasonable assumption for modelling load. This was done by creating a normal distribution within the code using the mean value of 0.62 and the standard deviation value of 0.12, which were calculated from Figure 7-20 gridwatch values. For a first approximation load and weather are not considered seasonally as the additional computational and analysis time is out with the time frame of this thesis. However, it is recommended for future analysis.

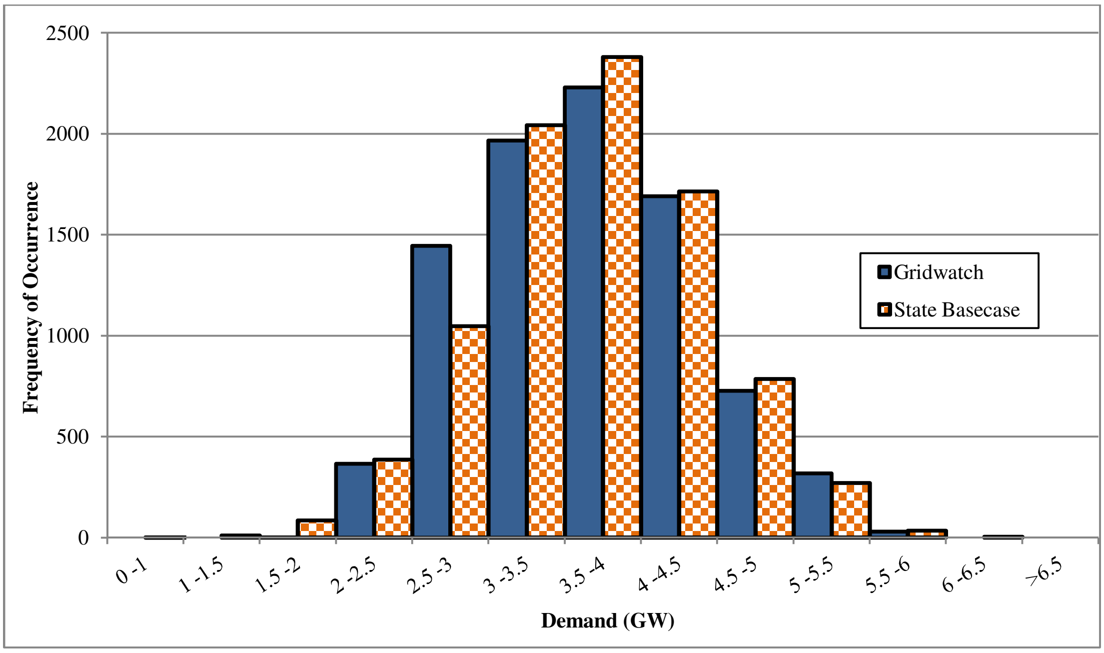


Figure 7-21 - Histogram of GB Yearly Hourly Load Profile for Gridwatch and State Basecase

Sequential Sampling

Unlike state sampling sequential sampling is able to step through a complete load profile. In these case studies the sequential sampling uses a load profile that was downloaded from grid watch [213] for the year 2012, as shown in Figure 7-21. The sequential code will step through the load profile for each time step. To include some more realistic variance a margin of error included within the load profile is added.

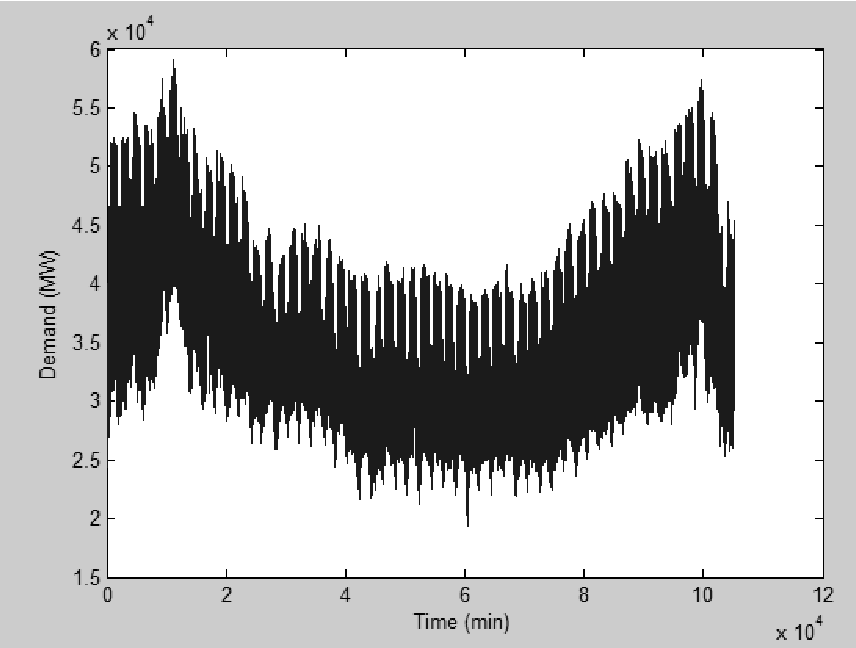


Figure 7-22 - GB Yearly Load Profile

7.5.3 Generation Set Up

For the generation dispatch set up for the OPF, it is important to note if there is a strong renewable presence in the system being analysed. In GB, wind power is prominent in the generation profile and therefore the dispatch of generation will vary depending on the wind that is occurring. It is necessary when dispatching generation within the simulation, to model the amount of wind power that can be generated within each area based on the wind gust values that are produced by the MC simulation. While GB does contain other renewable sources of generation, such as solar and hydro, these are not addressed within this work. Using the value of wind gusts it is possible to determine the value of wind speed as long as the relationship between wind gust and wind speed is known. This was determined using the reanalysis datasets of wind gusts and wind speeds from ERA-Interim and performing a correlation analysis. The result is shown in Figure 7-15. It is clear to see that there is a strong correlation between wind gusts and wind speeds with a R^2 value of 0.873. From this it is possible to determine a relationship between wind gusts and wind speeds; this is shown in equation 7-3.

$$Wind\ Speed = (0.6309 * Wind\ Gust) - 0.4377 \quad \textbf{7-3}$$

To include some variability in the values, a margin of error was included when generating the wind speed value which will allow for the fact that the R^2 value is not equal to 1. Once the value of wind speed per area is determined it is then possible to use this value to determine the value of wind power that is possible to be generated per area. This was done using the power curve from [214] as shown in Figure 7-22. From this is it now possible to dispatch the generation is the most desirable order. For this case there are five groups of generation type, these are shown in Table 7-42.

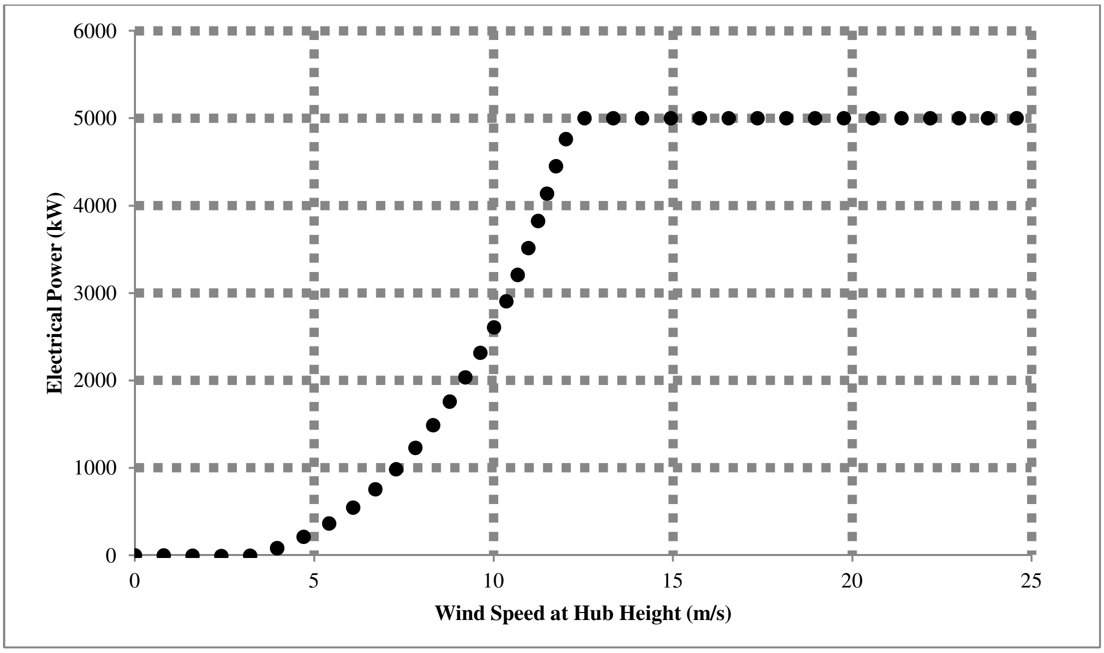


Figure 7-23 - Reproduction of Wind Speed Power Curve [214]

Table 7-42 - Generation Dispatch Order

Generation Type	Order
Wind	First
Hydro/Pumped Storage	Second
Nuclear	Third
Coal	Fourth
CCGT	Fifth

The model also includes 1320MW of spinning reserve that is split across five generators distributed throughout the GB network model. The OPF can now dispatch the generation for all areas in the desired order based on the amount of wind power that is being generated.

7.6 Summary

This chapter opened with a discussion about the differences between the state and sequential sampling processes, and what is required as inputs for each method. The second section of this chapter discussed an investigation into the relationship between outage durations and weather causes. It was found that there was a possible relationship between outage duration and weather causes but more investigation was required in order to develop a stronger relationship to be used as a method to quantify the impact on the transmission system. It is suggested that for future work this should be further investigated. In order to include durations of outages the cumulative frequency distributions were calculated for the outages classes for the sequential sampling simulation. The third section of this chapter investigated weather extremes, looking at the percentage of time a weather extreme event occurs and how this overlaps with outages. It was found that 'Lightning' outages occur over both extreme and normal days, confirming that they are not dictated by extreme events alone. However, both 'Wind, Gales and Windborne Objects' and 'SSB & Ice' outages were found to occur most during extreme events and that they generally do not occur during normal weather conditions. The fourth section of this chapter discussed the eight weather test cases that will be applied to investigate the changes in climate. Seven weather test cases were developed for the state sampling model and eight were developed for the sequential simulation. In each case the different weather variables were changed by different amounts to understand the effect they will have on the system. The final stage of this chapter considered the setup of the power system model that was used to analyse the effect of changes in weather on the GB system, discussing the simplified model used and the load and generation set up for both the state and sequential models.

The GB case study uses a simplified GB model developed at the University of Strathclyde and the representative GB model contains 40 bus, 124 branches and 84 generators. The load setup for the state and sequential sampling methodologies differ from each other. The state sampling model generates a random normal distribution and samples accordingly to get the load value. The sequential sampling model is able to step through a complete annual load profile. In these case studies the sequential sampling uses a load profile that was downloaded from grid watch [213]. For the generation dispatch it is important to consider the effects weather can have on the available generation of the system. In the case of GB there is a strong wind presence within the generation profile. It was therefore necessary when dispatching generation within the simulation to model the amount of wind power that was generated within each area based on the wind gust values that are produced by the MC simulation. While GB does contain other renewable sources of generation, such as solar and hydro, neither of these have been addressed within this work although it is recommended for future development.

This chapter has met research aims 7, to develop weather test cases using climate projections, and 8, investigate if a relationship exists between outage duration and weather cause, as discussed in Section 1.6. The following chapter shall discuss the effects of these weather tests cases on the security system indices and help provide a picture of how changes in climate will affect the transmission system.

Chapter 8 - Assessment of the Impact of Changed Weather on Power System Reliability

This chapter aims to apply the final stage of the presented methodology to the GB test case. This chapter uses all the information that has been developed previously to assess the impact on the transmission network. A Monte Carlo simulation is run in Matlab to build up a transmission network, and then the OPF is run using MATPOWER [190]. The change in the reliability indices are investigated using the weather test cases which were developed using climate change projections for UK as discussed and shown in Section 7.4. The two sections of this chapter shall discuss the state and sequential sampling model results and note the changes for the GB network. This will meet the final research aim stated in Section 1.6: using the model results and reliability indices to analyse the effects of different climate models on the GB test case. Table 8-1 shows the historical average failure rates per area, per year, per 100km for comparison.

Table 8-1 - Historical Average Failure Rates per area, per year, per 100km

Area	Lightning	Snow	Wind	Other Weather	Non-Weather
N Scotland	0.433	0.455	0.383	0.073	1.178
S Scotland	0.273	0.407	0.578	0.16	3.084
N England and N Wales	0.359	0.132	0.242	0.096	0.884
S England and S Wales	0.369	0.037	0.073	0.093	1.288

8.1 State Sampling Basecase and Future Weather Test Cases State Sampling Outage Results

The next sections shall discuss the failure rates and load indices results for the basecase and the different weather case studies developed in Section 7.4 for the state modelling technique, set-up as discussed in Chapter 7. For each of the other weather test cases only the weather being analysed was changed, all other weather remained the same allowing the change in each weather type changed to be fully analysed. The failure rates for all weathers and their associated confidence limits can be found in Appendix H; only the failure rates for the changed weather will be discussed within this thesis.

8.1.1 Basecase Analysis

The first state sampling case that was modelled was the basecase, this should be similar to the results calculated from the historical data and will determine how accurately the model reproduces the current weather and outages. Figure 8-1, Figure 8-2 and Figure 8-3 show the average yearly weather for North Scotland for CAPE, wind gusts and wind gusts on snow days respectively compared to the historical weather, the histograms for South Scotland, North England and North Wales and South England and South Wales can be found in Appendix H. Table 8-2 shows the maximum, minimum, average and standard deviation of the percentage change for each weather type compared to the historical weather data. From the figures and table it is clear to see when compared to historical weather the state model is able to reproduce CAPE values with only a 6% error. Larger errors exist for wind and wind gusts on snow days, with the model producing on average 16% lower values for wind and 74% higher values for wind gusts on snow days.

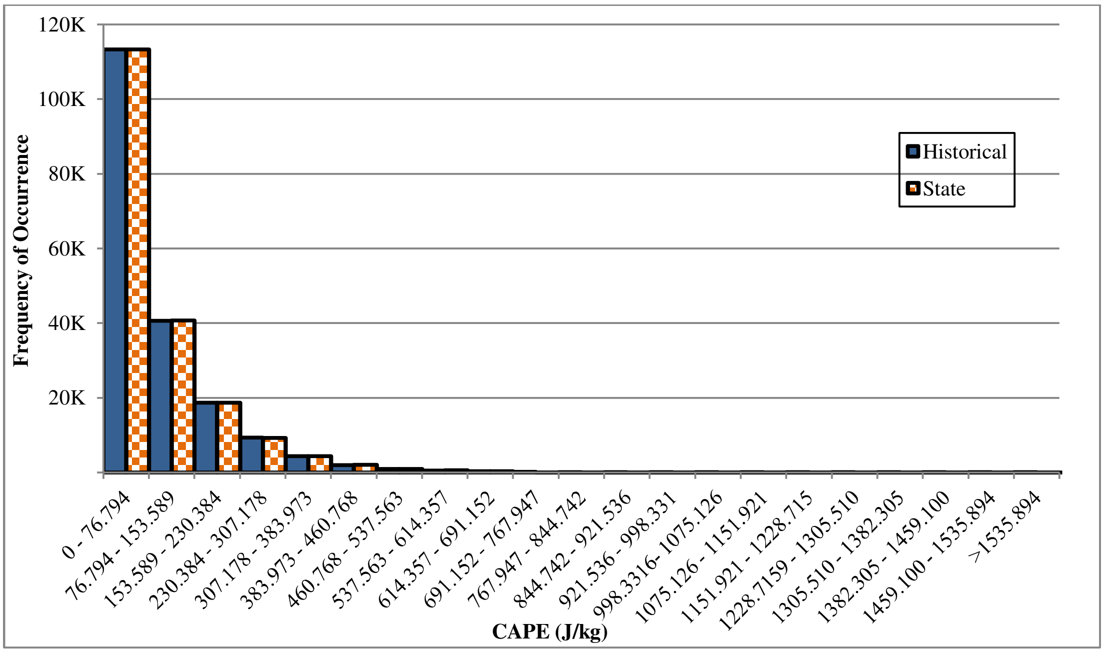


Figure 8-1 - State Basecase and Historical CAPE (J/kg) Distribution, North Scotland

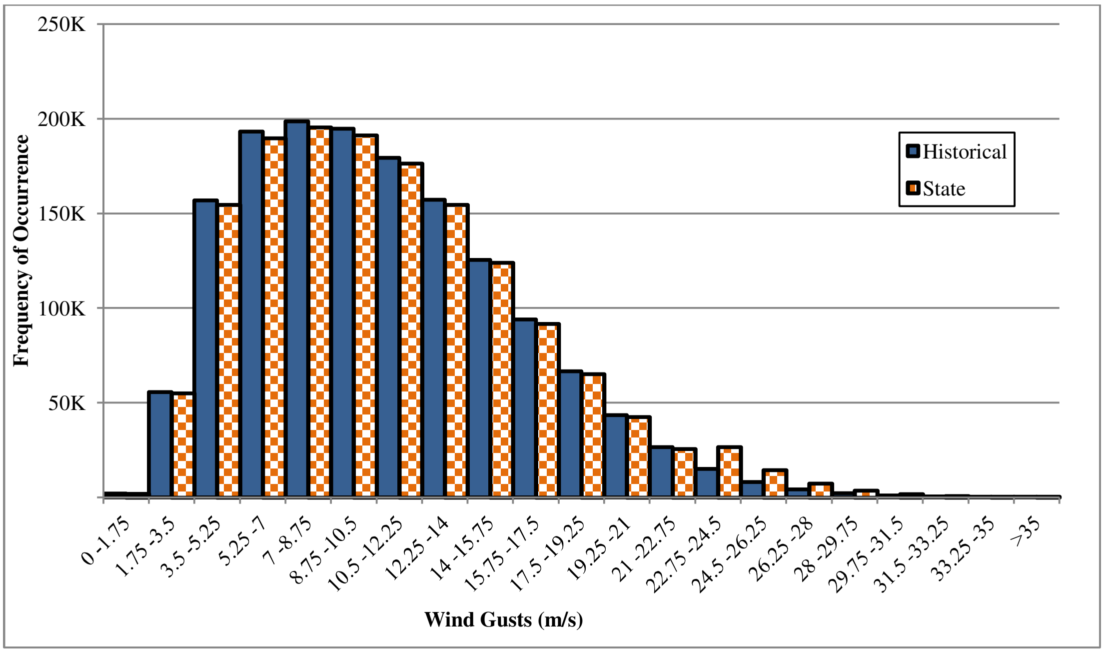


Figure 8-2 - State Basecase and Historical Wind Gusts (m/s) Distribution, North Scotland

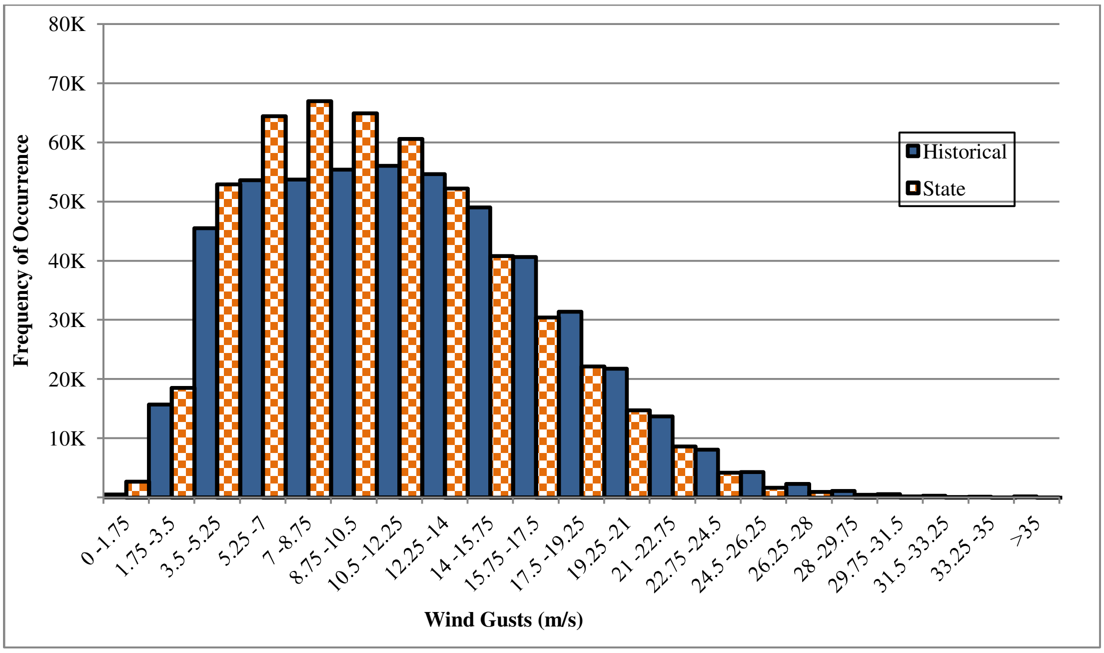


Figure 8-3 - State Basecase and Historical Wind Gusts on Snow Days (m/s) Distribution, North Scotland

Table 8-2 - Statistical Analysis of State Model Weather Generation Percentage Change Compared to Historical Weather

	CAPE (%)	Wind Gusts (%)	Wind Gusts on Snow Days (%)
Max	29.47	4.08	365.96
Min	-0.44	-40.82	-74.43
Average	5.98	-15.58	74.19
Standard Deviation	7.50	19.09	104.57

Table 8-3 shows the average failure rates per area, per year, per 100km. As explained in Section 7.1.1 when considering the probability of failure in the state model, it is necessary to include the longevity of a failure. To do this a new value, P(broken), was determined that considers both the probability of failure and the probability that there has been a failure in the previous recent time steps for each weather value. In order to compare the historical rates to the rates generated by the state model the historical rates have been altered by this "fix factor" and the results are shown in Table 8-4. Table 8-5 and Table 8-6 show the mean 95% upper and lower confidence limits for the failure rates, plus the percentage change in failure rates compared to the historical rates for the state sampling basecase. When compared to the historical rates it is found that the state model overestimates lightning-related failure especially for South Scotland, which can be attributed to the lack of data to sample from. The model also underestimates the averages failures for both snow and wind failures by up to 77% and 96% respectively. Indicating that while the state model is able to model weather with a reasonable accuracy it struggles with the more complex relationship of failures.

Table 8-3 - Average Failure Rates per area, per year, per 100km (State Basecase)

Area	Lightning	Snow	Wind	Other Weather	Non-Weather
N Scotland	0.943	0.035	0.211	0.359	4.917
S Scotland	0.934	0.040	0.391	0.888	19.402
N England and N Wales	1.027	0.032	0.157	0.395	7.038
S England and S Wales	0.875	0.007	0.067	0.543	14.213

Table 8-4 - Average Failure Rates per area, per year, per 100km * Fix Factor (Historical)

Area	Lightning	Snow	Wind	Other Weather	Non-Weather
N Scotland	0.762	0.944	0.735	0.303	5.071
S Scotland	0.468	0.906	1.407	0.943	18.681
N England and N Wales	0.837	0.447	0.681	0.384	7.993
S England and S Wales	0.868	0.135	0.211	0.384	12.290

Table 8-5 - Mean 95% Confidence Limit per area, per year, per 100km (State Basecase)

	Lightning		Snow		Wind		Other Weather		Non-Weather	
Area	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
N Scotland	0.602	1.284	0	0.344	0	0.714	0.332	0.387	4.576	5.258
S Scotland	0	2.434	0	1.018	0	2.113	0.82	0.956	17.996	20.807
N England and N Wales	0.52	1.534	0	0.423	0	0.836	0.367	0.423	6.543	7.533
S England and S Wales	0	1.967	0	0.729	0	1.325	0.503	0.583	13.185	15.24

Table 8-6 – Percentage Change in Failure Rates per area, per year, per 100km to the Historical Rates(State Basecase)

Area	Lightning	Snow	Wind	Other Weather	Non-Weather
N Scotland	23.67	-96.29	-71.27	18.49	-3.04
S Scotland	99.57	-95.59	-72.21	-5.85	3.86
N England and N Wales	22.66	-92.85	-76.93	2.86	-11.94
S England and S Wales	0.80	-94.82	-68.29	41.33	15.64

Table 8-7 shows the system index values for Loss of Energy Expectation (LOEE), Loss of Electrical Power (LOEP), Energy Index of Reliability (EIR), System Minutes of unavailability (SM), Loss of Load Probability (LOLP) and Loss of Load Expectation (LOLE) both days and hours for the state sampling basecase and the mean 95% confidence limits. The values displayed in Table 8-7 are higher than would be expected for the GB transmission system, where the available generation is expected to be less that demand on average no more than three hours per year. This should take into account outages, uncertainly in demand and changes in wind [215]. The reason that the state sampling model may be generating higher values may be down to how the demand is modelled, it generates a demand value from a random normal distribution, meaning that the model may constantly generate high demand values, but when wind values are low there is higher risk of load shedding. Bearing this reason in mind, the results for the other state case studies will be compared to the basecase to analyse changes in the values, as while it is understood that the values themselves are unrealistic, since the methodology is consistent, changes in these values can still be used as a way of comparison to understand the risk climate change may pose.

Table 8-7 - System Indices (State Basecase)

System Index	Mean	Mean 95% Confidence Limit
EENS/LOEE (MW)	18864	17336.2<18864<20391.8
LOEP (%)	0.005	0.005<0.005<0.005
EIR (%)	99.99	99.995<99.995<99.995
SM (minutes)	18.029	16.568<18.029<19.49
LOLP (%)	0.114	0.114<0.114<0.114
LOLE (days)	0.417	0.393<0.417<0.441
LOLE (hours)	10.017	9.44<10.017<10.595

8.1.2 Test Case One - 5% Wind Gust Increase

Table 8-8 shows the average failure rates per area, per year, per 100km and the mean 95% confidence limits for wind-related failures and the basecase, as well as the percentage change in wind failure rates compared to the basecase. There is a small change in the failure rates for both North Scotland and North England and North Wales, but both South Scotland and South England and South Wales show 7.8% and 8.9% increase in wind failure rates respectively compared to the basecase. This shows a small increase in failure rates with even a small increase in wind gusts. All four areas show a reduced range of mean 95% confidence limit compared to the basecase for weather test case one, indicating an increase confidence in where the failure rates will fall.

Table 8-8 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case One)

	Wind Plus 5%			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.207	0<0.207<0.597	-1.84	0.211	0<0.211<0.714
S Scotland	0.421	0<0.421<1.856	7.84	0.391	0<0.391<2.113
N England and N Wales	0.159	0<0.159<0.699	0.82	0.157	0<0.157<0.836
S England and S Wales	0.073	0<0.073<1.139	8.90	0.067	0<0.067<1.325

Table 8-9 shows the mean system indices and mean 95% confidence limits for weather test case one and the basecase and the percentage change between them. There is an increase in LOEE, LOEP and SM compared to the basecase indicating that the increase in wind can affect some of the system indices. However, there is a small decrease in the values of LOLP and LOLE showing that there is a decrease in the number of shedding events but an increase in the magnitude of these events.

Table 8-9 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case One)

	Wind Plus 5%			Basecase	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	20278	18352.4<20278<22203.6	7.50	18864	17336.2<18864<20391.8
LOEP (%)	0.0053	0.005<0.005<0.005	7.47	0.0049	0.005<0.005<0.005
EIR (%)	99.9947	99.995<99.995<99.995	0.00	99.9951	99.995<99.995<99.995
SM (minutes)	19.3780	17.539<19.378<21.217	7.48	18.0290	16.568<18.029<19.49
LOLP (%)	0.1123	0.112<0.112<0.112	-1.82	0.1144	0.114<0.114<0.114
LOLE (days)	0.4098	0.386<0.41<0.433	-1.82	0.4174	0.393<0.417<0.441
LOLE (hours)	9.8348	9.27<9.835<10.4	-1.82	10.0174	9.44<10.017<10.595

8.1.3 Test Case Two - 10% Wind Gust Increase

The average failure rates per area, per year, per 100km and the mean 95% confidence limits for wind-related failures and the basecase, as well as the percentage change in wind failure rates compared to the basecase are shown in Table 8-10. There is an increase in failure rates for all four areas compared to the basecase, with South Scotland seeing the biggest increase of over 22%. This suggests that a 10% increase in wind gusts will cause an increase to failure rates for all four areas within GB, which may affect system security. Again all four areas show a reduced range of the mean 95% confidence limits compared to the basecase, indicating increase confidence in predicting the failure rates.

Table 8-10 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Two)

	Wind Plus 10%			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.227	0<0.227<0.636	7.76	0.211	0<0.211<0.714
S Scotland	0.478	0<0.478<1.876	22.43	0.391	0<0.391<2.113
N England and N Wales	0.181	0<0.181<0.733	14.74	0.157	0<0.157<0.836
S England and S Wales	0.073	0<0.073<1.088	7.98	0.067	0<0.067<1.325

Table 8-11 shows the mean system indices and mean 95% confidence limits for weather test case two and the basecase, plus the percentage change between them. There is an increase in all system indices compared to the basecase. While the values of LOLP and LOLE show only a small increase, weather test case one showed a reduction in these values indicating that a 10% increase in wind increases the number of shedding events. LOEE, LOEP and SM show a larger increase but a smaller increase than was experienced in weather test case one showing less magnitude to these events.

Table 8-11 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Two)

	Wind Plus 10%			**Basecase**	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	19904	18273.4<19904<21534.6	5.51	18864	17336.2<18864<20391.8
LOEP (%)	0.0052	0.005<0.005<0.005	5.52	0.0049	0.005<0.005<0.005
EIR (%)	99.9948	99.995<99.995<99.995	0.00	99.9951	99.995<99.995<99.995
SM (minutes)	19.017	17.458<19.017<20.576	5.48	18.0290	16.568<18.029<19.49
LOLP (%)	0.1148	0.115<0.115<0.115	0.35	0.1144	0.114<0.114<0.114
LOLE (days)	0.4188	0.397<0.419<0.44	0.34	0.4174	0.393<0.417<0.441
LOLE (hours)	10.0522	9.536<10.052<10.568	0.35	10.0174	9.44<10.017<10.595

8.1.4 Overall Changes to Wind

To further investigate changes to failure rates based on changes to wind two other wind case tests were run; an increase of 25% and 50%. Figure 8-4 shows the percentage increase in failures for each test case compared to the basecase. From this it is illustrated that there is an increase in failure rates for all four areas for all wind gust profiles, with some areas seeing an almost 60% increase. Increases in failures by these proportions would have great effect on the operation of the transmission system and show that changes in wind can affect the failure rates experienced. Figure 8-5 shows the percentage change in the mean and median values for LOLE (days) compared to the basecase for the four weather test cases. It shows that while there is a small decrease in the LOLE value for test case one, there is a gradual increase in the mean LOLE value over the course of the weather test cases. This indicates that while there is an increase in the failure rates for all four weather tests cases there is only a small effect on the system indices. This assertion is based on the fact that the increased failures are fixed at a similar rate that they are now and that maintenance is maintained at its current level otherwise the system would be vulnerable to other load shedding events.

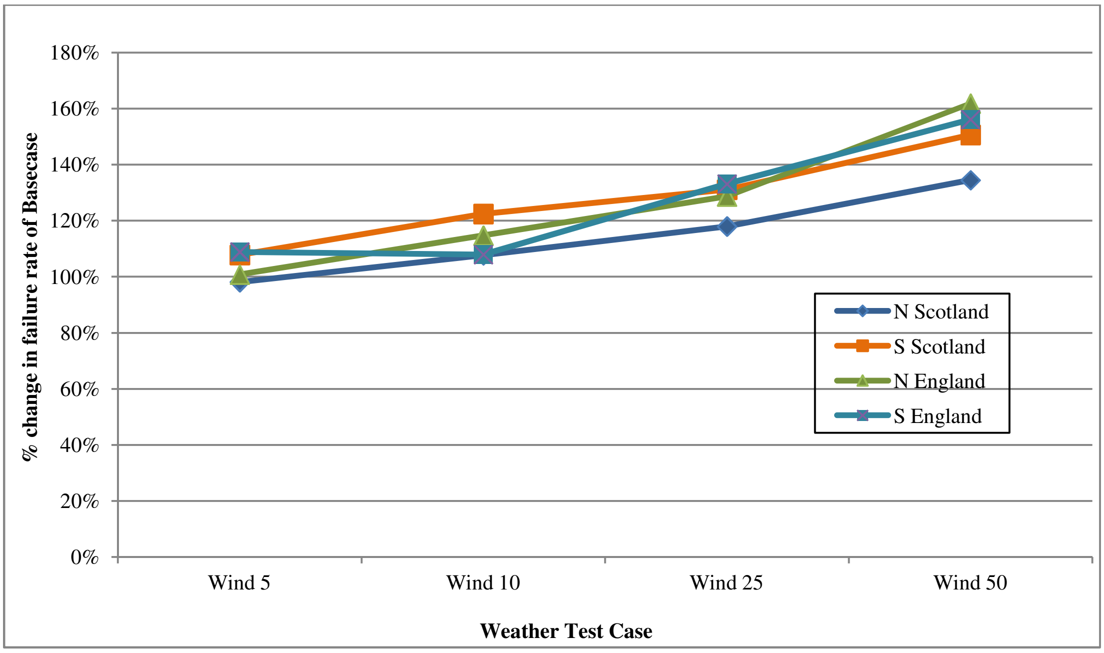


Figure 8-4 - Percentage change for State Basecase Failure Rate for Wind Failures

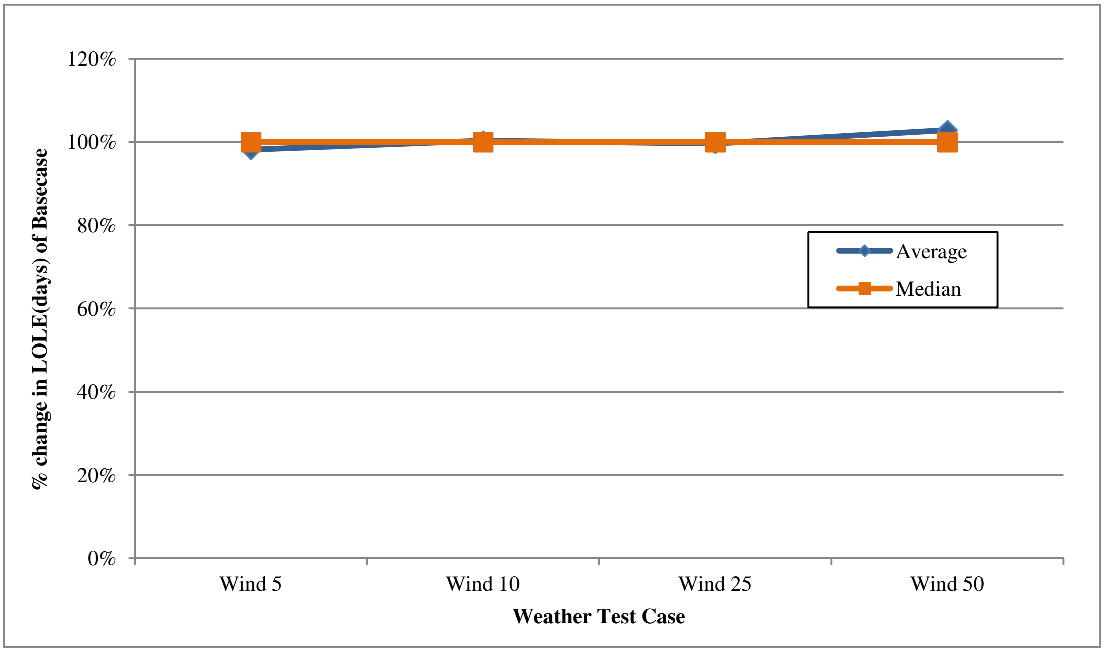


Figure 8-5 - Percentage change for State Basecase LOLE (days) for Wind Failures

8.1.5 Test Case Three - 25% CAPE Increase

Table 8-12 shows the average failure rates per area, per year, per 100km and the mean 95% confidence limits for weather test case three and the basecase, as well as the percentage change, and, Table 8-13 shows the mean system indices and mean 95% confidence limits for weather test case three and the basecase and the percentage change between them.

Table 8-12 - CAPE Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Three)

	CAPE Plus 25%			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	1.169	0.773<1.169<1.565	23.94	0.943	0.602<0.943<1.284
S Scotland	1.133	0<1.133<2.798	21.24	0.934	0<0.934<2.434
N England and N Wales	1.324	0.736<1.324<1.913	28.97	1.027	0.52<1.027<1.534
S England and S Wales	1.129	0<1.129<2.357	29.06	0.875	0<0.875<1.967

Table 8-13 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Three)

	CAPE Plus 25%			**Basecase**	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	19885	18097.4<19885<21672.6	5.41	18864	17336.2<18864<20391.8
LOEP (%)	0.0052	0.005<0.005<0.005	5.38	0.0049	0.005<0.005<0.005
EIR (%)	99.9948	99.995<99.995<99.995	0.00	99.9951	99.995<99.995<99.995
SM (minutes)	18.998	17.292<18.998<20.703	5.37	18.0290	16.568<18.029<19.49
LOLP (%)	0.1153	0.115<0.115<0.115	0.87	0.1144	0.114<0.114<0.114
LOLE (days)	0.421	0.394<0.421<0.449	0.86	0.4174	0.393<0.417<0.441
LOLE (hours)	10.1043	9.444<10.104<10.765	0.87	10.0174	9.44<10.017<10.595

It is apparent that there is an increase in all system indices for weather test case three compared to the basecase, showing an increase not only in magnitude but also load shedding events. There is an increase in the failure rates for all four areas compared to the basecase, with the largest increase in South England and South Wales with an increase of 29%. Most of the areas show an increase in the range of the mean 95% confidence limits compared to the basecase meaning there is slight decrease in confidence of the failure rates.

8.1.6 Test Case Four - 50% CAPE Increase

Table 8-14 shows the average failure rates per area, per year, per 100km and the mean 95% confidence limits for lightning-related failures and the basecase, as well as the percentage change in lightning failure rates compared to the basecase for weather test case four. There is a large increase in the failure rates compared to the basecase with North England and North Wales experiencing an increase of 56.9%. All four areas show a reduced range of the mean 95% confidence limits compared to the basecase, indicating increase confidence in predicting the failure rates.

Table 8-14 - CAPE Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Four)

	CAPE Plus 50%			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	1.382	1.332<1.382<1.432	46.51	0.943	0.602<0.943<1.284
S Scotland	1.359	1.307<1.359<1.412	45.48	0.934	0<0.934<2.434
N England and N Wales	1.611	1.582<1.611<1.641	56.89	1.027	0.52<1.027<1.534
S England and S Wales	1.336	1.302<1.336<1.37	52.70	0.875	0<0.875<1.967

The mean system indices and mean 95% confidence limits for weather test case four and the basecase are shown in Table 8-15. It also shows the percentage change between weather test case four and the basecase. There is an increase in LOEE, LOEP and SM compared to the basecase indicating that the increase in CAPE can affect some of the system indices. However, there is a small decrease in the values of LOLP and LOLE compared to the basecase. This shows that there is a decrease in the number of shedding events but an increase in the magnitude of these events when they occur.

Table 8-15 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Four)

	CAPE Plus 50%			Basecase	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	20991	18799.9<20991<23182.1	11.28	18864	17336.2<18864<20391.8
LOEP (%)	0.0055	0.006<0.006<0.006	11.33	0.0049	0.005<0.005<0.005
EIR (%)	99.9945	99.994<99.994<99.994	0.00	99.9951	99.995<99.995<99.995
SM (minutes)	20.061	17.966<20.061<22.155	11.27	18.0290	16.568<18.029<19.49
LOLP (%)	0.1128	0.113<0.113<0.113	-1.34	0.1144	0.114<0.114<0.114
LOLE (days)	0.4118	0.387<0.412<0.436	-1.34	0.4174	0.393<0.417<0.441
LOLE (hours)	9.8828	9.296<9.883<10.469	-1.34	10.0174	9.44<10.017<10.595

8.1.7 Overall Changes to CAPE

To further investigate changes to failure rates based on changes to CAPE two other test cases were analysed; an increase of 75% and 100%. Figure 8-6 shows the percentage increase in failures for each test case compared to the basecase. From this it is illustrated that there is an increase in failure rates for all four areas for all increases in CAPE, with certain areas seeing over a 100% increase. Increases by theses proportion would greatly effect on the operation of the transmission system and shows that changes in CAPE can affect the failure rates experienced. Figure 8-7 shows the percentage change in the mean and median values for LOLE (days) compared to the basecase. It shows that there is a slight decrease in the mean LOLE (days) value but that there is also an increase in the median LOLE (days) compared to the basecase. This indicates that while the extreme load shedding events are not greatly changed from the basecase but that the “average” year will experience an increase in the yearly LOLE (days) value. These assertions are based on the fact that the increased failures are fixed at a similar rate that they are now and that maintenance is maintained at its current level otherwise the system would be vulnerable to other load shedding events.

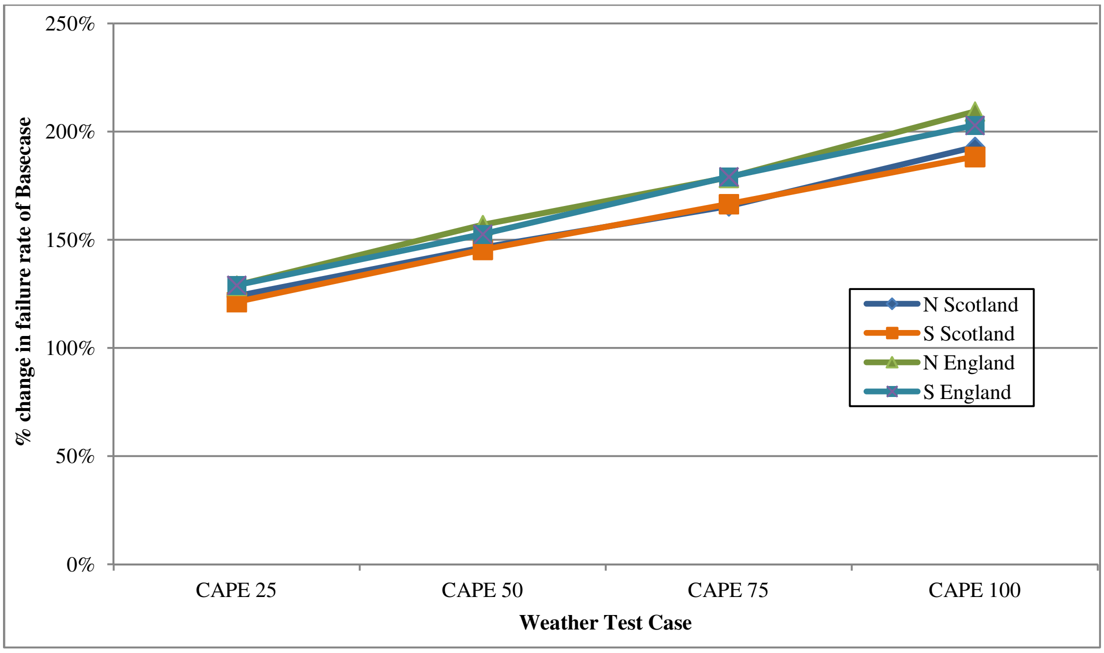


Figure 8-6 - Percentage change for State Basecase Failure Rate for Lightning Failures

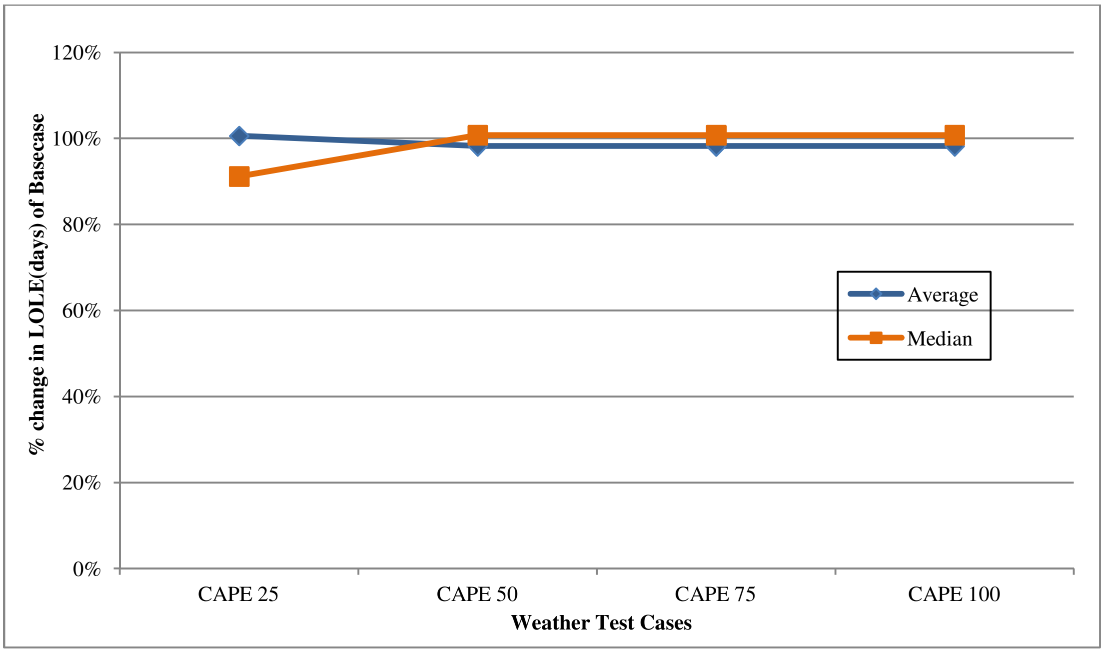


Figure 8-7 - Percentage change for State Basecase LOLE (days) for Lightning Failures

8.1.8 Test Case Five - Decrease in Snow Days (40-70%) + 5% Increase in Wind Gusts

The average failure rates per area, per year, per 100km and the mean 95% confidence limits for weather test case and the basecase, as well as the percentage change between them are displayed in Table 8-16. Compared to the basecase all four areas see a reduction in snow-related outages. Indicating that even with an increase in wind gusts the failure rates still fall due to the decrease in snow days. All four areas show an increase in the range of the mean 95% confidence limits compared to the basecase meaning there is slight decrease in confidence of the failure rates predictions.

Table 8-16 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Five)

	Less Snow + Wind Plus 5%			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.0297	0<0.03<0.432	-15.85	0.0353	0<0.035<0.344
S Scotland	0.0296	0<0.03<1.501	-26.32	0.0401	0<0.04<1.018
N England and N Wales	0.0276	0<0.028<0.582	-13.71	0.0320	0<0.032<0.423
S England and S Wales	0.0045	0<0.005<1.091	-37.14	0.0072	0<0.007<0.729

Table 8-17 shows the mean system indices and mean 95% confidence limits for weather test case five and the basecase and the percentage change between them.

Table 8-17 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Five)

	Less Snow + Wind Plus 5%			**Basecase**	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	21561	19592.6<21561<23529.4	14.29	18864	17336.2<18864<20391.8
LOEP (%)	0.0057	0.006<0.006<0.006	14.26	0.0049	0.005<0.005<0.005
EIR (%)	99.9943	99.994<99.994<99.994	0.00	99.9951	99.995<99.995<99.995
SM (minutes)	20.6	18.722<20.6<22.478	14.26	18.0290	16.568<18.029<19.49
LOLP (%)	0.1183	0.118<0.118<0.118	3.47	0.1144	0.114<0.114<0.114
LOLE (days)	0.4319	0.407<0.432<0.457	3.47	0.4174	0.393<0.417<0.441
LOLE (hours)	10.3652	9.773<10.365<10.958	3.47	10.0174	9.44<10.017<10.595

All of the system indices have increased in value compared to the basecase. Showing that while there was a reduction in failure rates there is an increase in the number of load shedding events and the magnitude of these events, suggesting that while snow is reducing the effects, the snow events could affect system security.

8.1.9 Test Case Six - Decrease in Snow Days (40-70%) + 10% Increase in Wind Gusts

The average failure rates per area, per year, per 100km and the mean 95% confidence limits for weather test case six and the basecase are shown in Table 8-18. It also displays the percentage change in snow-related failures compared to the basecase. As with the previous test case there is a reduction in failure rates, however, for three of the four areas there is less of a reduction compared to weather test case five. This implies that while the rates are reducing due to the reduction in snow the increase in wind does affect the failure rates and at some point might cancel out the effect of the reduction in snow. All four areas show an increase in the range of the mean 95% confidence limits compared to the basecase meaning there is slight decrease in confidence of the failure rates predictions.

Table 8-18 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Six)

	Less Snow + Wind Plus 10%			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.0284	0<0.028<0.49	-19.51	0.0353	0<0.035<0.344
S Scotland	0.0364	0<0.036<1.677	-9.21	0.0401	0<0.04<1.018
N England and N Wales	0.0313	0<0.031<0.668	-2.03	0.0320	0<0.032<0.423
S England and S Wales	0.0058	0<0.006<1.234	-20.00	0.0072	0<0.007<0.729

The mean system indices and 95% confidence limits for weather test case six and the basecase, plus the percentage change between them are shown in Table 8-19. Again all of the system indices have increased compared to the basecase. Showing that while there was a reduction in failure rates there is an increase in the number of load shedding events and their magnitude. While snow is reducing the effects on system security the increase in wind means they are not as severe as the previous test case.

Table 8-19 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Six)

	Less Snow + Wind Plus 10%			Basecase	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	20472	18655.2<20472<22288.8	8.52	18864	17336.2<18864<20391.8
LOEP (%)	0.005	0.005<0.005<0.005	8.49	0.0049	0.005<0.005<0.005
EIR (%)	99.995	99.995<99.995<99.995	0.00	99.9951	99.995<99.995<99.995
SM (minutes)	19.563	17.827<19.563<21.298	8.51	18.0290	16.568<18.029<19.49
LOLP (%)	0.118	0.118<0.118<0.118	2.95	0.1144	0.114<0.114<0.114
LOLE (days)	0.4297	0.406<0.43<0.453	2.95	0.4174	0.393<0.417<0.441
LOLE (hours)	10.313	9.751<10.313<10.875	2.95	10.0174	9.44<10.017<10.595

8.1.10 Overall Changes to Snow

Two further tests cases were developed analysing a decrease in snow but an increase in wind gusts on snow days by 25% and 50%. The percentage changes in failure rates compared to the basecase are shown in Figure 8-8. It is difficult to determine a pattern for all four areas, both North Scotland and North England and North Wales show an increase in failure rates for all test cases, whereas South England and South Wales show an increase for three test cases and a decrease for the fourth and South Scotland shows a decrease for the last two weather test cases. This implies that the more complex nature of snow failures made be too hard for this model to accurately predict. Figure 8-9 shows the percentage change in the mean and median values for LOLE (days) compared to the basecase.

Figure 8-9 shows that for the first two weather test cases both the mean and median value of LOLE (days) is slightly above the basecase, suggesting that the "average" year is slightly worse compared to what is experienced currently. While the third weather test case show a decrease in both of these values, suggesting that the change in both snow and wind have cancelled each other out. For the final test case there is an increase in both the mean and median values of LOLE (days) suggesting that the increase in wind has superseded the reduction in snow days.

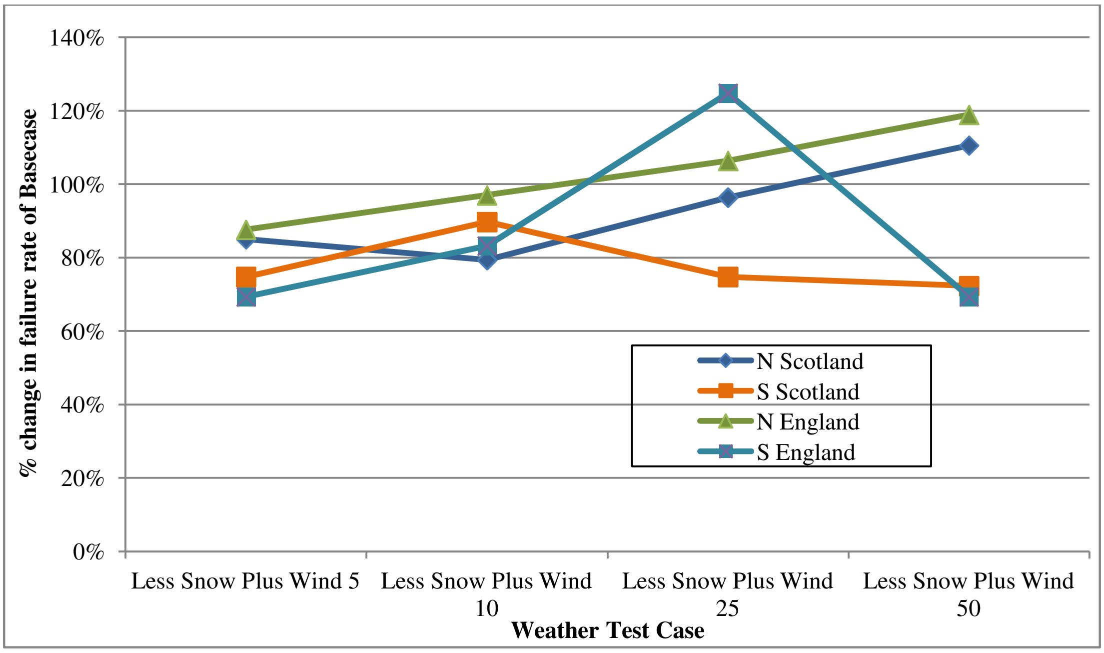


Figure 8-8 - Percentage change for State Basecase Failure Rate for Snow Failures

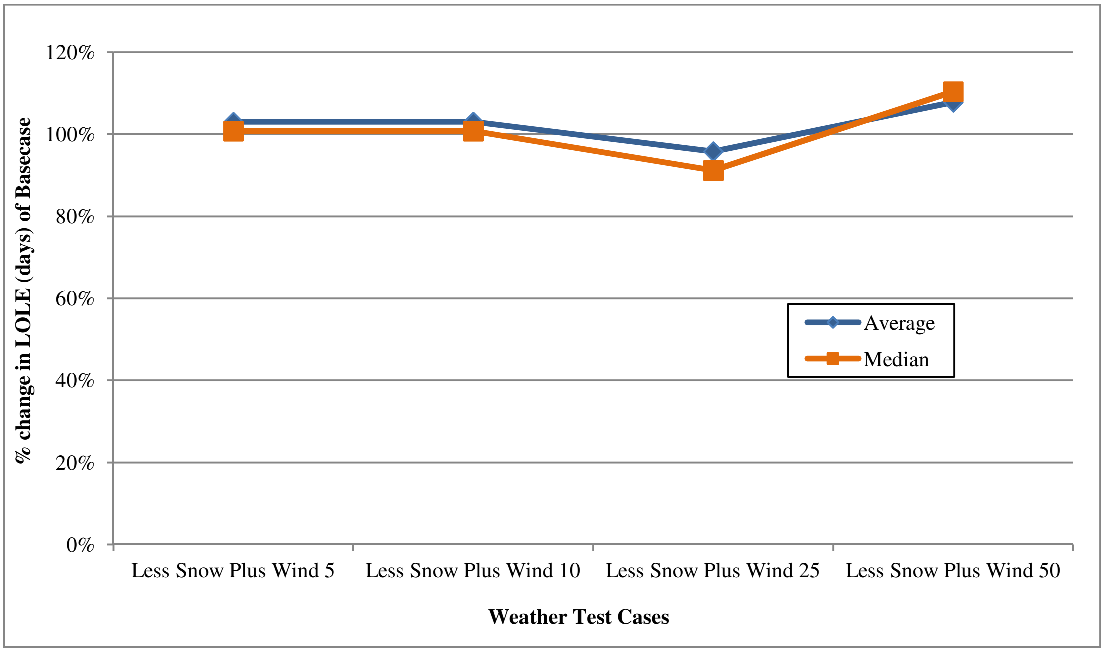


Figure 8-9 - Percentage change for State Basecase LOLE (days) for Snow Failures

8.1.11 Test Case Seven – Worst Case

Table 8-20 shows the percentage change in the failure rates per area, per year, per 100km compared to the basecase for the seventh weather test case. It is clear to see that overall there is an increase in weather-related failures due to the changes in weather, indicating that even with the reduction in failures due to snow, the increase in both lightning and wind-related failures outweigh this reduction.

Table 8-20 – Percentage Change in Failure Rates per area, per year, per 100km to the Basecase Rates(Weather Test Case Seven)

Area	Lightning	Snow	Wind	Other Weather	Non-Weather	Weather Total
N Scotland	46.06	-17.07	-0.41	4.91	-0.96	28.75
S Scotland	40.23	-11.84	15.14	-6.24	0.26	16.63
N England and N Wales	51.89	9.64	11.24	-1.60	-0.16	33.97
S England and S Wales	50.01	-11.43	12.27	-4.86	0.12	28.06

Table 8-21 shows the mean system indices and mean 95% confidence limits for weather test case seven and the basecase and the percentage change between weather test case seven and the basecase. It displays an increase in the values of LOEE, LEP and SM indicting an increased magnitude in load shedding events but a decrease in the values of LOLP and LOLE indicating a reduced number of load shedding events. These changes in the values of the system indices are based on the increase in modelled failure rates being fixed at the current repair rate, if the increase in failures are not corrected at this repair rate it will leave the system vulnerable to more load shedding events.

Table 8-21 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Seven)

	Worse Case			**Basecase**	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	19405	17468.9<19405<21341.0	2.87	18864	17336.2<18864<20391.8
LOEP (%)	0.0051	0.005<0.005<0.005	2.86	0.0049	0.005<0.005<0.005
EIR (%)	99.9949	99.995<99.995<99.995	0.00	99.9951	99.995<99.995<99.995
SM (minutes)	18.544	16.695<18.544<20.392	2.86	18.0290	16.568<18.029<19.49
LOLP (%)	0.1090	0.109<0.109<0.109	-4.69	0.1144	0.114<0.114<0.114
LOLE (days)	0.3978	0.379<0.398<0.417	-4.70	0.4174	0.393<0.417<0.441
LOLE (hours)	9.5478	9.09<9.548<10.006	-4.69	10.0174	9.44<10.017<10.595

8.1.12 State Sampling Conclusion

Table 8-22 and Table 8-23 show the percentage change in average weather failure rates for each weather test case in comparison to the basecase and the percentage change in LOLE (days) in comparison to the basecase respectively for the state sampling model. From Table 8-22 it is clear to see that as CAPE increases as does the failure rate in comparison to the basecase. It is also apparent, that for increases in wind, minus the 5% increase, there is an increase in failure rates. This anomaly in the trend could be down to an extreme event occurring, suggesting that possibly more trials may need to be run but it also shows the sensitivity in failure rates to extreme events. It is clear to see that the changes in snow do not follow any trend, confirming earlier assumptions that the state model is unable to deal with the complexities that surround the prediction of snow related outages. It is clear to see from the worst case results that, overall there is an increase in average failure rates when there are slight changes to the weather that is experienced, suggesting possible reliability issues if these climate change scenarios were to occur. From Table 8-23 it is clear to see what was suggested in earlier results discussions, that the state model is unable to fully deal with the complexities of load modelling and that more trials may need to be run to accurately model the effects to load indices.

Table 8-22 – Percentage Change in Average Weather Failure Rate, for each Weather Test Case, in Comparison to the Basecase (State)

Weather Test Case	N Scotland	S Scotland	N England and N Wales	S England and S Wales
Base	0	0	0	0
5% Wind Gust Increase	0.20	-0.58	-0.93	-0.10
10% Wind Gust Increase	0.04	0.01	0.00	0.00
25% Wind Gust Increase	0.05	0.02	0.05	0.01
50% Wind Gust Increase	0.06	0.08	0.07	0.04
25% CAPE Increase	0.15	0.07	0.18	0.16
50% CAPE Increase	0.27	0.18	0.35	0.30
75% CAPE Increase	0.40	0.25	0.52	0.46
100% CAPE Increase	0.57	0.35	0.70	0.60
Decrease in Snow Days (40-70%) + 5% Increase in Wind Gusts	0.01	0.01	0.01	-0.02
Decrease in Snow Days (40-70%) + 10% Increase in Wind Gusts	0.00	-0.02	0.00	0.00
Decrease in Snow Days (40-70%) + 25% Increase in Wind Gusts	-0.02	-0.02	0.03	0.01
Decrease in Snow Days (40-70%) + 50% Increase in Wind Gusts	0.02	0.01	0.01	0.00
Worst Case	0.29	0.17	0.34	0.28

Table 8-23 - Percentage change in LOLE (days), for each Weather Test Case, in Comparison to the Basecase (State)

Weather Test Case	% Change
Base	0.000
5% Wind Gust Increase	-0.017
10% Wind Gust Increase	0.004
25% Wind Gust Increase	-0.003
50% Wind Gust Increase	0.030
25% CAPE Increase	0.007
50% CAPE Increase	-0.017
75% CAPE Increase	-0.017
100% CAPE Increase	-0.017
Decrease in Snow Days (40-70%) + 5% Increase in Wind Gusts	0.031
Decrease in Snow Days (40-70%) + 10% Increase in Wind Gusts	0.031
Decrease in Snow Days (40-70%) + 25% Increase in Wind Gusts	-0.041
Decrease in Snow Days (40-70%) + 50% Increase in Wind Gusts	0.079
Worst Case	-0.046

8.2 Sequential Sampling Basecase and Future Weather Test Cases Sequential Sampling Outage Results

The next sections shall discuss the failure rates, load indices and system unavailability results for the basecase and the weather test cases set-up in Section 7.4 for the sequential sampling model, set-up as discussed in Chapter 7. For each other weather test cases only the weather being analysed was changed, all other weather remained the same allowing the change in each weather type changed to be fully analysed. The failure rates for all weathers and their associated confidence limits can be found in Appendix I; only the failure rates for the changed weather will be discussed within this thesis.

8.2.1 Basecase Analysis

The first sequential sampling case that was modelled was the basecase. As before this should be similar to the historical data and will determine how accurately it reproduces the current weather and outages. Figure 8-10, Figure 8-11 and Figure 8-12 show the average yearly weather that the sequential model reproduces for North Scotland for CAPE, wind gusts and wind gusts on snow days respectively as well as the historical weather frequency distributions. The frequency distributions for South Scotland, North England and North Wales and South England and South Wales can be found in Appendix I.

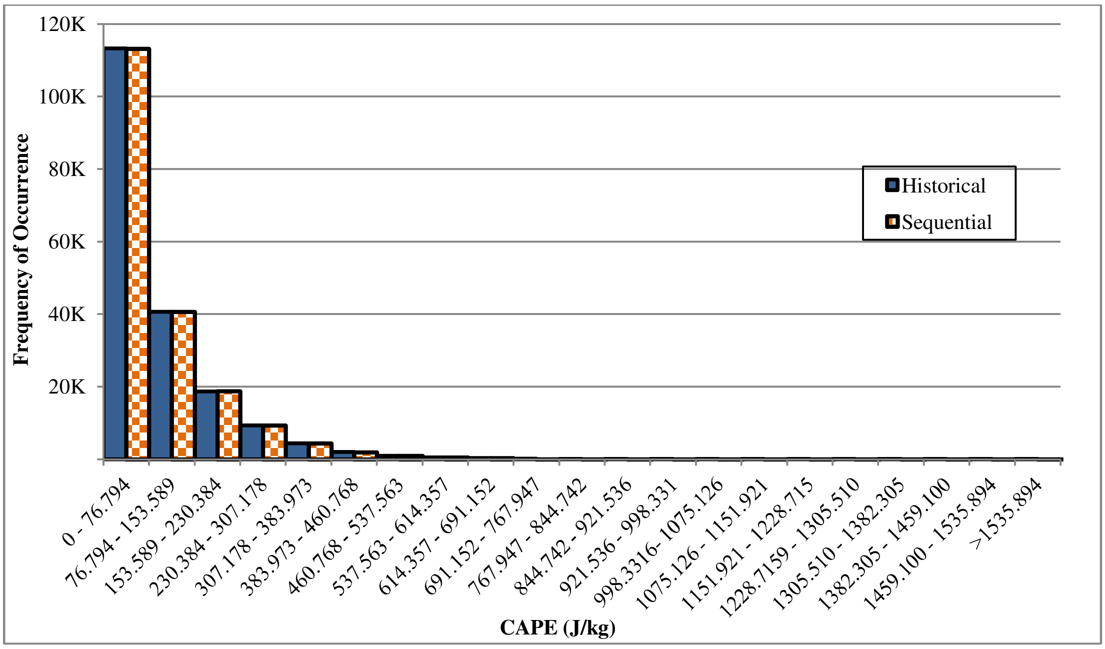


Figure 8-10 - Sequential Basecase and Historical CAPE (J/kg) Distribution, North Scotland

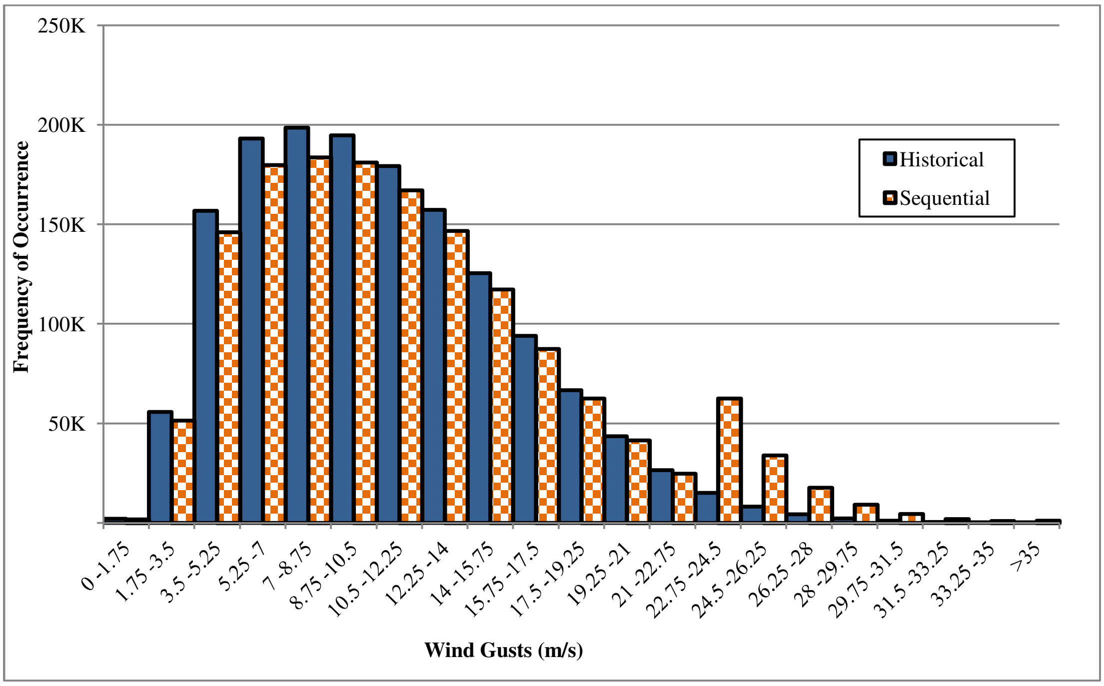


Figure 8-11 - Sequential Basecase and Historical Wind Gusts (m/s) Distribution, North Scotland

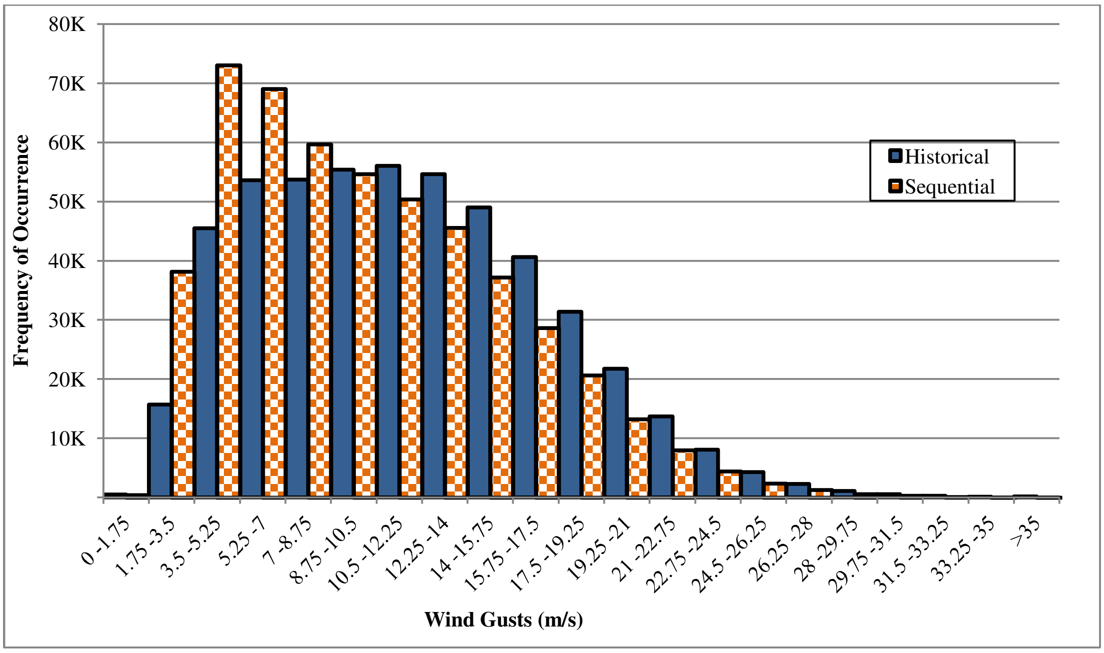


Figure 8-12 - Sequential Basecase and Historical Wind Gusts on Snow Days (m/s) Distribution, North Scotland

Table 8-24 shows the maximum, minimum, average and standard deviation of the percentage change for each weather type compared to the historical weather data. As the state model struggled to model wind and snow-related failures, for the sequential model, durations of extreme events were added as discussed in Section 7.1.2. Due to this addition it is found that wind gusts and wind gusts on snow days have larger errors when compared to the historical data than was experienced by the state model; on average 29% lower for wind gusts and 94% higher for wind gusts on snow days. However, CAPE shows little change from the state model with a 5.7% error as CAPE events have much shorter durations. This shows that the state model is more accurate at reproducing the historical weather.

Table 8-24 - Statistical Analysis of Sequential Model Weather Generation Percentage Change Compared to Historical Weather

	CAPE (%)	Wind Gusts (%)	Wind Gusts on Snow Days (%)
Max	37.54	12.02	227.52
Min	-1.00	-74.62	-59.67
Average	5.69	-28.65	94.16
Standard Deviation	8.45	41.04	90.40

The average failure rates per area, per year, per 100km and the mean 95% upper and lower confidence limits for the failure rates and the percentage change is failure rates compared to the historical rates for the sequential sampling basecase are shown in Table 8-25, Table 8-26 and Table 8-27 respectively. It is found that the sequential model also overestimates lightning-related failures compared to historical rates by up to 99.2%, which is similar to the state sampling modelling. As with the state model the sequential model underestimates both snow and wind-related failures by 76.5% and 50.9% respectively but there is less of an underestimation, apart from wind-related failures in England and Wales, which could be contributed to not enough historical data to sample extremes. However, overall the sequential model is more accurate at reproducing the historical weather failures rates due to the changes made when sampling wind and snow extremes.

Table 8-25 - Average Failure Rates per area, per year, per 100km (Sequential Basecase)

Area	Lightning	Snow	Wind	Other Weather	Non-Weather
N Scotland	0.532	0.106	0.254	0.102	1.129
S Scotland	0.544	0.144	0.402	0.146	3.162
N England and N Wales	0.432	0.086	0.119	0.098	0.764
S England and S Wales	0.374	0.021	0.053	0.127	1.519

Table 8-26 - Mean 95% Confidence Limit per area, per year, per 100km (Sequential Basecase)

	Lightning		Snow		Wind		Other Weather		Non-Weather	
Area	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
N Scotland	0.500	0.563	0.091	0.121	0.231	0.277	0.090	0.115	1.089	1.170
S Scotland	0.507	0.580	0.126	0.161	0.368	0.436	0.128	0.163	3.079	3.246
N England and N Wales	0.415	0.448	0.080	0.093	0.107	0.131	0.089	0.106	0.743	0.786
S England and S Wales	0.359	0.390	0.017	0.025	0.047	0.060	0.118	0.137	1.482	1.557

Table 8-27 – Percentage Change in Failure Rates per area, per year, per 100km to the Historical Rates (Sequential Basecase)

Area	Lightning	Snow	Wind	Other Weather	Non-Weather
N Scotland	22.80	-76.65	-33.62	40.25	-4.14
S Scotland	99.15	-64.72	-30.41	-8.95	2.54
N England and N Wales	20.23	-34.51	-50.94	1.88	-13.54
S England and S Wales	1.45	-43.20	-26.90	36.91	17.94

Table 8-28 shows the average yearly unavailability of the system in the basecase. When comparing these values to Section 4.3.6 it is clear the sequential sampling model reproduces the unavailability of the network caused by weather. The overall unavailability of the network is slightly higher, indicating a slight error with non-weather-related outages.

Table 8-28 - System Availability (%) and Unavailability (%) (Sequential Basecase)

	Weather		Non-Weather		Overall	
Area	Avail.	Unavail.	Avail.	Unavail.	Avail.	Unavail.
N Scotland	99.993	0.007	99.974	0.026	99.968	0.032
S Scotland	99.990	0.010	99.896	0.104	99.886	0.114
N England and N Wales	99.986	0.014	99.911	0.089	99.896	0.104
S England and S Wales	99.987	0.013	99.852	0.148	99.840	0.160

The mean system index values and the mean 95% confidence limits are shown in Table 8-29. These values will be used to compare the effect of changes in the weather have on the system indices. When compared to the state basecase the mean values of the system indices are more realistic within the sequential basecase. This is due to the sequential model stepping through a load profile and the weather values are based on the previous values making the simulated situations more realistic, as the GB transmission system is limited to 3 hours of LOLE within a year, which would be just over 1 day per ten years [216], the sequential model is within these limitations.

Table 8-29 - System Indices (Sequential Basecase)

System Index	Mean	Mean 95% Confidence Limit
EENS/LOEE (MW)	814	632.4<814<995.6
LOEP (%)	0.00024	0<0<0
EIR (%)	99.99976	100<100<100
SM (minutes)	0.784	0.609<0.784<0.959
LOLP (%)	0.01102	0.011<0.011<0.011
LOLE (days)	0.0402	0.033<0.04<0.047
LOLE (hours)	0.96522	0.802<0.965<1.129

8.2.2 Test Case One - 5% Wind Gust Increase

The average failure rates per area, per year, per 100km and the mean 95% confidence limits for weather test case one and the basecase, as well as the percentage change in wind failure rates between them are shown in Table 8-30. Unlike the state sampling model, there is an increase in failure rates for all four areas, with the highest increase in North Scotland by 74.6%. With an increase of this magnitude it is possible that the system could be vulnerable.

As with the basecase there is a small mean 95% confidence range, indicating a high certainly that the failure rates will within this range.

Table 8-30 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case One)

	Wind Plus 5%			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.444	0.414<0.444<0.474	74.619	0.254	0.231<0.254<0.277
S Scotland	0.634	0.59<0.634<0.678	57.612	0.402	0.368<0.402<0.436
N England and N Wales	0.194	0.178<0.194<0.21	63.388	0.119	0.107<0.119<0.131
S England and S Wales	0.075	0.067<0.075<0.082	39.768	0.053	0.047<0.053<0.06

Both the system availability and unavailability, for weather test case one, are shown in Table 8-31. Compared to the results from the basecase it is clear that England and Wales experience a small increase in system unavailability due to weather, suggesting that changes in wind could indicate that the system may be vulnerable to further outages.

Table 8-31 - System Availability (%) and Unavailability (%) (Test Case One)

	Weather		**Non-Weather**		**Overall**	
Area	Avail.	Unavail.	Avail.	Unavail.	Avail.	Unavail.
N Scotland	99.993	0.007	99.975	0.025	99.969	0.031
S Scotland	99.990	0.010	99.897	0.103	99.887	0.113
N England and N Wales	99.982	0.018	99.909	0.091	99.892	0.108
S England and S Wales	99.986	0.014	99.857	0.143	99.845	0.155

The mean system indices and mean 95% confidence limits for weather test case one and the basecase and the percentage change between them are displayed in Table 8-32. It is apparent that all system indices have increased compared to the basecase indicating an increase in the number of load shedding events and magnitude. However, when evaluating the mean 95% confidence limits for the values of LOEE, and SM it is found that they have a large range indicating low confidence on where the value will lie, suggesting high sensitivity to extreme values of load shedding. Whereas, the range for the value of LOLE is similar to that of the basecase case suggesting more confidence of where these results shall lie and therefore more confidence in the change compared to the basecase.

Table 8-32 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case One)

	Wind Plus 5%			Basecase	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	2496	702.233<2496<4289.767	206.63	814	632.422<814<995.578
LOEP (%)	0.00074	0.001<0.001<0.001	206.78	0.00024	0<0<0
EIR (%)	99.999	99.999<99.999<99.999	0.00	99.999	100<100<100
SM (minutes)	2.412	0.677<2.412<4.147	207.65	0.784	0.609<0.784<0.959
LOLP (%)	0.01221	0.012<0.012<0.012	10.81	0.01102	0.011<0.011<0.011
LOLE (days)	0.0446	0.037<0.045<0.052	10.95	0.0402	0.033<0.04<0.047
LOLE (hours)	1.06957	0.89<1.07<1.249	10.81	0.96522	0.802<0.965<1.129

8.2.3 Test Case Two - 10% Wind Gust Increase

Table 8-33 presents the average failure rates per area, per year, per 100km and the mean 95% confidence limits for test case two and the basecase, as well as the percentage change between them. All four areas show an increase in the failure rates compared to the basecase, in three of the areas this increase is over 100%. There is a small mean 95% confidence range, indicating a high certainly that the failure rates will fall near to the shown values. An increase by these amounts could affect the security of the transmission system.

Table 8-33 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Two)

	Wind Plus 10%			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.634	0.6<0.634<0.668	149.24	0.254	0.231<0.254<0.277
S Scotland	0.969	0.921<0.969<1.016	140.81	0.402	0.368<0.402<0.436
N England and N Wales	0.269	0.251<0.269<0.287	126.50	0.119	0.107<0.119<0.131
S England and S Wales	0.103	0.094<0.103<0.112	92.66	0.053	0.047<0.053<0.06

Table 8-34 displays the system availability and unavailability for weather test case two. South Scotland and England and Wales all see an increase in system unavailability due to weather suggesting that a change to wind could affect system reliability.

Table 8-34 - System Availability (%) and Unavailability (%) (Test Case Two)

	Weather		Non-Weather		Overall	
Area	Avail.	Unavail.	Avail.	Unavail.	Avail.	Unavail.
N Scotland	99.993	0.007	99.973	0.027	99.966	0.034
S Scotland	99.988	0.012	99.896	0.104	99.884	0.116
N England and N Wales	99.978	0.022	99.908	0.092	99.887	0.113
S England and S Wales	99.986	0.014	99.858	0.142	99.845	0.155

The mean system indices and mean 95% confidence limits for weather test case two and the basecase and the percentage change between them are displayed in Table 8-35. There is an increase in shedding events and the magnitude of MW shed due to an increase in wind gusts of 10%. These increases could affect the systems security and reliability; therefore, change may be needed. As with weather test case one the mean 95% confidence limits for the values of LOEE, and SM have a large range suggesting low confidence in the value, suggesting high sensitivity to extreme values. The range for the value of LOLE is similar to that of the basecase case suggesting more confidence in the results.

Table 8-35 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Two)

	Wind Plus 10%			Basecase	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	1887	694.116<1887<3079.884	131.82	814	632.422<814<995.578
LOEP (%)	0.0006	0.001<0.001<0.001	131.89	0.0002	0<0<0
EIR (%)	99.999	99.999<99.999<99.999	0.00	99.999	100<100<100
SM (minutes)	1.819	0.667<1.819<2.971	132.02	0.784	0.609<0.784<0.959
LOLP (%)	0.0144	0.014<0.014<0.014	30.63	0.0110	0.011<0.011<0.011
LOLE (days)	0.0525	0.043<0.053<0.062	30.60	0.0402	0.033<0.04<0.047
LOLE (hours)	1.2609	1.044<1.261<1.478	30.63	0.9652	0.802<0.965<1.129

8.2.4 Overall Changes to Wind

Two other wind case tests were run; an increase of 25% and 50%. The percentage increases in failures for each test case, compared to the basecase are presented in Figure 8-13. All four areas experience an increase in wind-related failure, with South Scotland seeing the highest increase of almost 800%. Increases in failures by theses proportion would have great effect on the operation of the transmission system and shows that changes in wind can affect the failure rates experienced.

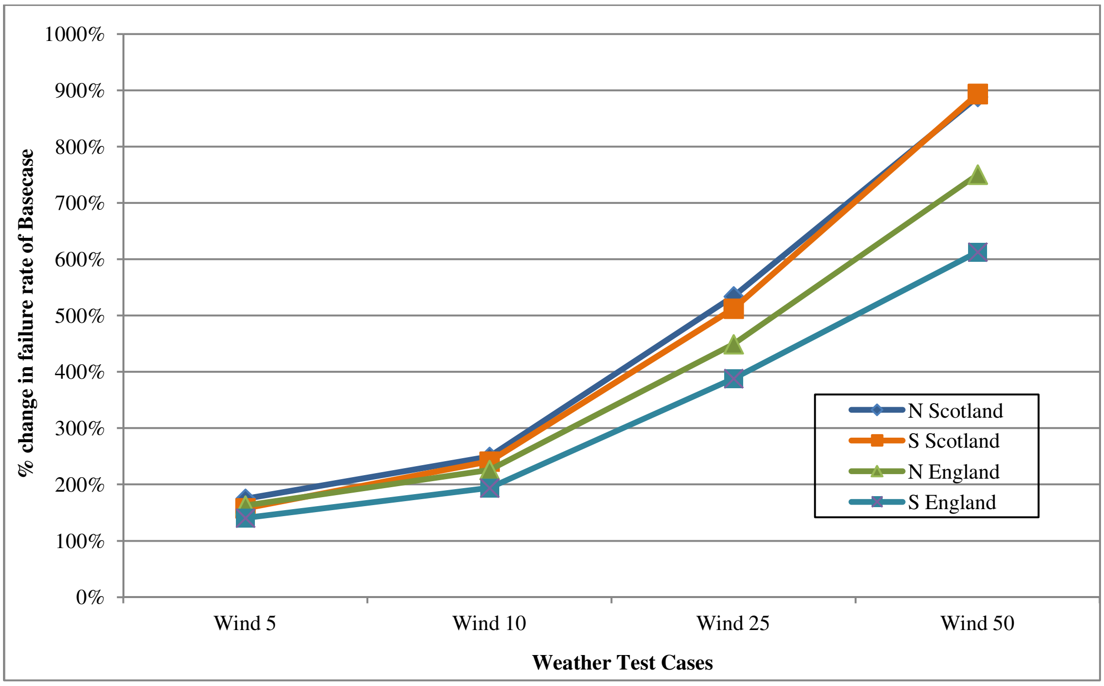


Figure 8-13 - Percentage Change for Sequential Basecase Failure Rate for Wind Failures

The percentage change in the mean and median values for LOLE (days) compared to the basecase for the four weather test cases are displayed in Figure 8-14. Is shows that there is little change to the median value compared to the basecase, suggesting that the “average” year is mainly unchanged. However, it is clear from the mean value for the first three test cases that the extremes are much more affected by the change in wind. The fourth weather test case, when the wind is increased by 50%, there is a drop of the mean values of LOLE (days) compared to the basecase. This means that there are fewer time steps which experience load being shed this can be attributed to having increased wind generation. The wind generation is more flexible and is placed throughout the network unlike conventional generation which tends to be in a specific place. This means that when a failure occurs in this test case there is more localised generation to meet the demand and generation is not required to travel through the failed branch. This assessment is made under the assumption that repair rates would remain at the same rate as currently experienced in order to maintain system security or changes would be required to compensate for these changes.

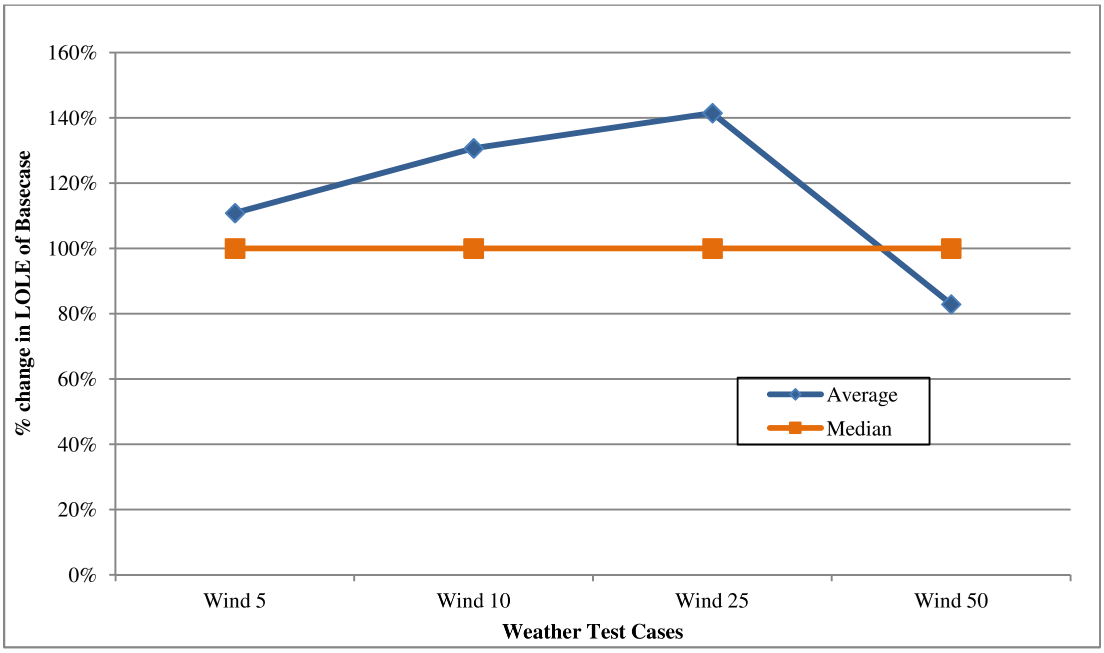


Figure 8-14 - Percentage change for Sequential Basecase LOLE (days) for Wind Failures

8.2.5 Test Case Three - 25% CAPE Increase

The average failure rates per area, per year, per 100km and the mean 95% confidence limits for weather test case three and the basecase, plus the percentage change in lightning failures between them are shown in Table 8-36. It is discernible that all four areas see an increase in failure rates with the largest increase in South England and South Wales of 27.3%. All four areas show a small range for the confidence limits, showing a high certainty that the failure rates will fall near to the shown value.

Table 8-36 - CAPE Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Three)

	CAPE plus 25%			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.756	0.723<0.756<0.788	42.15	0.532	0.5<0.532<0.563
S Scotland	0.720	0.684<0.72<0.756	32.43	0.544	0.507<0.544<0.58
N England and N Wales	0.616	0.598<0.616<0.633	42.62	0.432	0.415<0.432<0.448
S England and S Wales	0.552	0.53<0.552<0.573	47.39	0.374	0.359<0.374<0.39

Table 8-37 shows the system availability and unavailability for weather test case three. There are small increases for system unavailability due to weather, suggesting sensitivity to changes in CAPE.

Table 8-37 - System Availability (%) and Unavailability (%) (Test Case Three)

	Weather		Non-Weather		Overall	
Area	Avail.	Unavail.	Avail.	Unavail.	Avail.	Unavail.
N Scotland	99.992	0.008	99.976	0.024	99.969	0.031
S Scotland	99.989	0.011	99.897	0.103	99.886	0.114
N England and N Wales	99.983	0.017	99.910	0.090	99.893	0.107
S England and S Wales	99.986	0.014	99.855	0.145	99.843	0.157

The mean system indices and mean 95% confidence limits for weather test case three and the basecase and the percentage change between them are displayed in Table 8-38. There is an increase in all system indices, showing that the increase in CAPE causes an increase in both load shedding events and the MWs shedded. However, the mean 95% confidence limits for the values of LOEE, and SM have a large range suggesting low confidence in the values, suggesting high sensitivity to extreme values of load shedding. The range for the value of LOLE is similar to that of the basecase case suggesting more confidence in these results.

Table 8-38 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Three)

	CAPE plus 25%			Basecase	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	1438	573.723<1438<2302.277	76.66	814	632.422<814<995.578
LOEP (%)	0.00043	0<0<0	76.73	0.00024	0<0<0
EIR (%)	99.999	100<100<100	0.00	99.999	100<100<100
SM (minutes)	1.386	0.551<1.386<2.222	76.79	0.784	0.609<0.784<0.959
LOLP (%)	0.01142	0.011<0.011<0.011	3.60	0.01102	0.011<0.011<0.011
LOLE (days)	0.0417	0.034<0.042<0.049	3.73	0.0402	0.033<0.04<0.047
LOLE (hours)	1.00000	0.826<1<1.174	3.60	0.96522	0.802<0.965<1.129

8.2.6 Test Case Four - 50% CAPE Increase

Table 8-39 displays the average failure rates per area, per year, per 100km and the mean 95% confidence limits for test case four and the basecase, as well as the percentage change between them. There is an increase in failure rates for all four areas for lightning-related outages, with the largest increase in North England and North Wales of 87.9%. There is a small range for the confidence limits, indicating a high certainly that the failure rates will fall near to the shown value. The results for system availability and unavailability for weather test case four are shown in Table 8-40. There are slight increases to system unavailability due to weather for all four regions, with North England and North Wales being the most affected, suggesting a decrease in system availably due to the changes to CAPE.

Table 8-39 - CAPE Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Four)

	CAPE Plus 50%			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.976	0.938<0.976<1.014	83.50	0.532	0.5<0.532<0.563
S Scotland	0.941	0.899<0.941<0.982	73.01	0.544	0.507<0.544<0.58
N England and N Wales	0.811	0.79<0.811<0.833	87.94	0.432	0.415<0.432<0.448
S England and S Wales	0.687	0.664<0.687<0.711	83.60	0.374	0.359<0.374<0.39

Table 8-40 - System Availability (%) and Unavailability (%) (Test Case Four)

	Weather		**Non-Weather**		**Overall**	
Area	Avail.	Unavail.	Avail.	Unavail.	Avail.	Unavail.
N Scotland	99.991	0.009	99.974	0.026	99.966	0.034
S Scotland	99.988	0.012	99.896	0.104	99.884	0.116
N England and N Wales	99.981	0.019	99.910	0.090	99.891	0.109
S England and S Wales	99.985	0.015	99.857	0.143	99.843	0.157

Table 8-41 presents the mean system indices and mean 95% confidence limits for weather test case four and the basecase and the percentage change between them. There is an increase in all system indices. However, the mean 95% confidence limits for the values of LOEE, and SM have a large range suggesting low confidence on where the value will lie, suggesting high sensitivity to extreme values. The range for LOLE is smaller suggesting more confidence of where the results will lie.

Table 8-41 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Four)

	CAPE plus 25%			**Basecase**	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	1274	439.099<1274<2108.901	56.51	814	632.422<814<995.578
LOEP (%)	0.00038	0<0<0	56.61	0.00024	0<0<0
EIR (%)	99.999	100<100<100	0.00	99.999	100<100<100
SM (minutes)	1.227	0.422<1.227<2.031	56.51	0.784	0.609<0.784<0.959
LOLP (%)	0.01122	0.011<0.011<0.011	1.80	0.01102	0.011<0.011<0.011
LOLE (days)	0.0409	0.034<0.041<0.048	1.74	0.0402	0.033<0.04<0.047
LOLE (hours)	0.98261	0.811<0.983<1.155	1.80	0.96522	0.802<0.965<1.129

8.2.7 Overall Changes to CAPE

Two other tests were investigated; an increase in CAPE of 75% and 100%. Figure 8-15 shows the percentage increase in failures for each test case compared to the basecase. The percentage change in the mean and median values for LOLE (days) compared to the basecase are shown in Figure 8-16.

Figure 8-15 shows that all four areas experience an almost liner increase in failure rates, with North Scotland and South England and South Wales seeing the highest increase of around 150%. An increase by this proportion could have a great effect on the operation of the transmission network and in order to maintain the current values of system security repair rates would need to remain the same. Figure 8-16 shows that there no change in the median LOLE (days) value but that there is a slight increase in the mean LOLE (days). This indicates that while the “average” yearly load shedding events are not greatly changed, there are more extreme years where there is a higher value of yearly LOLE (days). These assertions are based on the fact that the failures are fixed at the current repair rate, otherwise the system would be vulnerable to other load shedding events.

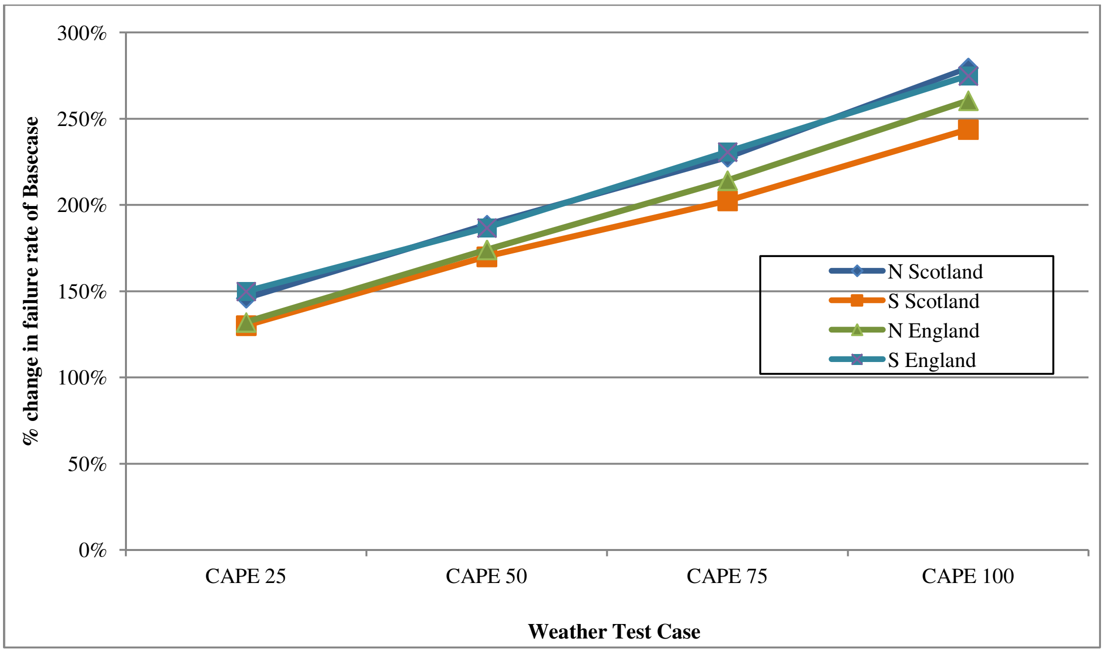


Figure 8-15 - Percentage Change for Sequential Basecase Failure Rate for Lightning Failures

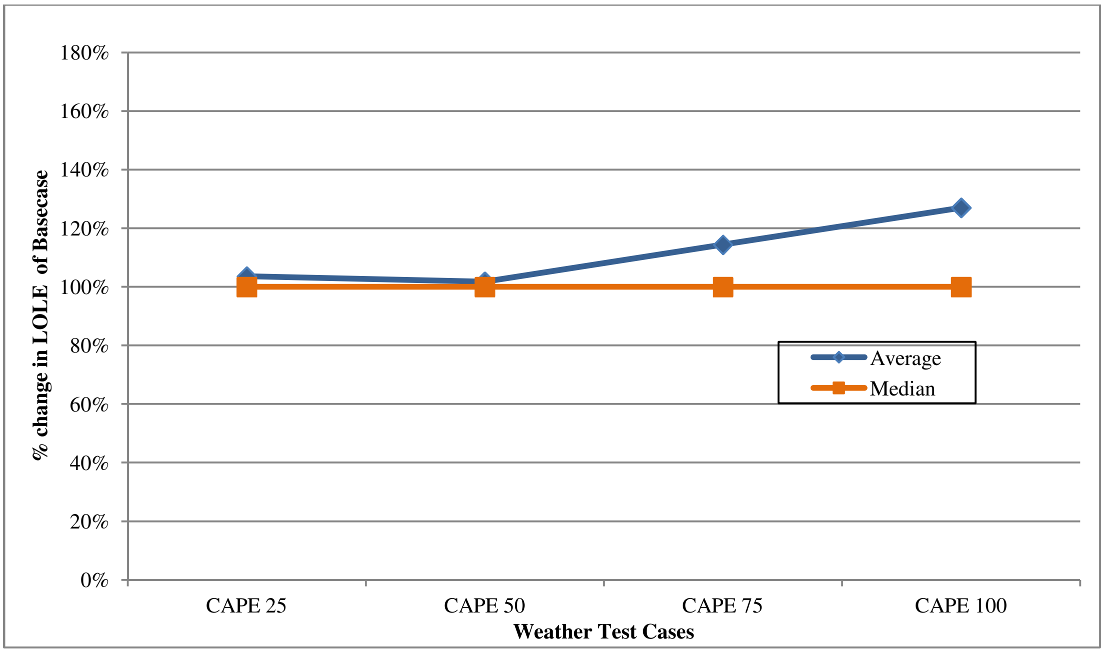


Figure 8-16 - Percentage Change for Sequential Basecase LOLE (days) for Lightning Failures

8.2.8 Test Case Five - Decrease in Snow Days (40-70%) + 5% Increase in Wind Gusts

Table 8-42 presents the average failure rates per area, per year, per 100km and the mean 95% confidence limits for test case five and the basecase, plus the percentage change between them. There is a reduction in snow-related failures for all four areas, with England

and Wales seeing the largest. This suggests that even with an increase in wind gusts on snow days, the reduction of snow has a much larger effect on the failure rates. Table 8-43 shows the system availability and unavailability for weather test case five. There is minimal decrease system unavailability due to weather suggesting that there is little effect on yearly system unavailability due to a reduction in snow and an increase in wind gusts on snow days.

Table 8-42 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Five)

	Less Snow + Wind Plus 5%			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.088	0.076<0.088<0.1	-17.00	0.106	0.091<0.106<0.121
S Scotland	0.095	0.08<0.095<0.11	-33.82	0.144	0.126<0.144<0.161
N England and N Wales	0.053	0.047<0.053<0.06	-38.27	0.086	0.08<0.086<0.093
S England and S Wales	0.011	0.008<0.011<0.014	-48.04	0.021	0.017<0.021<0.025

Table 8-43 - System Availability (%) and Unavailability (%) (Test Case Five)

	Weather		**Non-Weather**		**Overall**	
Area	Avail.	Unavail.	Avail.	Unavail.	Avail.	Unavail.
N Scotland	99.994	0.006	99.972	0.028	99.966	0.034
S Scotland	99.989	0.011	99.897	0.103	99.887	0.113
N England and N Wales	99.986	0.014	99.907	0.093	99.894	0.106
S England and S Wales	99.987	0.013	99.855	0.145	99.843	0.157

The mean system indices and mean 95% confidence limits for weather test case five and the basecase and the percentage change between them are displayed in Table 8-44. All of the system indices have increased; however, the mean 95% confidence limits for the values of LOEE, and SM have a large range suggesting low confidence on where the value will lie, suggesting high sensitivity to extreme values. The range for the value of LOLE is smaller indicting more confidence of these results, so while snow-related failures are reducing the effects of snow events could affect system security.

Table 8-44 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Five)

	Less Snow + Wind Plus 5%			Basecase	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	2057	598.471<2057<3515.529	152.70	814	632.422<814<995.578
LOEP (%)	0.0006	0.001<0.001<0.001	152.77	0.00024	0<0<0
EIR (%)	99.999	99.999<99.999<99.999	0.00	99.999	100<100<100
SM (minutes)	1.979	0.578<1.979<3.38	152.42	0.784	0.609<0.784<0.959
LOLP (%)	0.0128	0.013<0.013<0.013	16.22	0.01102	0.011<0.011<0.011
LOLE (days)	0.0467	0.039<0.047<0.055	16.17	0.0402	0.033<0.04<0.047
LOLE (hours)	1.1217	0.929<1.122<1.315	16.22	0.96522	0.802<0.965<1.129

8.2.9 Test Case Six - Decrease in Snow Days (40-70%) + 10% Increase in Wind Gusts

The average failure rates per area, per year, per 100km and the mean 95% confidence limits for snow-related failures and the basecase, plus the percentage change in snow failure rates compared to the basecase for weather test case six are presented in Table 8-45. There is a reduction in snow-related failures for all areas showing that the reduction in snow has more of an effect that the increase in wind. However, for the two areas in England and Wales there is less of a decrease in failures compared to the previous test case suggesting that the increase in wind does have an effect.

Table 8-45 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Six)

	Less Snow + Wind Plus 10%			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.088	0.074<0.088<0.102	-17.00	0.106	0.091<0.106<0.121
S Scotland	0.094	0.08<0.094<0.109	-34.19	0.144	0.126<0.144<0.161
N England and N Wales	0.064	0.057<0.064<0.071	-25.89	0.086	0.08<0.086<0.093
S England and S Wales	0.015	0.011<0.015<0.018	-30.39	0.021	0.017<0.021<0.025

The system availability and unavailability for weather test case six are displayed in Table 8-46. There is minimal decrease system unavailability due to weather suggesting that there is little effect on yearly system unavailability due to a reduction in snow and an increase in wind gusts on snow days.

Table 8-46 - System Availability (%) and Unavailability (%) (Test Case Six)

	Weather		**Non-Weather**		**Overall**	
Area	Avail.	Unavail.	Avail.	Unavail.	Avail.	Unavail.
N Scotland	99.993	0.007	99.973	0.027	99.967	0.033
S Scotland	99.990	0.010	99.895	0.105	99.886	0.114
N England and N Wales	99.985	0.015	99.908	0.092	99.893	0.107
S England and S Wales	99.987	0.013	99.855	0.145	99.843	0.157

Table 8-47 presents the mean system indices and mean 95% confidence limits for weather test case six and the basecase and the percentage change. All are similar to the basecase, suggesting that while there is a decrease in snow and snow-related failures there is minimal change to the system indices meaning that if this weather case studied occurred little would be required to change in order to maintain current levels system security.

Table 8-47 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Six)

	Less Snow + Wind Plus 10%			**Basecase**	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	801	606.674<801<995.326	-1.60	814	632.422<814<995.578
LOEP (%)	0.00024	0<0<0	-1.61	0.00024	0<0<0
EIR (%)	99.999	100<100<100	0.00	99.999	100<100<100
SM (minutes)	0.771	0.583<0.771<0.958	-1.66	0.784	0.609<0.784<0.959
LOLP (%)	0.01122	0.011<0.011<0.011	1.80	0.01102	0.011<0.011<0.011
LOLE (days)	0.0409	0.033<0.041<0.049	1.74	0.0402	0.033<0.04<0.047
LOLE (hours)	0.98261	0.782<0.983<1.183	1.80	0.96522	0.802<0.965<1.129

8.2.10 Test Case Seven - Decrease in Snow Days (40-70%) + Increased Snow Duration + 10% Increase in Wind Gusts

The average failure rates per area, per year, per 100km and the mean 95% confidence limits for weather test case seven and the basecase, plus the percentage change between them are shown in Table 8-48. There is a decrease in the snow-related failures even with an increase in snow event durations compared to the basecase. Compared to the previous test case it is found that the changes to North Scotland and to England and Wales are minimal suggesting that the increase in duration has little effect of the numbers of failure experienced. South Scotland sees an increase compared to the previous case, suggesting that it is more vulnerable to increased durations of snow events.

Table 8-48 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Seven)

	Less Snow + Increase Snow Duration + Wind Plus 10%			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.089	0.076<0.089<0.102	-16.19	0.106	0.091<0.106<0.121
S Scotland	0.115	0.099<0.115<0.13	-20.22	0.144	0.126<0.144<0.161
N England and N Wales	0.066	0.059<0.066<0.072	-24.20	0.086	0.08<0.086<0.093
S England and S Wales	0.014	0.011<0.014<0.017	-32.35	0.021	0.017<0.021<0.025

The results for system availability and unavailability for weather test case seven are shown in Table 8-49. There is a minimal increase in system unavailability due to weather suggesting that there is little effect on yearly system unavailability.

Table 8-49 - System Availability (%) and Unavailability (%) (Test Case Seven)

	Weather		**Non-Weather**		**Overall**	
Area	Avail.	Unavail.	Avail.	Unavail.	Avail.	Unavail.
N Scotland	99.992	0.008	99.975	0.025	99.968	0.032
S Scotland	99.989	0.011	99.894	0.106	99.884	0.116
N England and N Wales	99.986	0.014	99.911	0.089	99.897	0.103
S England and S Wales	99.988	0.012	99.858	0.142	99.847	0.153

Table 8-50 displays the mean system indices and mean 95% confidence limits for weather test case seven and the basecase and the percentage change between them. All system indices have increase for this weather test case, indicating that the increase in snow event duration has an effect on system security. The mean 95% confidence limits for LOEE are not are large as previous test cases suggesting more confidence in the returned results.

Table 8-50 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Seven)

	Wind Plus 5%			**Basecase**	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	1341	766.857<1341<1915.143	64.74	814	632.422<814<995.578
LOEP (%)	0.0004	0<0<0	64.77	0.00024	0<0<0
EIR (%)	99.999	100<100<100	0.00	99.999	100<100<100
SM (minutes)	1.29	0.739<1.29<1.841	64.54	0.784	0.609<0.784<0.959
LOLP (%)	0.01211	0.012<0.012<0.012	9.91	0.01102	0.011<0.011<0.011
LOLE (days)	0.0442	0.036<0.044<0.052	9.95	0.0402	0.033<0.04<0.047
LOLE (hours)	1.06087	0.874<1.061<1.248	9.91	0.96522	0.802<0.965<1.129

8.2.11 Overall Changes to Snow

Three further tests cases were developed analysing a decrease in snow but an increase in wind gusts on snow days by 25% and 50% and an increase in snow event durations with a 50% increase in wind. The percentage changes in failure rates compared to the basecase are shown in Figure 8-17. Unlike the state sampling techniques there is a more discernible trend within the snow failure rates. For all increases in wind below 25% the failure rates are below the basecase, indicating that the reduction in snow supersedes the increase in wind. However, above this value the failure rates are above the basecase, indicating that after this point the snow reduction fails to cancel out the wind increase. The percentage change in the mean and median values for LOLE (days) compared to the basecase are shown in Figure 8-18. It shows that there no change in the median LOLE (days) value but that there is a slight increase in the mean LOLE (days) compared to the basecase, which generally increases for all test cases. This indicates that while the “average” yearly load shedding events are not greatly changed from the basecase, there are more extreme years where there is a higher value of yearly LOLE (days).

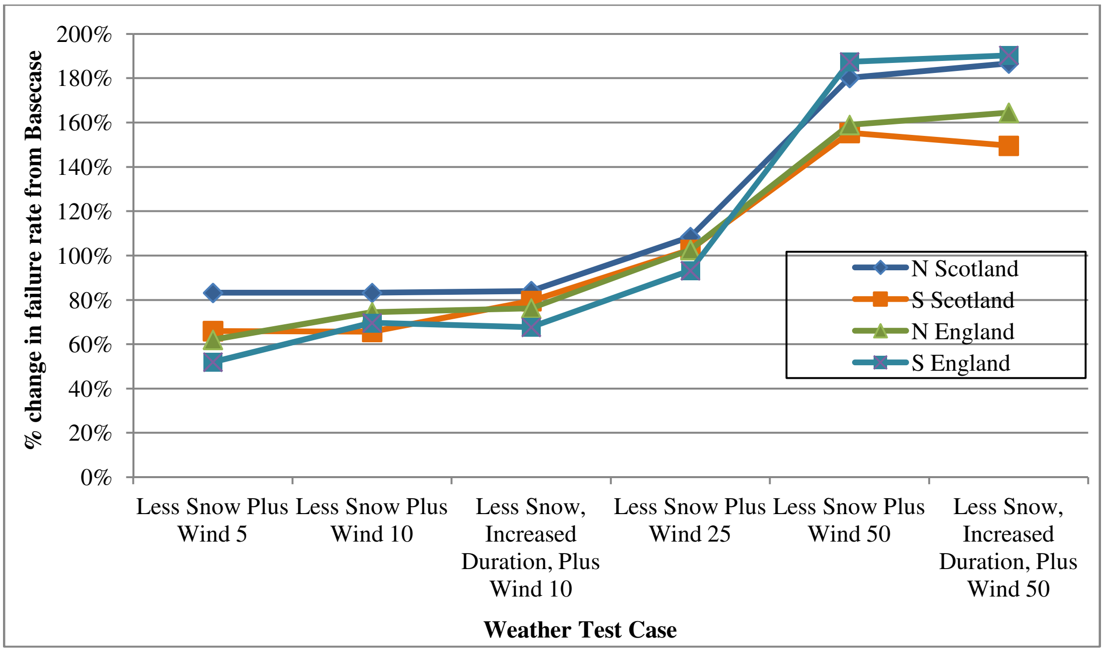


Figure 8-17 - Percentage change for Sequential Basecase Failure Rate for Snow Failures

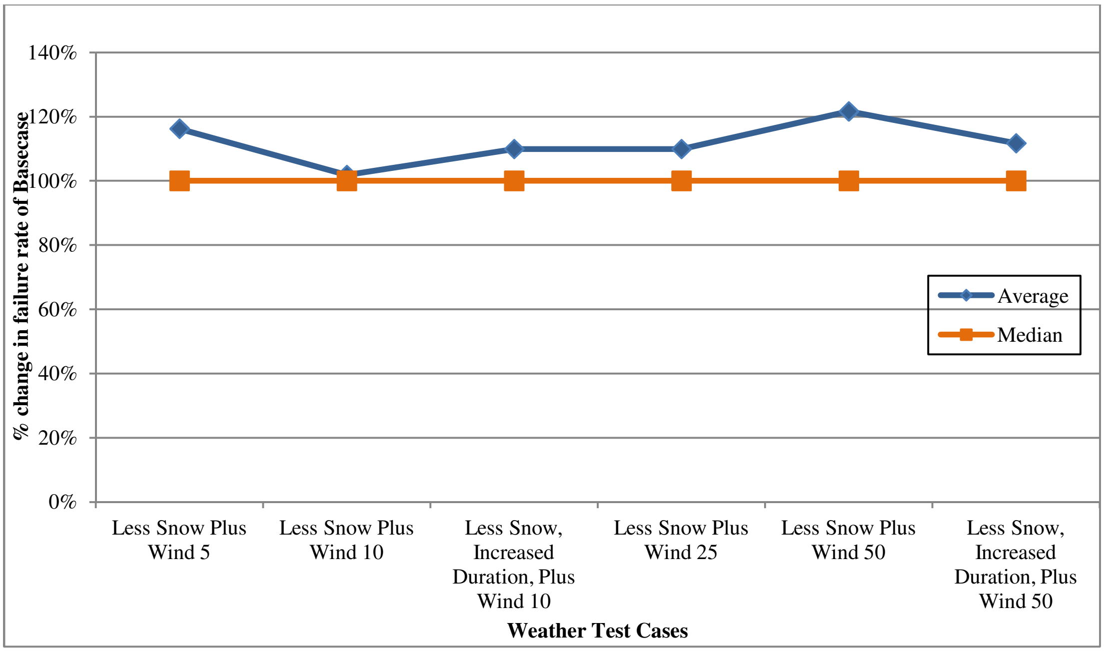


Figure 8-18 - Percentage change for Sequential Basecase LOLE (days) for Snow Failures

8.2.12 Test Case Eight – Worst Case

The percentage change in the failure rates per area, per year, per 100km compared to the basecase are displayed in Table 8-51. There is an overall increase in weather-related failures, indicating that even with the reduction in failures due to snow; the increase in lightning and wind-related failures supersedes this. If an increase in failure rates by these proportions where to occur it could have a great effect on the operation of the transmission network. To maintain current values of system security repair rates would need to remain the same to maintain system security or changes would be required to compensate for this increase. The results for system availability and unavailability for weather test case eight are presented in Table 8-52. There is a decrease in system unavailability for all four areas suggesting that if these weather changes were all to occur the system would have reduced availability.

Table 8-51 – Percentage Change in Failure Rates per area, per year, per 100km to the Basecase Rates(Weather Test Case Eight)

Area	Lightning	Snow	Wind	Other Weather	Non-Weather	Weather Total
N Scotland	86.00	-23.08	138.24	-1.68	-0.61	78.68
S Scotland	68.84	-20.22	140.16	10.14	0.88	74.79
N England and N Wales	85.98	-27.39	116.67	-6.97	1.78	65.22
S England and S Wales	99.23	-41.18	97.30	0.49	-0.68	72.10

Table 8-52 - System Availability (%) and Unavailability (%) (Test Case Eight)

	Weather		Non-Weather		Overall	
Area	Avail.	Unavail.	Avail.	Unavail.	Avail.	Unavail.
N Scotland	99.989	0.011	99.975	0.025	99.964	0.036
S Scotland	99.987	0.013	99.897	0.103	99.884	0.116
N England and N Wales	99.976	0.024	99.910	0.090	99.886	0.114
S England and S Wales	99.983	0.017	99.854	0.146	99.838	0.162

The mean system indices and mean 95% confidence limits for weather test case seven and the basecase and the percentage change between them are shown in Table 8-53. It displays an increase in all system indices indicating an increase in load shedding events and magnitude. The mean 95% confidence limits for the values of LOEE, and SM have a large range suggesting low confidence on where the value will lie, suggesting high sensitivity to extreme values. Whereas, the range for the value of LOLE is lower suggesting more confidence of where these results shall lie, meaning with these weather changes occur there could be an almost 20% increase in the yearly value of LOLE.

Table 8-53 – System Indices, Mean 95% Confidence Limits and Percentage change from the Basecase (Test Case Eight)

	Worse Case			Basecase	
System Index	Mean	Mean 95% Confidence Limit	Percentage Change from the Basecase	Mean	Mean 95% Confidence Limit
EENS/ LOEE (MW)	1475	638.936<1475<2311.064	81.20	814	632.422<814<995.578
LOEP (%)	0.0004	0<0<0	81.25	0.00024	0<0<0
EIR (%)	99.999	100<100<100	0.00	99.999	100<100<100
SM (minutes)	1.416	0.621<1.416<2.211	80.61	0.784	0.609<0.784<0.959
LOLP (%)	0.0132	0.013<0.013<0.013	19.82	0.01102	0.011<0.011<0.011
LOLE (days)	0.0482	0.04<0.048<0.056	19.90	0.0402	0.033<0.04<0.047
LOLE (hours)	1.1565	0.967<1.157<1.346	19.82	0.96522	0.802<0.965<1.129

8.2.1 Sequential Sampling Conclusion

Table 8-54 and Table 8-55 show the percentage change in average weather failure rates for each weather test case in comparison to the basecase and the percentage change in LOLE (days) in comparison to the basecase respectively for the sequential sampling model. From Table 8-54 it is clear to see that as CAPE increases as does the failure rate in comparison to the basecase. It is also clear, that in increases in wind also follows the same trend. It is apparent that for the first change in snow there is a decrease in comparison to the basecase, but as the wind gusts increase, so do the failure rates, showing that the decrease in snow is cancelled out by the increase in wind when snow does occur. It is clear to see from the worst case results that, overall there is an increase in average failure rates when there are slight changes to the weather that is experienced, suggesting possible reliability issues if these climate change scenarios were to occur.

From Table 8-55 it is apparent to see that there is a general increase in the average LOLE (days) with the increase in weather for both wind and CAPE. Again snow shows no trend in the changes of LOLE (days), suggesting that LOLE (days) is sensitive to the extreme snow storms that occur during these times and that possibly more trials may need to be run to accurately model the effects to load indices or a split required in load indices between normal and adverse and extreme conditions.

Table 8-54 - Percentage Change in Average Weather Failure Rate, for each Weather Test Case, in Comparison to the Basecase (Sequential)

	N Scotland	S Scotland	N England and N Wales	S England and S Wales
Base	0	0	0	0
5% Wind Gust Increase	0.14	0.15	0.12	0.04
10% Wind Gust Increase	0.39	0.45	0.23	0.07
25% Wind Gust Increase	1.11	1.32	0.60	0.25
50% Wind Gust Increase	2.03	2.56	1.02	0.47
25% CAPE Increase	0.22	0.17	0.25	0.28
50% CAPE Increase	0.44	0.34	0.53	0.53
75% CAPE Increase	0.65	0.47	0.80	0.82
100% CAPE Increase	0.92	0.68	1.08	1.09
Decrease in Snow Days (40-70%) + 5% Increase in Wind Gusts	-0.01	-0.03	-0.03	0.00
Decrease in Snow Days (40-70%) + 10% Increase in Wind Gusts	0.00	-0.05	-0.01	0.00
Decrease in Snow Days (40-70%) + 25% Increase in Wind Gusts	0.04	0.02	0.01	-0.02
Decrease in Snow Days (40-70%) + 50% Increase in Wind Gusts	0.12	0.11	0.07	0.05
Decrease in Snow Days (40-70%) + 10% Increase in Wind Gusts + Duration	0.04	-0.03	-0.03	-0.03
Decrease in Snow Days (40-70%) + 50% Increase in Wind Gusts + Duration	0.13	0.06	0.09	0.02
Worst Case	0.79	0.75	0.65	0.72

Table 8-55 - Percentage change in LOLE (days), for each Weather Test Case, in Comparison to the Basecase (Sequential)

Weather Test Case	% Change
Base	0
5% Wind Gust Increase	0.11
10% Wind Gust Increase	0.31
25% Wind Gust Increase	0.41
50% Wind Gust Increase	-0.17
25% CAPE Increase	0.04
50% CAPE Increase	0.02
75% CAPE Increase	0.14
100% CAPE Increase	0.27
Decrease in Snow Days (40-70%) + 5% Increase in Wind Gusts	0.16
Decrease in Snow Days (40-70%) + 10% Increase in Wind Gusts	0.02
Decrease in Snow Days (40-70%) + 25% Increase in Wind Gusts	0.10
Decrease in Snow Days (40-70%) + 50% Increase in Wind Gusts	0.22
Worst Case	0.10

8.3 Summary

This chapter aimed to apply the final stage of the presented methodology to the GB test case and meet the final research aim as described in Section 1.6, to use the model results to assess the effects of climate projections on the GB test case. This chapter uses all the information that has been developed in the previous chapters to finally assess the impacts on the transmission network. As previously discussed, two models were created using Monte Carlo simulations, a state and sequential model, to assess the impact of weather and climate change. It was found that while the state model was able to reproduce weather closer to the historical, the sequential model was closer to the historical failure rates. The sequential model has the addition of extreme weather events durations which leads it to being less accurate compared to the state model when reproducing weather.

The state model overestimates lighting-related failures by up to 242% but underestimates both snow and wind-related failures by 92.3% and 44.9% respectively, in comparison to the historical failure rates. The state model also struggles to model the load indices, which could be attributed to how demand is modelled and the state sampling methodology. For the changes in wind, the state model found that there was an increase in failure rates. This was more apparent in the England and Wales areas at the higher wind gusts changes. However, there was little change in the load indices, suggesting that while increases in wind affect the failure rates they do not have a great deal effect on the load indices of the system. When the CAPE is increased it was found that there was a similar rise in failure rates i.e. as CAPE increased by 25% so did the failure rates. This type of increase could have a large impact on the system security and reliability. It also found that mean LOLE (days) were not greatly different from the basecase, but that the median values showed a slight increase. This would indicate that while the extreme years are relatively unchanged the average year will experience an increase in the yearly LOLE (days). The state model struggles to model the failure rates for snow due to the complexity of this weather type and its associated failures due to the simplistic nature of the state model. For the load indices related to the change in snow it was found that in the first two weather test cases both the mean and median value of LOLE (days) was slightly above the basecase, suggesting that the “average” year is slightly worse compared to what is experienced currently. While the third weather test case show a decrease in both of these values, suggesting that the change in both snow and wind have cancelled each other out. There is an increase in both the mean and median values of LOLE (days) suggesting that the increase in wind has outweighed the reduction in snow days. For the final case it was found that there was an overall increase to weather-related failures, even with the decrease in snow-related failures, and that the magnitude of load shedding events increased but there was a slight reduction in the number of events that occurred. The state model shows that the system is vulnerable to an increase in different weather types with both changes to CAPE and wind gusts showing an increase in failure rates, however, there were small changes to the load indices suggesting that the system would be able to cope with this. These assertions are based on the current repair rates and maintenance levels; if this was not the case there may be further risks to system security and reliability.

The sequential model also overestimates lightning-related failures but has less of an overestimation than the state model. It also underestimates the failure rates for snow and wind-related failures but there is less of an underestimation. The sequential model is also able to more accurately model the system indices, suggesting a more accurate model for judging the change on the GB system. Unlike the state model, when wind is increased, the sequential model shows a large increase in the wind-related failures, with one test case seeing an increase of up to 800%. When analysing the system indices it was found that the average yearly LOLE (days) is largely unchanged but there are more extreme LOLE (days) years. However, the final weather test case shows a decrease in LOLE (days) which could be contributed to increased availability of wind generation. For the changes in CAPE it was found that there were large increases in the failure rates, with some cases showing increases of around 150%. As with the wind test cases it was found that there were changes to the extreme years of average LOLE (days) but that the average year was unchanged. Unlike the state model the sequential was more able to deal with modelling snow-related failures. When the wind gusts on snow days were increased by less than 25% it was found that there was a decrease in the failure rates, the reduction in snow cancelling out the increase in wind. However, an increase in wind gusts by 25% or more increased the failure rates in comparison to the basecase, showing that the increase in wind had outweighed the reduction in snow. Even with these changes it was found that there was little change to the load indices, suggesting that changes in snow have little effect on the system indices and are unlikely to affect system security. For the final weather test case it was found that there was an overall increase in failure rates, showing that the reduction in snow-related failures does not cancel out the increase in lighting and wind-related failures. There was also an increase in all system indices, suggesting that if the worst changes in weather were to occur there would be increases in the magnitude and number of load shedding events. If all these weather changes, and an increase in failure rates by these proportions, were to occur it could have a great effect on the operation of the transmission network. In order to maintain the current values of system security repair rates would need to remain the same in order to maintain system security or changes would be required to compensate for this increase.

Chapter 9 - Conclusions and Further Work

This thesis has presented a methodology developed to assess the impact of weather and climate change on transmission networks, and has evaluated the current effects that weather has on a GB test case. It has evaluated the possible effect of future weather based on possible climate change projections, and has met all the research aims set in Section 1.6. This chapter will cover the overall conclusions of the thesis and points that should be considered for future development of this research.

9.1 Conclusion

This thesis has looked at the current effects that weather can have on the operation of the GB transmission network using a developed methodology, and attempts to assess the future impact that climate change could have. There were 9 main aims that were developed when heading into this research:

1. Summarise existing work modelling weather and the effect of climate change on power networks
2. Develop a methodology to assess the impact of weather and climate change on power networks
3. Complete an analysis of GB outage datasets, to check how accurate the records are and to understand what the current effects of weather are
4. Compare observational and reanalysis data and lightning strike data and (CAPE), to verify reanalysis data as a suitable replicator of past weather data
5. Investigate a correlation between weather variables and weather-related outages and identify the prevailing weather for weather related outages.
6. Establish fragility curves of failure for the dominant weather-related outages based on the weather occurring and standard probabilities for other outages
7. Develop weather test cases using climate projections that can be used within the model to determine the risk to the GB transmission network
8. Investigate if a relationship exists between the duration of an outage and the weather variable that caused the outage

9. Using the model results and reliability indices analyse the effects of different climate models on the GB test case.

It was found that all power systems are vulnerable to extreme weather events which cause physical damage to equipment and lead to long repair and restoration times. This leaves power systems vulnerable to further outages, therefore, this is a topic with a large amount of interest. However, GB networks are unaware of how climate change will affect their networks and are unclear how to adapt. IPCC's 2014 Synthesis Report stated that "Warming of the climate system is unequivocal." But with different weather variables and models the confidence of climate projections can vary. Where high confidence exists with a weather variable the projections models will produce similar results, where low confidence exists, the models will produce different results. For example, lightning is predicted to increase in most climate projection models, whereas low confidence is described in respect of wind and snow weather variables and storm predictions.

Past work tends to consider whole networks as one area rather than different areas. Power networks can experience different weather conditions at the same time. Due to the ease of quantification of the impact of weather on power network users, a large quantity of past work focuses on distribution networks and either ignores the transmission network or imagines that it is fine during extreme events, which is not the case. This leads to an incomplete picture of how each weather variable can affect the systems being analysed and how their combined effects can affect the power system as a whole. When considering the effects of weather on power networks there is a tendency to consider a sole weather variable or single weather state, only specific weather combinations and to ignore all others, weather as a whole represented by just two or three different aggregate states rather than separate individual variables.

Modelling components' failure rates as a function of weather represents a key novelty in reliability and resilience research. It allows the development of seamless spatio-temporal simulation and infrastructure impact of weather fronts moving across large-scale networks. Models have been developed which contain a brief outline of how to analyse outages but do not contain enough detail to be effectively applied to different networks and maintain some level of consistency. To accurately model the probabilities of a network failure due to weather, it is important to consider the relationship between a weather variable and the rate of occurrence of failures in different classes of prevailing weather. The relationship of probability of an outage to a weather variable should be quantified and used as part of an assessment that considers the probability of occurrence of different values of weather variables. This provides the basis for understanding the possible impacts of changes to weather.

A contribution of this research is the development of a methodology that can be used to assess the current effects of weather on a given power system and what the possible future effects of climate change will be. The proposed methodology will be primarily applicable to the transmission network and adaptable around the world. It considers each weather variable as one continuously varying weather state rather than a two or three weather state model, allowing for a much more realistic modelling of the weather conditions. Another contribution of this research was to apply this methodology to a test case of the GB transmission network and quantify the impact on the GB transmission network. This allowed the development of the GB fragility curves for weather related outages by completing a 30 year outage review of the GB network where all outages were classified in terms of weather variables and values. A quantitative analysis and relationship developed between the three main weather causes of outages in GB; Lightning, Snow and Wind. This is unique to the authors' knowledge for GB.

Stage One of the methodology is a pre-analysis stage, which allows the datasets that will be used to be explored and allow characteristics of both the weather and outage datasets to be understood. Stage Two develops strong relationships between weather variables and outages types. Stage Three uses these relationships to develop conditional probabilities that can be used to determine the probability of an outage based on the weather variable value. Stage Four is the weather and outage sampling step in this methodology where Monte Carlo simulation uses historical or climate projections to generate weather variable values and then determine if outages occur on the network based on the conditional probabilities that are developed in Stage Three. The final stage of this methodology, Stage Five, uses the network built in Stage Four to provide the basis for a power system analysis, in this case a load flow, to determine the effects of weather on the network that is being analysed. The demand profile for the load flow is provided by the user, and the generation is dispatched based on a merit order, and weather dependant generation uses the weather variable values determined in Stage Four. These five stages allow for a thorough investigation of the effects of weather and climate on transmission networks and can be easily adapted to suit the network under analysis.

Aspects of the work that is contained within this thesis have been implemented by SSE in their control centre. Used on a daily basis for better network operation during extreme or adverse weather. This was implemented by Bellrock Technology. The first stage of implementation uses the conditional probabilities that are developed and displayed in Chapter 6 of this thesis. It feeds current weather data into the program and with the developed conditional probabilities, and the route length, the risk of failure per branch is calculated. Initially the 400kV and 275kV network in the SSE area in the North of Scotland had the model implemented for the weather variables of Wind Gusts and Wind Gusts on Snow Days, and later Lightning data was included. The second stage is to implement a similar application for the 132kV network. Why is this important? It helps with the mobility of engineers before the fact, recalling outages from maintenance, reducing load to allow for self supporting network, gives numbers for how bad it could be and allows more flexibility in good weather.

This was a challenging PhD, not only for the management of the large quantity of data but for the range of topics: climate change, weather, statistics, power systems, modelling, and probabilities but all research aims stated in Section 1.6 were met as discussed below:

1. Summarise existing work modelling weather and its effect on power networks
    a. There are varying levels of confidence in climate change predictions making it difficult to assess the risk that it make pose to the transmission networks
    b. Previous work focuses on distribution networks, focuses on areas as a whole or focuses on a single weather type or weather as a whole
2. Develop a methodology to assess the impact of weather and climate change
    a. Developed a 5 stage methodology that can be adapted to different networks
3. Complete an analysis of GB outage datasets, to check how accurate the records are and to understand what the current effects of weather
    a. Historical analysis of GB found that ‘Wind, Gales and Windborne Objects’ and ‘SSB & Ice’ outages are highly dependent on major events whereas ‘Lightning’ is a more consistent. These are the top three causes of weather outages in GB
    b. Investigation into weather extremes, found that ‘Lightning’ outages occur both in extreme and normal days, confirming they are not dictated by extreme events. Both ‘Wind, Gales and Windborne Objects’ and ‘SSB & Ice’ outages were found to occur during extreme events, and generally do not occur under normal conditions
4. Compare observational and reanalysis data and lightning strike data and (CAPE), to verify reanalysis data as a suitable replicator of past weather data

    a. Reanalysis was an acceptable replication of past observation data. CAPE was also investigated to determine if it was a good proxy for lightning strikes

5. Investigate a correlation between weather variables and weather-related outages and identify the prevailing weather for weather related outages
    a. ‘Wind, Gales and Windborne Objects’ outages were found to be highly correlated with wind gusts. Lightning strikes are correlated with ‘Lightning’ outages, but there is difficulty in projecting lightning strikes for future weather, therefore, CAPE which is also correlated, was used as the indicator
    b. ‘SSB & Ice’ outages were tested against different weather variables but due to the complex nature a more complex relationship was required. The best indicator was determined to be wind gusts on snow days
6. Establish fragility curves of failure for the dominant weather-related outages based on the weather occurring and standard probabilities for other outages
    a. Fragility curves for ‘SSB & Ice’, ‘Lightning’ and ‘Wind, Gales and Windborne Objects’ outages, as well as probabilities of occurrence for non-weather and ‘Other Weather’ outages were developed
    b. Higher wind gust values there is a higher probability of failure for both ‘Wind, Gales and Windborne Objects’ and ‘SSB & Ice’ outages with the two areas in Scotland having the highest probability of failure
    c. At higher values of CAPE there is a higher probability of failure with South Scotland having the highest probability of failure due to the rarest value of CAPE causing multiple outages
7. Develop weather test cases using climate projections that can be used within the model to determine the risk to the GB transmission network
    a. Seven weather test cases were developed for the state sampling model and eight for the sequential simulation. In each case the different weather variables were changed by different amounts to understand the effect they will have
8. Investigate if a relationship exists between the duration of an outage and the weather variable that caused the outage
    a. It was found that there was a possible relationship between outage duration and weather causes but more investigation was required in order to develop a stronger relationship. It is suggested that for future work this should be further investigated

   b. In order to include durations of outages the cumulative frequency distributions were calculated for the outages classes for the sequential sampling simulation.

9. Using the model results and reliability indices analyse the effects of different climate models on the GB test case.
   a. It was found that while the state model was able to reproduce weather closer to the historical data the sequential model was closer to the historical failure rates
   b. Both the state and sequential model overestimate lightning failures but underestimate both snow and wind-related failure, however, the sequential model has less of an error compared to the state model
   c. The state model struggles to model the load indices, conversely, the sequential model is able to more accurately model the system indices which could be contributed to how demand is modelled and the state sampling methodology.
   d. The state model showed that the system is vulnerable to an increase in different weather types with both changes to CAPE and wind gusts showing an increase in failure rates. However, only small changes to the load indices occurred. These are based on the current repair rates and maintenance levels being maintained; this would unlikely be the case with some of the magnitude of increases and there may be further risks to system security.
   e. It is unable to deal with the complexities of modelling snow-related failures
   f. The sequential model shows a large increase in the wind and lightning related failures. It was found that there were changes to the extreme years of average LOLE (days) but that the average year was unchanged
   g. The sequential was more able to deal with modelling snow-related failures
   h. When the wind gusts on snow days were increased by less than 25% there was a decrease in the failure rates. However, past 25% the failure rates increased, showing that the increase in wind had superseded the reduction in snow
   i. Even with this it was found that there was little change to the load indices suggesting that changes in snow have little effect on the system indices and are unlikely to affect system security
   j. For the final weather test case it was found there was an overall increase in failure rates, showing the reduction in snow-related failures did not cancel

out the increase in lighting and wind-related failures. There was an increase in all system indices, suggesting there would be increases in the magnitude and number of load shedding events.

The two main contribution of this research was to develop a methodology to assess the impact of weather and climate change on transmission networks and quantify the impact on the GB transmission network and the GB fragility curves. The methodology presented in this thesis shows that the system is vulnerable to increases in weather. It has shown that the different areas of GB are vulnerable to possible changes in weather in different ways and therefore cannot be tackled as a country wide solution and will need to be area specific. This methodology is able to be applied to other networks with different dominant weather variables as it analyses different weather types separately, allowing different countries with different expected changes to also be assessed. In conclusion, the methodology developed is easily applicable for different transmission networks to assess the impact of weather and climate change.

9.2 Future work

As with any interesting topic, once initial research has been conducted and the first set of questions answered more questions and areas of further research are always found. The suggested areas of further work are as follows:

- There is a difference in classification of transmission between England and Wales and Scotland. To allow for a complete analysis of all voltage levels it would necessary to acquire 132kV outage data for all of the areas analysed. This extra data would provide reinforcement of the relationships that were developed, this was unable to be completed due to time restrains
- More specific analysis on the historical datasets would also be an important extension to the research on a per area per asset basis to determine if specific lines are more vulnerable, as well as locational analysis. This would allow for a better understanding if certain areas are more vulnerable to certain types of an outages for example does a costal line experience more ‘Wind, Gales and Windborne Objects’ than an urban line
- This extended analysis is also suggested to cover analysis of misclassified data, which would improve the correlation and probability analysis of the system by understanding further how data can be misclassified

- Consider that higher weather values which have a low probability of causing an outage may be because circuits have been previously tripped at lower weather value
- The probability development undertaken during this thesis has been on calculated per area, per year. In practice this is not a complete representation of the differences in weather experienced throughout the year. The results presented during this thesis are in no way invalidated by the omission of seasonal conditional probabilities and seasonal modelling, but the addition of seasonal modelling would provide more details of the effects on a seasonal basis
- During the sequential sampling modelling the next weather value is determined based on the previous weather value and while this is a good first estimate a more complex development would provide more accurate results, for example considering not only the previous one weather value but the previous x weather values
- Improving the way that the model generates extreme weather would allow for better outage predications for 'Wind, Gale, and Windborne Objects' and 'SSB & Ice' outages
- Consider different case studies that could be developed for different weather conditions. For example, more detailed modelling for the 'Other Weather' outages
- Consider that there may be increases to the failure repair rates as failures increase, currently the model assumes that the repair rates constant even if the failures increase
- Another area of further investigation is to strengthen the lightning-related outage probabilities to further define the relationship between lightning strikes and CAPE
- Throughout this work lessons were learnt and from this developments were made to the five stage methodology as shown in Figure 9-1. A resampling section is added to increase the data available for analysis, a stopping criterion is added to increase the accuracy of the failure rates and the weather that is generated in Stage Three is used to generate load and generation profiles as the weather has a strong influence over what these look like. These improvements as well as the above suggested work would benefit the results discussed in the section and improve the accuracy of the modelling work, leading to an improved system to be used by transmission companies around the world

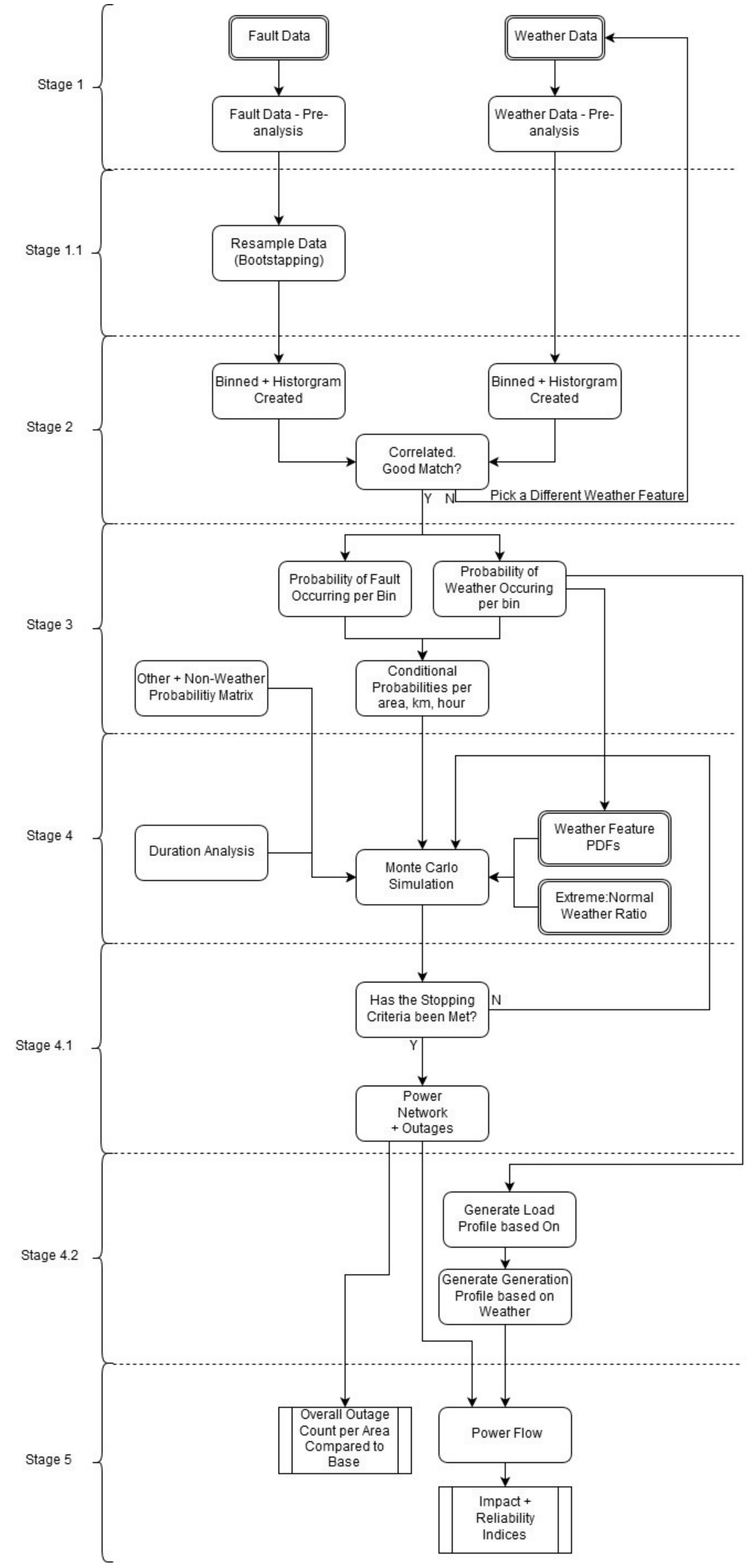


Figure 9-1 - Improved Five Stage Methodology

- It is suggested as a point of future work that the weather variables that are generated in Stage Four are used to influence the demand profile, as on wet and windy days the demand is higher, and on hot days the demand tends to be lower.
- Currently the model uses the generated wind values to influence the generation profile. This could be further developed to include other weather types for renewable generation Including the other sources of renewable generation, such as solar and hydro, in the same way as wind is considered would allow for a more realistic GB generation profile to be developed
- It was presented during this thesis that the confidence and agreement in climate projects is variable, as the agreement and confidence in projections increases this will allow for better and more reliable modelling. Using different projections on a per area basis would provide more confidence in the generated results
- It is recommended that this should address not only the system technical measures such as starting up of reserve generation and network reconfiguration but also logistical issues such as availability of staff, access to sites and communications which are particular issues in especially severe events. Considering a more precise assessment of overloads would highlight the risk of outages directly disconnecting demand or of cascades of outages doing so
- This thesis showed that duration data that was provided by the companies was often poor and had to be resampled in order to provide a fuller data set. If better outage durations were available this would improve the data and possibly provide more conclusive results for the duration investigation
- Further investigation into the development of a relationship between duration and weather type is required using a two or three stage model, along with more datasets containing information about availability of replacement equipment, and the logistics surrounding physically completing the repair would allow better modelling of high impact, low probability events that lead to long outages
- The work that has been started within this thesis can be developed so that it can be used for online security assessment. Currently the weather is considered over the four areas of GB, with some additional work this can then be turned in to profiling weather systems moving across GB. This means that forecasts of bad weather could be pre-modelled and combined with the probability of failure and then be used to model the weather systems moving across the network, showing the possible locations of outages

- Another possibility is using a previous weather case study to model a day where a large storm occurred and the weather values are known. By repeating this process for the same weather event it would be possible to demine how bad it could have been. This would be a useful tool in control centres when expecting a large storm to hit to help determine the possible outages, and allow for contingences to be developed for the worst case scenario.

These suggestions of further work would allow for a fuller picture to be generated to understanding the effects of weather and climate change on transmission networks, both in GB and around the world.

Chapter 10 - References

[1] The Globe and Mail, "*No climate-change deniers to be found in the reinsurance business",* [online] Available at: http://www.theglobeandmail.com/report-on-business/rob-magazine/an-industry-that-has-woken-up-to-climate-change-no-deniers-at-global-resinsurance-giant/article15635331/?page=all, 2014.

[2] Bank of England, [online] Available at: http://www.bankofengland.co.uk/publications/Pages/speeches/2015/844.aspx, 2015.

[3] Alyson Kenward, and U. Raja, BLACKOUT: EXTREME WEATHER, CLIMATE CHANGE AND POWER OUTAGES, Climate Central, Available at: http://www.climatecentral.org/news/weather-related-blackouts-doubled-since-2003-report-17281, 2014

[4] Swiss Re, "*Swiss Re's sigma on natural catastrophes and man-made disasters in 2012",* [online] Available at: http://www.swissre.com/media/news_releases/nr_20130327_sigma_natcat_2012.html, 2014.

[5] SwissRe, Natural catastrophes and man-made disasters in 2012: A year of extreme weather events in the US, Available at: http://www.swissre.com/media/news_releases/nr_20130327_sigma_natcat_2012.html, 2013

[6] R. J. Campbell, Weather-Related Power Outages and Electric System Resiliency, Congressional Research Service Report for Congress, Available at: https://www.fas.org/sgp/crs/misc/R42696.pdf, 2012

[7] J. Houghton, *Global Warming: The Complete Briefing*, p.^pp. 220-225: Cambridge University Press, 2009.

[8] Alex Hill, "*Making the Weather?",* [online] Available at: http://www.scottishpolicynow.co.uk/article/making-the-weather?utm_medium=email&utm_campaign=Scottish+Policy+Now+-+Issue+10&utm_content=Scottish+Policy+Now+-+Issue+10+CID_42f59d35633be25c2dc6593311d3cc1e&utm_source=Email%20marketing&utm_term=more, 2014.

[9] Met Office, "*Helping the UK prepare",* [online] Available at: http://www.metoffice.gov.uk/climate-guide/science/uk, 2015.

[10] U. G. Knight, *Power Systems in Emergencies: From Contingency Planning to Crisis Management*, Chichester: John Wiley and Sons Ltd., 2001.

[11] J. Sundell., D. Beck., F. György., K. Gustafsson., J. L. Harris., E. Herbert., A. Kapče., P. Lienhart., A. Maissis., I. Pierre., and K. Szynol., Impacts of Severe Storms on Electric Grids Task Force on Power Outages, Eurelectric, Available at: http://www.eurelectric.org/Download/Download.aspx?DocumentFileID=39179, 2006

[12] National Post - Jake Edmiston, "*Thousands of Canadians enter sixth day without power after 'worst ever blackout'",* [online] Available at: http://news.nationalpost.com/2013/12/26/thousands-of-canadians-enter-sixth-day-without-power-after-worst-ever-blackout/, 2015.

[13] P. Southwell, Disaster recovery within a Cigre strategic framework: Network resilience, trend and areas of future work, Phil Southwell Chair of SC C1 on behalf on the CIGRE technical Committee, Available at: http://www.e-cigre.org/Order/select.asp?ID=1705162, 2014

[14] Energex, "*Energex power restoration fast facts",* [online] Available at: https://www.energex.com.au/media-centre/media-releases/releases/2013/energex-power-restoration-fast-facts-@-1pm,-tuesday,-29-january, 2014.

[15] Energex, "*Energex power restoration fast facts @11am",* [online] Available at: https://www.energex.com.au/media-centre/media-releases/releases/2013/energex-power-restoration-fast-facts-@11am, 2014.

[16] American Association for the Advancement of Science, "*In Australia, Record Weather Fuels Climate Policy Process",* [online] Available at: http://news.sciencemag.org/environment/2013/02/australia-record-weather-fuels-climate-policy-process, 2015.

[17] The Independent Ian Johnston, "*UK weather: Storms are clear sign of climate change and worse to come will lead to conflict and war, says Lord Stern ",* [online] Available at: http://www.independent.co.uk/environment/nature/uk-weather-storms-are-clear-sign-of-climate-change-and-worse-to-come-will-lead-to-conflict-and-war-says-lord-stern-9127344.html, 2014.

[18] R. Billinton, and J. R. Acharya, “Weather-based distribution system reliability evaluation,” *Generation, Transmission and Distribution, IEE Proceedings,* vol. 153, no. 5, pp. 499-506, 2006.

[19] Executive Office of the President, Economic Benefits of Increasing Electric Grid Resilience to Weather Outages, Available at: http://energy.gov/downloads/economic-benefits-increasing-electric-grid-resilience-weather-outages, 2013

[20] C. B. V. Barros, T. F. Stocker, D. Qin, D. J. Dokken, K. L. Ebi, M. D. Mastrandrea, K. J. Mach, G.-K. Plattner, S. K. Allen, M. Tignor, and P. M. Midgley, IPCC, 2012: Managing the Risks of Extreme

Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, UK, and New York, NY, USA, Available at: http://www.ipcc-wg2.gov/SREX/, 2012

[21] Asian Development Bank (ADB), Climate Risk and Adaptation in the Electric Power Sector, Mandaluyong City, Philippines Available at: http://www.adb.org/publications/climate-risk-and-adaptation-electric-power-sector, 2012

[22] A. Martikainen, M.-L. Pykälä, and J. Farin, Recognizing climate change in electricity network design and construction, VTT, JULKAISIJA UTGIVARE Available at: www.vtt.fi/inf/pdf/tiedotteet/2007/T2419.pdf, 2007

[23] L. M. Beard, J. B. Cardell, I. Dobson, F. Galvan, D. Hawkins, W. Jewell, M. Kezunovic, T. J. Overbye, P. K. Sen, and D. J. Tylavsky, “Key Technical Challenges for the Electric Power Industry and Climate Change,” *Energy Conversion, IEEE Transactions on,* vol. 25, no. 2, pp. 465-473, 2010.

[24] Cabinet Office, Keeping the Country Running: Natural Hazards and Infrastructure, Civil Contingencies Secretariat, Cabinet Office, Available at: https://www.gov.uk/government/publications/keeping-the-country-running-natural-hazards-and-infrastructure, 2011

[25] M. Keogh, and C. Cody, Resilience in Regulated Utilities, The National Association of Regulatory Utility Commissioners (NARUC), Available at: https://www.google.co.uk/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&ved=0ahUKEwic3tDkqLjKAhVGORoKHSY-CPoQFgglMAA&url=http%3A%2F%2Fwww.naruc.org%2FGrants%2FDocuments%2FResilience%2520in%2520Regulated%2520Utilities%2520ONLINE%252011_12.pdf&usg=AFQjCNGwvnIXU0tCloefd-9a4s4Xxq_fWg, 2013

[26] DNV GL, "*Adaptation To A Changing Climate* ", [online] Available at: https://www.dnvgl.com/technology-innovation/broader-view/adaptation-to-climate-change/our-approach.html, 2015.

[27] Met Office UK, "*What is climate change*", [online] Available at: http://www.metoffice.gov.uk/climate-guide/climate-change, 2015.

[28] Jansen, E., J. Overpeck, K.R. Briffa, J.-C. Duplessy, F. Joos, V. Masson-Delmotte, D. Olago, B. Otto-Bliesner, W.R. Peltier, S. Rahmstorf, R. Ramesh, D. Raynaud, D. Rind, O. Solomina, R. Villalba and D. Zhang, "*Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*", [online] Available at: http://www.ipcc.ch/publications_and_data/ar4/wg1/en/faq-6-2.html 2015.

[29] R. K. Pachauri, and L. A. M. (eds.), Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, IPCC, Geneva, Switzerland, 151 pp. Available at: http://www.ipcc.ch/report/ar5/syr/, 2014

[30] WMO, Weather Extremes in a Changing Climate: Hindsight on Foresight, vol. 1075, World Meterology Organization, Available at: https://www.wmo.int/pages/mediacentre/news/documents/1075_en.pdf, 2011

[31] World Meteorological Organization, "*Current extreme weather events*", [online] Available at: http://www.wmo.int/pages/mediacentre/news/extremeweathersequence_2010_en.html, 2015.

[32] Met Office, "*Winter 2009/10*", [online] Available at: http://www.metoffice.gov.uk/about-us/who/how/case-studies/winter09-10, 2013.

[33] W. Cai, S. Borlace, M. Lengaigne, P. van Rensch, M. Collins, G. Vecchi, A. Timmermann, A. Santoso, M. J. McPhaden, L. Wu, M. H. England, G. Wang, E. Guilyardi, and F.-F. Jin, “Increasing frequency of extreme El Nino events due to greenhouse warming,” *Nature Clim. Change,* vol. 4, no. 2, pp. 111-116, 02//print, 2014.

[34] W. Cai, G. Wang, A. Santoso, M. J. McPhaden, L. Wu, F.-F. Jin, A. Timmermann, M. Collins, G. Vecchi, M. Lengaigne, M. H. England, D. Dommenget, K. Takahashi, and E. Guilyardi, “Increased frequency of extreme La Nina events under greenhouse warming,” *Nature Clim. Change,* vol. 5, no. 2, pp. 132-137, 02//print, 2015.

[35] M. D. Mastrandrea, C. B. Field, T. F. Stocker, O. Edenhofer, K. L. Ebi, D. J. Frame, H. Held, E. Kriegler, K. J. Mach, P. R. Matschoss, G.-K. Plattner, G. W. Yohe, and F. W. Zwiers, Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties, Intergovernmental Panel on Climate Change (IPCC), Available at: http://www.ipcc.ch, 2010

[36] N. Nakicenovic, J. Alcamo, G. Davis, B. de Vries, J. Fenhann, S. Gaffin, K. Gregory, A. Grubler, T. Y. Jung, T. Kram, E. L. La Rovere, L. Michaelis, S. Mori, T. Morita, W. Pepper, H. M. Pitcher, L. Price, K. Riahi, A. Roehrl, H.-H. Rogner, A. Sankovski, M. Schlesinger, P. Shukla, S. J. Smith, R. Swart, S. van Rooijen, N. Victor, and Z. Dadi, *Special Report on Emissions Scenarios : a special report of Working Group III of the Intergovernmental Panel on Climate Change*, 2000.

[37] Intergovernmental Panel on Climate Change (IPCC), "*Climate Change 2007: Working Group I: The Physical Science Basis*", [online] Available at: https://www.ipcc.ch/publications_and_data/ar4/wg1/en/spmsspm-projections-of.html, 2013.

[38] World Meteprplogical Organization (WMO), "*Climate Projections*", [online] Available at: https://www.wmo.int/pages/themes/climate/climate_projections.php, 2013.

[39] G. J. Jenkins, J. M. Murphy, D.M.H. Sexton, J. A. Lowe, P. Jones, and C. G. Kilsby, UK Climate Projections: Briefing report, Met Office Hadley Centre, Available at: http://ukclimateprojections.defra.gov.uk, 2009

[40] Met Office Hadley Centre, "*HadRM3 - Uk Climate Projections",* [online] Available at: http://ukclimateprojections.metoffice.gov.uk/23234, 2013.

[41] UK Climate Projections, "*About the Weather Generator",* [online] Available at: http://ukclimateprojections.metoffice.gov.uk/22540, 2013.

[42] UK Climate Projections, "*11-member RCM: technical notes",* [online] Available at: http://ukclimateprojections.metoffice.gov.uk/22594, 2013.

[43] United States Environmental Protection Agency (EPA), "*Future Climate Change",* [online] Available at: http://www.epa.gov/climatechange/science/future.html, 2015.

[44] Earth Science Communications Team at NASA's Jet Propulsion Laboratory, "*The current and future consequences of global change ",* [online] Available at: http://climate.nasa.gov/effects/, 2015.

[45] D. M. Romps, J. T. Seeley, D. Vollaro, and J. Molinari, “Projected increase in lightning strikes in the United States due to global warming,” *Science,* vol. 346, no. 6211, pp. 851-854, November 14, 2014, 2014.

[46] NIWA, "*Climate research projects",* [online] Available at: https://www.niwa.co.nz/climate/research-projects, 2015.

[47] NIWA, "*Risk of drought and extreme winds under climate change",* [online] Available at: https://www.niwa.co.nz/climate/research-projects/risk-of-drought-and-extreme-winds-under-climate-change, 2015.

[48] ECMWF, "*ENSEMBLES",* [online] Available at: http://www.ecmwf.int/en/research/projects/ensembles, 2013.

[49] P. v. d. Linden, and J. F. B. Mitchell, ENSEMBLES: Climate Change and its Impacts: Summary of research and results from the ENSEMBLES project*,* Met Office Hadley Centre, FitzRoy Road, Exeter EX1 3PB, UK., Available at: http://ensembles-eu.metoffice.com/, 2009

[50] R. Schaeffer, A. S. Szklo, A. F. Pereira de Lucena, B. S. Moreira Cesar Borba, L. P. Pupo Nogueira, F. P. Fleming, A. Troccoli, M. Harrison, and M. S. Boulahya, “Energy sector vulnerability to climate change: A review,” *Energy,* vol. 38, no. 1, pp. 1-12, 2//, 2012.

[51] University of Cambridge and the World Energy Council, Climate Change: Implications for the Energy Sector. Key Findings from the Intergovernmental Panel on Climate Change Fifth Assessment Report, Available at: www.bnlce.com/fileadmin/downloads/Climate-Change-Implications-for-the-Energy-Sector-Summary-from-IPCC-AR5-2014-Full-report.pdf, 2014

[52] NationalGrid, Adapting to Climate Change, Managing the Risks - National Grid, Available at: http://www.oursouthwest.com/climate/registry/100200-case-study-national-grid.pdf, 2010

[53] S. Mirasgedis, Y. Sarafidis, E. Georgopoulou, V. Kotroni, K. Lagouvardos, and D. P. Lalas, “Modeling framework for estimating impacts of climate change on electricity demand at regional level: Case of Greece,” *Energy Conversion and Management,* vol. 48, no. 5, pp. 1737-1750, 5//, 2007.

[54] M. Ruth, and A.-C. Lin, “Regional energy demand and adaptations to climate change: Methodology and application to the state of Maryland, USA,” *Energy Policy,* vol. 34, no. 17, pp. 2820-2833, 11//, 2006.

[55] S. J. Parkpoom, and G. P. Harrison, “Analyzing the Impact of Climate Change on Future Electricity Demand in Thailand,” *Power Systems, IEEE Transactions on,* vol. 23, no. 3, pp. 1441-1448, 2008.

[56] D. Ward, “The effect of weather on grid systems and the reliability of electricity supply,” *Climatic Change,* vol. 121, no. 1, pp. 103-113, 2013/11/01, 2013.

[57] L. Makkonen, “Modeling power line icing in freezing precipitation,” *Atmospheric Research,* vol. 46, no. 1–2, pp. 131-142, 1998.

[58] M. BOURDAGES, P. GUILBAULT, M. IORDANESCU, J. TARNOWSKI, and R. DESBIENS, “An experimental overhead distribution line for ice loading rupture tests ” in CIRED 17th International Conference on Electricity Distribution, Barcelona, 2004.

[59] T. B. Gutwin, “Application of BCTC standardized risk estimation model to assess risk due to ice storms,” in International Conference on Probabilistic Methods Applied to Power Systems, pp. 970-974, 2004.

[60] A. F. Mensah, and L. Duenas-Osorio, “Outage predictions of electric power systems under Hurricane winds by Bayesian networks,” in International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), pp. 1-6, 2014.

[61] Y. Liu, and C. Singh, “Evaluation of hurricane impact on composite power system reliability considering common-cause failures,” *International Journal of Systems Assurance Engineering and Management,* vol. 1, no. 2, pp. 135-145, 2010.

[62] S. D. Guikema, R. Nateghi, S. M. Quiring, A. Staid, A. C. Reilly, and M. Gao, “Predicting Hurricane Power Outages to Support Storm Response Planning,” *Access, IEEE,* vol. 2, pp. 1364-1373, 2014.

[63] L. Gengfeng, Z. Peng, P. B. Luh, L. Wenyuan, B. Zhaohong, C. Serna, and Z. Zhibing, “Risk Analysis for Distribution Systems in the Northeast U.S. Under Wind Storms,” *Power Systems, IEEE Transactions on,* vol. 29, no. 2, pp. 889-898, 2014.

[64] N. Balijepalli, S. S. Venkata, C. W. Richter, Jr., R. D. Christie, and V. J. Longo, “Distribution system reliability assessment due to lightning storms,” *Power Delivery, IEEE Transactions on,* vol. 20, no. 3, pp. 2153-2159, 2005.

[65] D. Zhu, D. Cheng, R. P. Broadwater, and C. Scirbona, “Storm modeling for prediction of power distribution system outages,” *Electric Power Systems Research,* vol. 77, no. 8, pp. 973-979, 6//, 2007.

[66] P. Kankanala, A. Pahwa, and S. Das, “Exponential regression models for wind and lightning caused outages on overhead distribution feeders,” in North American Power Symposium (NAPS), pp. 1-4, 2011.

[67] P. Kankanala, A. Pahwa, and S. Das, “Regression models for outages due to wind and lightning on overhead distribution feeders,” in IEEE Power and Energy Society General Meeting, pp. 1-4, 2011.

[68] S. Hongchun, H. Ran, Z. Guangbin, Z. Hai, and C. Peng, “Lightning Withstand Level Calculation and Anti-lightning Method Research for Transmission Lines Across Heavily Icing Region,” in Asia-Pacific Power and Energy Engineering Conference (APPEEC), pp. 1-6, 2010.

[69] M. R. Bhuiyan, and R. N. Allan, “Inclusion of weather effects in composite system reliability evaluation using sequential simulation,” *Generation, Transmission and Distribution, IEE Proceedings-,* vol. 141, no. 6, pp. 575-584, 1994.

[70] D. P. Gaver, F. E. Montmeat, and A. D. Patton, “Power System Reliability I-Measures of Reliability and Methods of Calculation,” *Power Apparatus and Systems, IEEE Transactions on,* vol. 83, no. 7, pp. 727-737, 1964.

[71] R. Billinton, and K. E. Bollinger, “Transmission System Reliability Evaluation Using Markov Processes,” *Power Apparatus and Systems, IEEE Transactions on,* vol. PAS-87, no. 2, pp. 538-547, 1968.

[72] L. Yong, and C. Singh, “Reliability Evaluation of Composite Power Systems Using Markov Cut-Set Method,” *Power Systems, IEEE Transactions on,* vol. 25, no. 2, pp. 777-785, 2010.

[73] R. Billinton, and W. Li, “A novel method for incorporating weather effects in composite system adequacy evaluation,” *Power Systems, IEEE Transactions on,* vol. 6, no. 3, pp. 1154-1160, 1991.

[74] R. Billinton, and G. D. Singh, “Reliability assessment of transmission and distribution systems considering repair in adverse weather conditions,” in Electrical and Computer Engineering, 2002. IEEE CCECE 2002. Canadian Conference on, pp. 88-93 vol.1, 2002.

[75] R. Billinton, and G. Singh, “Application of adverse and extreme adverse weather: modelling in transmission and distribution system reliability evaluation,” in Generation, Transmission and Distribution, IEE Proceedings-, pp. 115-120, 2006.

[76] D. Liang, H. Yong-hong, and H. Wei-heng, “Transmission and Distribution System Reliability Evaluation Based on Three-State Weather Model,” in Asia-Pacifi Power and Energy Engineering Conference (APPEEC), pp. 1-4, 2011.

[77] D. Jayaweera, and S. Islam, “Security assessment in active distribution networks with change in weather patterns,” in International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), pp. 1-6, 2014.

[78] M. A. Rios, D. S. Kirschen, D. Jayaweera, D. P. Nedic, and R. N. Allan, “Value of security: modeling time-dependent phenomena and weather conditions,” *Power Systems, IEEE Transactions on,* vol. 17, no. 3, pp. 543-548, 2002.

[79] D. O. Koval, S. Bin, S. Shen, and A. A. Chowdhury, “Modeling Severe Weather Related High Voltage Transmission Line Forced Outages,” in IEEE PES Transmission and Distribution Conference and Exhibition, pp. 788-793, 2006.

[80] K. Alvehag, and L. Soder, “A Stochastic Weather Dependent Reliability Model for Distribution Systems,” in Probabilistic Methods Applied to Power Systems, 2008. PMAPS '08. Proceedings of the 10th International Conference on, pp. 1-8, 2008.

[81] K. Alvehag, and L. Soder, “A Reliability Model for Distribution Systems Incorporating Seasonal Variations in Severe Weather,” *Power Delivery, IEEE Transactions on,* vol. 26, no. 2, pp. 910-919, 2011.

[82] W. Peng, and R. Billinton, “Reliability cost/worth assessment of distribution systems incorporating time-varying weather conditions and restoration resources,” *Power Delivery, IEEE Transactions on,* vol. 17, no. 1, pp. 260-265, 2002.

[83] J. Lassila, T. Kaipia, J. Haakana, and J. Partanen, “Major blackouts in the development of electricity distribution networks,” in IEEE PES General Meeting | Conference & Exposition, pp. 1-5, 2014.

[84] P. Carer, and C. Briend, “Weather Impact on Components Reliability: A Model for MV Electrical Networks,” in Proceedings of the 10th International Conference on Probabilistic Methods Applied to Power Systems, pp. 1-7, 2008.

[85] S. Todd, and G. Ancell, “Transmission planning and unexpected events: An economic framework,” in International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), pp. 1-6, 2014.

[86] R. H. Milton Edimu, C T Gaunt, “Applying probability distribution functions to model system failures due to adverse weather,” in Power Systems Computation Conference (PSCC), Stockholm, Sweden, pp. 7, 2011.

[87] Z. Yujia, A. Pahwa, and Y. Shie-Shien, “Modeling Weather-Related Failures of Overhead Distribution Lines,” *Power Systems, IEEE Transactions on,* vol. 21, no. 4, pp. 1683-1690, 2006.

[88] NIWA, "*Climate and electricity system",* [online] Available at: https://www.niwa.co.nz/climate/research-projects/climate-and-electricity-system, 2015.

[89] G. C. Marano, R. Greco, and M. Mezzina, “Stochastic approach for analytical fragility curves,” *KSCE Journal of Civil Engineering,* vol. 12, no. 5, pp. 305-312, 2008.

[90] J. Winkler, L. Dueñas-Osorio, R. Stein, and D. Subramanian, “Performance assessment of topologically diverse power systems subjected to hurricane events,” *Reliability Engineering & System Safety,* vol. 95, no. 4, pp. 323-336, 4//, 2010.

[91] Newcastle University, "*RESNET: Resilient Electricity Networks",* [online] Available at: http://www.ncl.ac.uk/ceser/researchprogramme/systemsmodelling/resnetresilientelectricitynetworks/, 2015.

[92] M. Panteli, and P. Mancarella, “Modeling and Evaluating the Resilience of Critical Electrical Power Infrastructure to Extreme Weather Events,” *Systems Journal, IEEE,* vol. PP, no. 99, pp. 1-10, 2015.

[93] M. Shinozuka, M. Feng, X. Dong, S. E. Chang, T.-C. Cheng, X. Jin, and M. A. Saadeghvaziri, Advances in Seismic Performance Evaluation of Power Systems, National Science Foundation, Earthquake Engineering Research Centers Program, Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.522.2072&rep=rep1&type=pdf, 2003

[94] Z. Galias, “Probabilistic Model for Studying Blackouts in Power Networks,” *IEEE Journal on Emerging and Selected Topics in Circuits and Systems,* vol. 7, no. 2, pp. 218-227, 2017.

[95] L. Duchesne, E. Karangelos, and L. Wehenkel, "Machine learning of real-time power systems reliability management response." pp. 1-6, 2017

[96] B. Canizes, J. Soares, Z. Vale, and C. Lobo, “Optimal Approach for Reliability Assessment in Radial Distribution Networks,” *IEEE Systems Journal,* vol. PP, no. 99, pp. 1-11, 2017.

[97] F. Qiu, and P. Li, “An Integrated Approach for Power System Restoration Planning,” *Proceedings of the IEEE,* vol. 105, no. 7, pp. 1234-1252, 2017.

[98] "Effects of dependent and common mode outages on the reliability of bulk electric system — Part II: Outage data analysis." pp. 1-5, 2014

[99] "Effects of dependent and common mode outages on the reliability of bulk electric system — Part I: Basic concepts." pp. 1-5, 2014

[100] N. Yodo, P. Wang, and Z. Zhou, “Predictive Resilience Analysis of Complex Systems Using Dynamic Bayesian Networks,” *IEEE Transactions on Reliability,* vol. PP, no. 99, pp. 1-10, 2017.

[101] H. Di, Z. Yu, G. Chuangxin, Z. Jinjiang, H. Liu, and D. Yubing, "Failure probability model of transmission and transformation equipment for risk assessment." pp. 1-5, 2016

[102] M. D. Jong, G. Papaefthymiou, and P. Palensky, “A framework for incorporation of infeed uncertainty in power system risk-based security assessment,” *IEEE Transactions on Power Systems,* vol. PP, no. 99, pp. 1-1, 2017.

[103] T. Dokic, P. Dehghanian, P. C. Chen, M. Kezunovic, Z. Medina-Cetina, J. Stojanovic, and Z. Obradovic, "Risk Assessment of a Transmission Line Insulation Breakdown Due to Lightning and Severe Weather." pp. 2488-2497, 2016

[104] B. Rothstein, and S. Parey, *Impacts of and Adaptation to Climate Change in the Electricity Sector in Germany and France Climate Change Adaptation in Developed Nations*: Springer Netherlands, 2011.

[105] NERC, High-Impact, Low-Frequency Event Risk to the North American Bulk Power System, North American Electrical Reliability Corporation (NERC), Available at: www.nerc.com/pa/CI/Resources/Documents/HILF%20Report.pdf, 2010

[106] NERC, Severe Impact Resilience: Considerations and Recommendations, North American Electrical Reliability Corporation (NERC), Available at: http://www.nerc.com/comm/OC/SIRTF%20Related%20Files%20DL/SIRTF_PrelimDraft_Nov_30_2011.pdf, 2012

[107] QUANTA-Technology, Extreme Weather Event Analysis & System Hardening Qualifications, QUANTA Technology, Available at: https://www.google.co.uk/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&ved=0ahUKEwi1sJje1rPKAhWH1BoKHczKDVEQFgggMAA&url=http%3A%2F%2Fquanta-technology.com%2Fsites%2Fdefault%2Ffiles%2Fdoc-files%2FASSET%2520OPS%2520Extreme%2520Weather%2520Event%2520Analysis%2520System%2520Hardening.pdf&usg=AFQjCNGBthDKHg22__wHHz-L5sUByz6FBw, 2013

[108] N. Abi-Samra, Hardening Transmission and Distribution Systems Against Extreme Weather Events, QUANTA Technology, Available at: https://www.google.co.uk/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0ahUKEwjW2K6H1bPKAhVKDxoKHeDSDvcQFgglMAA&url=http%3A%2F%2Fquanta-technology.com%2Fsites%2Fdefault%2Ffiles%2Fdoc-files%2FHardening%2520TD%2520Systems%2520Against%2520Extreme%2520Weather%2520Events%2520-%2520formatted.pdf&usg=AFQjCNHYbVmBMboe0S_o_bpFFOKSKV6BXg, 2013

[109] E. V. Badolato, J. Bleiweis, J. D. Craig, and J. Horace W. Fleming, Hurricane Hugo: Lessons Learned in Energy Emergency Preparedness, Strom Thurmond Institute, Available at: https://www.google.co.uk/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&ved=0ahUKEwjN6tXX2LPKAhWLvxQKHXbWDlUQFgggMAA&url=https%3A%2F%2Fcoast.noaa.gov%2Fhes%2Fdocs%2Fgeneral_info%2FHURRICANE%2520HUGO%2520LESSONS%2520LEARNED%2520IN%2520ENERGY%2520EMERGENCY%2520PREPAREDNESS.pdf&usg=AFQjCNE7VNSozHDgjghKIjDe-1fE6HDE7Q, 1990

[110] QUANT Technology, "*ASSET MANAGEMENT ",* [online] Available at: http://quanta-technology.com/expertise-areas/asset-management, 2014.

[111] P. B. C. Moser, E.Gnansounou, R.Barben, "Climate Change and its Influence on the Planning and Operation of Electric Power Systems," in Cigre Paris Conference 2008, Paris, 2008.

[112] M. Kezunovic, I. Dobson, and Y. Dong, "Impact of extreme weather on power system blackouts and forced outages: New challenges," in Seventh Balkan Power Conf, Šibenik, Croatia, Univerza v Ljubljani, pp. 5 pp, 2008.

[113] L. C. Cradden, and G. P. Harrison, "Adapting overhead lines to climate change: Are dynamic ratings the answer?," *Energy Policy,* vol. 63, no. 0, pp. 197-206, 2013.

[114] M. Mirza, "Mainstreaming Climate Change for Extreme Weather Events & Management of Disasters: An Engineering Challenge," in IEEE EIC Climate Change Technology, pp. 1-10, 2006.

[115] D. Rübbelke, and S. Vögele, Distributional consequences of climate change impacts on the power sector: who gains and who loses ?, Tech. Rep. 349 Centre for European Policy Studies,, Brussels Available at: http://www.ceps.eu/publications/distributional-consequences-climate-change-impacts-power-sector-who-gains-and-who-loses, 2011

[116] The National Archives, "*Climate Change Act 2008",* [online] Available at: http://www.legislation.gov.uk/ukpga/2008/27/part/1/enacted, 2012.

[117] Department for Environment, Food & Rural Affairs (DEFRA), "*Climate change adaptation",* [online] Available at: https://www.gov.uk/government/collections/climate-change-guidance, 2013.

[118] Scottish Power, Climate Change Adaption Report: Final Report, SP Energy Networks, Available at: http://archive.defra.gov.uk/environment/climate/documents/sp-energy-networks.pdf, 2011

[119] SSE, Climate Change Adaptation Report, Available at: http://archive.defra.gov.uk/environment/climate/documents/adapt-reports/04distribute-trans/sse-power-distribution.pdf, 2011

[120] Ofgem, Adaptation to Climate Change: Report to Defra, Available at: http://archive.defra.gov.uk/environment/climate/documents/adapt-reports/10regulators/regs-ofgem.pdf, 2011

[121] ENA, "Electricity Networks Climate Change Adaptation Report," 1, Available at: http://archive.defra.gov.uk/environment/climate/documents/ena-networks.pdf, [2011].

[122] Cranfield University, Evaluating the Risk Assessment of Adaptation Reports under the Adaptation Reporting Power, Prepared for the Department for Environment, Food and Rural Affairs by Cranfield University, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/82751/annex-b-cranfield-uni-report-arp.pdf, 2012

[123] OFGEM, "*The GB electricity transmission network",* [online] Available at: https://www.ofgem.gov.uk/electricity/transmission-networks/gb-electricity-transmission-network, 2015.

[124] National Grid, "*Distribution Network Operator (DNO) Companies ",* [online] Available at: http://www2.nationalgrid.com/uk/Our-company/electricity/Distribution-Network-Operator-Companies/, 2015.

[125] J. Osborn, and C. Kawann, Reliability of the U.S. Electricity System: Recent Trends and Current Issues, Energy Analysis Department Environmental Energy Technologies Division Ernest Orlando Lawrence Berkeley National Laboratory University of California, Prepared for the Assistant Secretary for Energy Efficiency and Renewable Energy U.S. Department of Energy Available at: https://emp.lbl.gov/publications/reliability-us-electricity-system, 2001

[126] National Grid, "*What we do in the Electricity Industry",* [online] Available at: http://www2.nationalgrid.com/uk/our-company/electricity/, 2015.

[127] H. Thornton, Investigating the Relationship between Electricity Network Resilience and Weather, Met Office Hadley Centre, Available at: http://www.ep2.org.uk/climate/pdf_hazel_emergency/EP2_WP3__Network_Resilience_Report_v2.pdf, 2008

[128] L. McColl., and E. Palin, Baseline Climate Risk Assessment for the Electricity Network: National Grid, Met Office Hadley Centre, Available at: Met Office, 2010

[129] L. McColl., and E. Palin, Future Climate Risk Assessment for the Electricity Network: National Grid, Met Office Hadley Centre, Available at: Met Office, 2010

[130] "ERA-40 dataset", European Centre for Medium-Range Weather Forecasts (ECMWF), [online] Available at: http://www.ecmwf.int/en/forecasts/datasets/era-40-dataset-sep-1957-aug-2002 20/8/2013.

[131] L. McColl, E. Palin, H. Thornton, D. H. Sexton, R. Betts, and K. Mylne, “Assessing the potential impact of climate change on the UK’s electricity network,” *Climatic Change,* vol. 115, no. 3-4, pp. 821-835, 2012/12/01, 2012.

[132] ARCC network, "*ARIES: Adaptation and Resilience in Energy Systems",* [online] Available at: http://www.arcc-network.org.uk/project-summaries/aries/#.VpeGiFJZiso, 2014.

[133] ARCC network, "*RESNET: Resilient Electricity Networks for Great Britain ",* [online] Available at: http://www.arcc-network.org.uk/project-summaries/resnet/#.VpeGj1JZisq, 2014.

[134] University of Liverpool, "*ARCoES: Adaptation and Resilience of Coastal Energy Supply",* [online] Available at: https://www.liverpool.ac.uk/geography-and-planning/research/adaptation-and-resilience-of-coastal-energy-supply/, 2014.

[135] ARCC Network, "*ARCC: About Us",* [online] Available at: http://www.arcc-network.org.uk/about-arcc/#.VpeH21JZiso, 2014.

[136] M. Panteli, and P. Mancarella, “Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies,” *Electric Power Systems Research,* vol. 127, pp. 259-270, 10//, 2015.

[137] "Power System Reliability," *Reliability and Safety Engineering*, pp. 305-321, London: Springer London, 2010.

[138] P. Kundur, *Power System Stability and Control*: McGraw-Hill, Inc, 1993.

[139] A. Bose, and K. Tomsovic, "Power System Security," *Wiley Encyclopedia of Electrical and Electronics Engineering*: John Wiley & Sons, Inc., 2001.

[140] K. Bell, D. Bones, V. Stanisic, W. Zhang, S. Henry, K. Vennemann, T. Paulun, A. Berizzi, M. Cremenescu, L. Naidoo, R. v. Heerden, P. Schaemaker, S. Bruijns, A. Ozkaya, D. Chan, and J. Seelke, Planning to Manage Power Interruption Events, Working Group C1.17 CIGRE Available at: http://strathprints.strath.ac.uk/35227/, 2010.

[141] D. S. Kirschen, “Power system security,” *Power Engineering Journal,* vol. 16, no. 5, pp. 241-248, 2002.

[142] B. Lee, F. Preston, and G. Green, Preparing for High-impact, Low-probability Events - Lessons from Eyjafjallajökull, Chatham House, Available at: www.chathamhouse.org/sites/files/.../public/.../r0112_highimpact.pdf, 2012

[143] National Grid, Balancing Principles Statement vol. 12.0, Available at: http://www2.nationalgrid.com/UK/Industry-information/Electricity-codes/Balancing-framework/Transmission-license-C16-statements/, 2014

[144] National Grid, National Electricity Transmission System: Security and Quality of Supply Standard, vol. 2.2, Available at: http://www2.nationalgrid.com/uk/industry-information/electricity-codes/sqss/the-sqss/, 2012

[145] R. Allan, and R. Billinton, “Power system reliability and its assessment. I. Background and generating capacity,” *Power Engineering Journal,* vol. 6, no. 4, pp. 191-196, 1992.

[146] R. Allan, and R. Billinton, “Power system reliability and its assessment. III. Distribution systems and economic considerations,” *Power Engineering Journal,* vol. 7, no. 4, pp. 185-192, 1993.

[147] “IEEE Guide for Electric Power Distribution Reliability Indices,” *IEEE Std 1366-2012 (Revision of IEEE Std 1366-2003)*, pp. 1-43, 2012.

[148] J. Ding, K. R. W. Bell, and I. M. Elders, “A method for the evaluation and optimisation of power losses and reliability of supply in a distribution network.,” in the 19th Power Systems Computation Conference (PSCC), Genoa, Italy, pp. 1-8, 2016.

[149] R. Allan, and R. Billinton, “Power system reliability and its assessment. 2. Composite generation and transmission systems,” *Power Engineering Journal,* vol. 6, no. 6, pp. 291-297, 1992.

[150] B. Tianshu, Q. Xiaohui, H. Renmu, and Y. Qixun, “Risk theory based on-line power system security assessment,” in Electric Utility Deregulation and Restructuring and Power Technologies, 2008. DRPT 2008. Third International Conference on, pp. 704-708, 2008.

[151] A. A. Chowdhury, and S. M. Islam, “Development and application of probabilistic criteria in value-based transmission system adequacy assessment,” in Australasian Universities Power Engineering Conference, pp. 1-9, 2007.

[152] J. D. McCalley, A. A. Fouad, V. Vittal, A. A. Irizarry-Rivera, B. L. Agrawal, and R. G. Farmer, “A risk-based security index for determining operating limits in stability-limited electric power systems,” *Power Systems, IEEE Transactions on,* vol. 12, no. 3, pp. 1210-1219, 1997.

[153] NationalGrid, Report to the Gas and Electricity Markets Authority. National Electricity Transmission System 2011-2012 Performance Report, National Grid, Available at: http://www2.nationalgrid.com/UK/Industry-information/Electricity-transmission-operational-data/Report-explorer/Performance-Reports/, 2014

[154] Laerd Statistics, "*Measures of Central Tendency",* [online] Available at: https://statistics.laerd.com/statistical-guides/measures-central-tendency-mean-mode-median.php, 2013.

[155] Wolfram MathWorld, "*Skewness",* [online] Available at: http://mathworld.wolfram.com/Skewness.html, 2013.

[156] Math is Fun Advanced, "*Skewed Data",* [online] Available at: http://www.mathsisfun.com/data/skewness.html, 2013.
[157] P. T. v. Hippel, "Mean, Median, and Skew: Correcting a Textbook Rule," *Journal of Statistics Education,* vol. 13, 2005.
[158] Murray. R. Spiegel, and K. J. Stephens, *Schaum's Outlines - Statistics*: McGraw-Hill, 2008.
[159] Statistics Explained, "*Internet Glossary of Statistical Terms",* [online] Available at: http://www.animatedsoftware.com/statglos/statglos.htm#index, 2013.
[160] Dell - StatSoft, "*Confideence Interval for the Mean",* [online] Available at: http://www.statsoft.com/textbook/statistics-glossary/c#Confidence%20Interval, 2013.
[161] MathsRevision, "*Cumulative Frequency Graphs",* [online] Available at: http://www.mathsrevision.net/gcse-maths-revision/statistics-handling-data/cumulative-frequency-graphs, 2013.
[162] Dell - StatSoft, "*Correlation",* [online] Available at: http://www.statsoft.com/Textbook/Basic-Statistics#Correlationsb, 2013.
[163] Martha K. Smith, "*COMMON MISTEAKS MISTAKES IN USING STATISTICS: Spotting and Avoiding Them",* [online] Available at: https://www.ma.utexas.edu/users/mks/statmistakes/skeweddistributions.html, 2013.
[164] David M. Lane, "*Log Transformations",* [online] Available at: http://onlinestatbook.com/2/transformations/log.html, 2013.
[165] J. H. McDonald, *Handbook of Biological Statistics (3rd Ed)*, p.^pp. 140-144: Sparky House Publishing, Baltimore, Maryland, 2014.
[166] Douglas C. Montgomery, and G. C. Runger, *Applied Statistics and Probability for Engineers*: John Wiley & Sons, Inc., 2002.
[167] Wikipedia, "*Probability",* [online] Available at: http://en.wikipedia.org/wiki/Probability, 2015.
[168] R. E. Walpole, R. H. Myers, S. L. Myers, and K. Ye, *Probability & Statistics for Engineers & Scientists*: Pearson Education International, 2007.
[169] Wolfram - MathWorld, "*Bayesian Analysis",* [online] Available at: http://mathworld.wolfram.com/BayesianAnalysis.html, 2014.
[170] Explorable, "*Stratified Sampling Method",* [online] Available at: https://explorable.com/stratified-sampling, 2014.
[171] RiskAMP, "What is Monte Carlo Simulation?," Available at: https://www.riskamp.com/files/RiskAMP%20-%20Monte%20Carlo%20Simulation.pdf, [2014].
[172] D. S. Kirschen, K. R. W. Bell, D. P. Nedic, D. Jayaweera, and R. N. Allan, "Computing the value of security," *Generation, Transmission and Distribution, IEE Proceedings-,* vol. 150, no. 6, pp. 673-678, 2003.
[173] W. Li, *Probabilistic Transient Stability Assessment*: John Wiley & Sons, Inc., 2005.
[174] P. Henneaux, and P. E. Labeau, "Improving Monte Carlo simulation efficiency of level-I blackout probabilistic risk assessment," in International Conference on Probabilistic Methods Applied to Power Systems (PMAPS) pp. 1-6, 2014.
[175] M. Schlapfer, and P. Mancarella, "Probabilistic Modeling and Simulation of Transmission Line Temperatures Under Fluctuating Power Flows," *Power Delivery, IEEE Transactions on,* vol. 26, no. 4, pp. 2235-2243, 2011.
[176] A. R. Abu El Wafa, I. Helal, and G. Haggag, "Monte Carlo simulation in generating capacity adequacy assessment (state sampling technique)," in Power Systems Conference, 2006. MEPCON 2006. Eleventh International Middle East, pp. 541-546, 2006.
[177] A. C. G. Melo, M. V. F. Pereira, and A. M. Leite da Silva, "Frequency and duration calculations in composite generation and transmission reliability evaluation," *Power Systems, IEEE Transactions on,* vol. 7, no. 2, pp. 469-476, 1992.
[178] D. Vose, "The pros and cons of Latin Hypercube sampling," Available at: https://www.linkedin.com/pulse/20140708131747-483951-the-pros-and-cons-of-latin-hypercube-sampling, [2014].
[179] W. Dongtao, Y. Yixin, F. Chuan, Z. Jingyu, W. Jianzhong, J. Hongjie, and C. Xiaoming, "Security Region Based Probabilistic Security Assessment of Power Transmission System a Basic Concepts." pp. 1-5, 2005
[180] Mathpages, "*Markov Modeling for Reliability. Part 2: Markov Model Fundamentals",* [online] Available at: http://www.mathpages.com/home/kmath232/part2/part2.htm, 2015.
[181] Wolfram MathWorld, "*Markov Chain ",* [online] Available at: http://mathworld.wolfram.com/MarkovChain.html, 2015.
[182] MathWorks, "*Hidden Markov Models (HMM)",* [online] Available at: http://uk.mathworks.com/help/stats/hidden-markov-models-hmm.html?s_tid=gn_loc_drop, 2015.
[183] Artificial Intelligence foundations of computational agents, "*Decision Processes",* [online] Available at: http://artint.info/html/ArtInt_224.html, 2015.
[184] P. Kundur, J. Paserba, V. Ajjarapu, G. Andersson, A. Bose, C. Canizares, N. Hatziargyriou, D. Hill, A. Stankovic, C. Taylor, T. V. Cutsem, and V. Vittal, "Definition and classification of power system

stability IEEE/CIGRE joint task force on stability terms and definitions," *IEEE Transactions on Power Systems,* vol. 19, no. 3, pp. 1387-1401, 2004.

[185] S. J. Chapman, *Electric Machinery and Power System Fundamentals*: McGraw-Hill, 2002.

[186] R. Preece, "Improving the Stability of Meshed Power Networks," University of Manchester, Springer International Publishing Switzerland, 2013.

[187] M. Belivanis, and K. R. W. Bell, "Representative GB Network Model: Notes," University of Strathclyde, 2011.

[188] J. D. Glover, M. S. Sarma, and T. Overbye, *Power Systems Analysis and Design 4th Edition*: PWS Publishers, 2010.

[189] PowerWorld, "*Generator Economic Merit Order Dispatch",* [online] Available at: http://www.powerworld.com/WebHelp/Content/MainDocumentation_HTML/Generator_Economic_Merit_Order_Dispatch.htm, 2015.

[190] R. D. Zimmerman, C. E. Murillo-Sánchez, and R. J. Thomas, "MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education," *Power Systems, IEEE Transactions on,* vol. 26, no. 1, pp. 12-19, 2011.

[191] R. D. Zimmerman, and C. E. Murillo-Sanchez, Matpower 6.0b1 User's Manual, Available at: http://www.pserc.cornell.edu/matpower/#docs, 2016

[192] Met Office (2008), "Met Office MetDB system: Surface, upper air and satellite data ", NCAS British Atmospheric Data Centre.

[193] M. O. UK, "Met Office Integrated Data Archive System (MIDAS) Land and Marine Surface Stations Data (1853-current)," NCAS British Atmospheric Data Centre, 2012.

[194] D. P. Dee, S. M. Uppala, A. J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, M. A. Balmaseda, G. Balsamo, P. Bauer, P. Bechtold, A. C. M. Beljaars, L. van de Berg, J. Bidlot, N. Bormann, C. Delsol, R. Dragani, M. Fuentes, A. J. Geer, L. Haimberger, S. B. Healy, H. Hersbach, E. V. Hólm, L. Isaksen, P. Kållberg, M. Köhler, M. Matricardi, A. P. McNally, B. M. Monge-Sanz, J. J. Morcrette, B. K. Park, C. Peubey, P. de Rosnay, C. Tavolato, J. N. Thépaut, and F. Vitart, "The ERA-Interim reanalysis: configuration and performance of the data assimilation system," *Quarterly Journal of the Royal Meteorological Society,* vol. 137, no. 656, pp. 553-597, 2011.

[195] European Centre for Medium Range Weather Forecasts (ECMWF), "ERA Interim, Daily fields," Available at: http://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/, 2008.

[196] European Centre for Medium Range Weather Forecasts (ECMWF), "*MARS",* [online] Available at: https://software.ecmwf.int/wiki/display/UDOC/MARS, 2013.

[197] EA Technology, "*Lightning Location System",* [online] Available at: http://www.eatechnology.com/products-and-services/optimise-network-operations/lightning-location-system, 2015.

[198] About Education, "*What Makes the Wind Blow in Gusts",* [online] Available at: http://weather.about.com/od/w/g/wind_gusts.htm, 2016.

[199] Weather Bug, "*Wind Speed/Direction",* [online] Available at: http://weather.weatherbug.co.uk/weather-glossary/W/Wind%20Speed/Direction.html, 2016.

[200] Goddard Earth Sciences Data and Information Services Center (GES DISC) - NASA, "*Snow Water Equivalent",* [online] Available at: http://disc.gsfc.nasa.gov/hydrology/data-holdings/parameters/snow_water_equivalent.shtml, 2015.

[201] Earth Science Communications Team at NASA's Jet Propulsion Laboratory, "*Competing Forces Muddle the Picture",* [online] Available at: http://earthobservatory.nasa.gov/Features/ClimateStorms/page4.php, 2013.

[202] C. Price, and D. Rind, "A simple lightning parameterization for calculating global lightning distributions," *Journal of Geophysical Research: Atmospheres,* vol. 97, no. D9, pp. 9919-9933, 1992.

[203] BBC, "*Big freeze chaos in north",* [online] Available at: http://news.bbc.co.uk/1/hi/uk/1192149.stm, 2015.

[204] Met Office, "*UK Snow 2010",* [online] Available at: http://www.metoffice.gov.uk/learning/learn-about-the-weather/weather-phenomena/case-studies/snow2010, 2015.

[205] The Tornado & Storm Research Organisation (TORRO), "*Windstorms",* [online] Available at: http://www.torro.org.uk/site/wind_info.php, 2015.

[206] Met Office, "*Early winter storms, late 2011",* [online] Available at: http://www.metoffice.gov.uk/climate/uk/interesting/2011_decwind, 2015.

[207] Weather Cast, "*The Great Boxing Day Storm of 1998",* [online] Available at: http://www.weathercast.co.uk/weather-news/news/ch/2460ce1d42e4f3a2b349b768bc560068/article/the_great_boxing_day_storm_of_1998.html, 2015.

[208] NationalGrid, Report to the Gas and Electricity Markets Authority. National Electricity Transmission System 2010-2011 Performance Report, National Grid, Available at: http://www2.nationalgrid.com/UK/Industry-information/Electricity-transmission-operational-data/Report-explorer/Performance-Reports/, 2014

[209] NationalGrid, ETYS 2012 Document - Appendix B, National Grid, Available at: http://www2.nationalgrid.com/UK/Industry-information/Future-of-Energy/Electricity-ten-year-statement/2012/, 2012

[210] G. Upton, and I. Cook, "A Dictionary of Statistics (2 rev. ed.) ", Oxford University Press, 2008.

[211] P. Boorman, G. Jenkins, J. Murphy, and K. Burgess, "Future changes in lightning from the UKCP09 ensemble of regional climate model projections," Met Office Hadley Centre, Available at: http://ukclimateprojections.metoffice.gov.uk/22594, [November 2010].

[212] S. Brown, P. Boorman, and J. Murphy, "Interpretation and use of future snow projections from the 11-member Met Office Regional Climate Model ensemble," Met Office Hadley Centre, Available at: http://ukclimateprojections.metoffice.gov.uk/22594, [November 2010].

[213] "*G.B. National Grid Status",* [online] Available at: http://www.gridwatch.templar.co.uk/, 2016.

[214] AREVA, "Technical data M5000," 2010.

[215] Department of Energey and Climate Change, Annex C: Reliability Standard Methodology, Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/267613/Annex_C_-_reliability_standard_methodology.pdf, 2016

[216] Science and Technology Committee, "*The Resilience of the Electricity System - CHAPTER 3: WILL THE LIGHTS GO OUT?",* [online] Available at: http://www.publications.parliament.uk/pa/ld201415/ldselect/ldsctech/121/12106.htm, 2016.

[217] European Centre for Medium Range Weather Forecasts (ECMWF), "*ECMEF Web API Home",* [online] Available at: https://software.ecmwf.int/wiki/display/WEBAPI/ECMWF+Web+API+Home, November 2013.

Appendix A: Weather Data Download Information

This appendix contains the ERA-Interim, from ECMWF, table of parameters used to extract weather data for this analysis. The easiest way to download the ERA-Interim weather information is to use their application programming interface (API) to access meteorological archival retrieval system (MARS). You give MARS a request and it will return the data used in the request as displayed in [217]. The following base request was used and it was run once per weather type per year:

```
{"dataset", "interim"},
{"stream", "oper"},
{"levtype", "sfc"},
{"step", “3/6/9/12”},
{"grid", "0.75/0.75"},
{"time", "00/12"},
{"type", "fc"},
{"class", "ei"},
{"area", "60/-15/45/3"},
{"param", param},
{"date",dateParam}
```

Where:

param:

Snowfall: 144.128
Lightning: 59.128
WindGusts: 49.128
WindSpeedU: 165.128
WindSpeedV: 166.128
SnowDepth: 141.128
MinTemperature: 202.128
SnowDensity: 33.128

dataParam:

Runs once per year, from 1980 to 2012
<year>-01-01/to/<year>-12-31

Appendix B: RTS Time Graphs

This appendix contains the information related to Section 4.2.3. It contains the tables for each weather type, the count of outages with and without a RTS time, the distribution used for best fit, its associated parameters, and the histogram of the outage duration data on the left and then the resampled data on the right for non-weather and weather related outages.

B-1 Weather

SSB & Ice - Exponential Distribution, 4>150, Mu = 3.32088

Table B-1 – SSB & Ice Outages RTS Time Count

Company	With RTS Times	Without RTS Times
A	1	155
B	436	0
C	562	19
Total	999	174

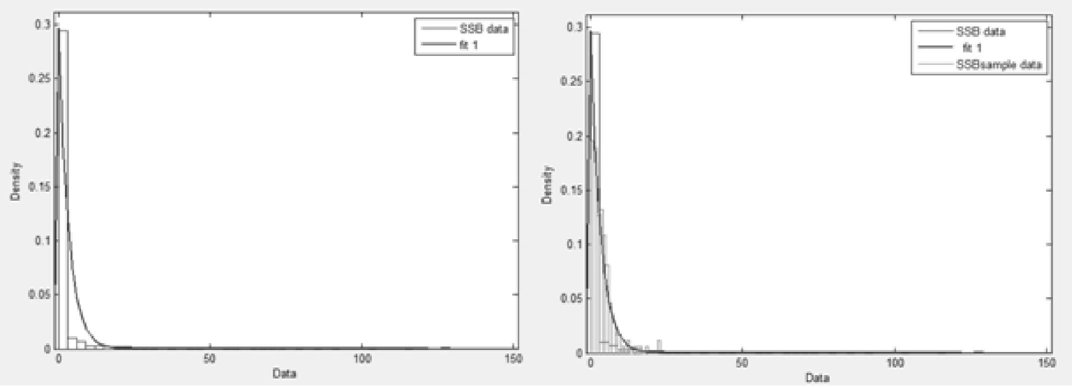


Figure 10-1 – SSB & Ice Fit

Wind, Gales & Windborne Objects - Exponential Distribution, 12>150, Mu = 2.47503

Table B-2 - Wind, Gales & Windborne Objects Outages RTS Time Count

Company	With RTS Times	Without RTS Times
A	6	286
B	619	0
C	459	30
Total	1084	316

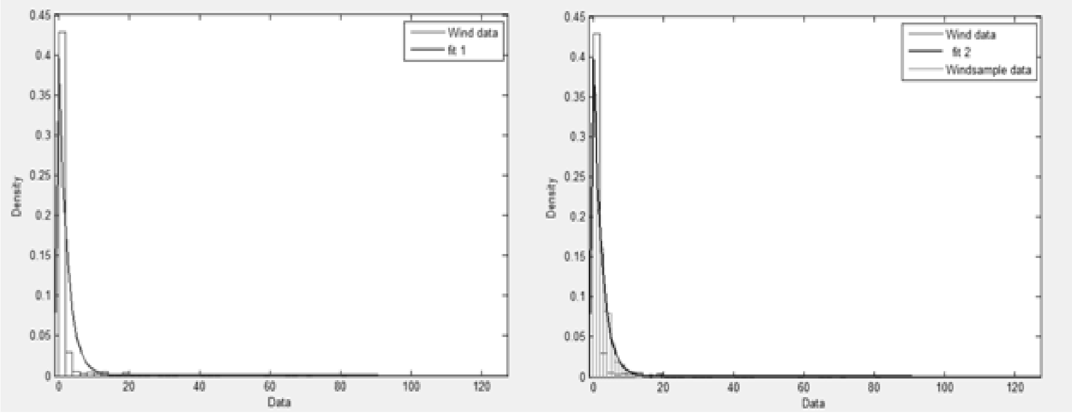


Figure 10-2 – Wind, Gales & Windborne Objects Fit

Rain & Flooding - Exponential Distribution, 1>150, Mu = 3.86244

Table B-3 - Rain & Flooding Outages RTS Time Count

Company	With RTS Times	Without RTS Times
A	5	44
B	12	0
C	25	0
Total	42	44

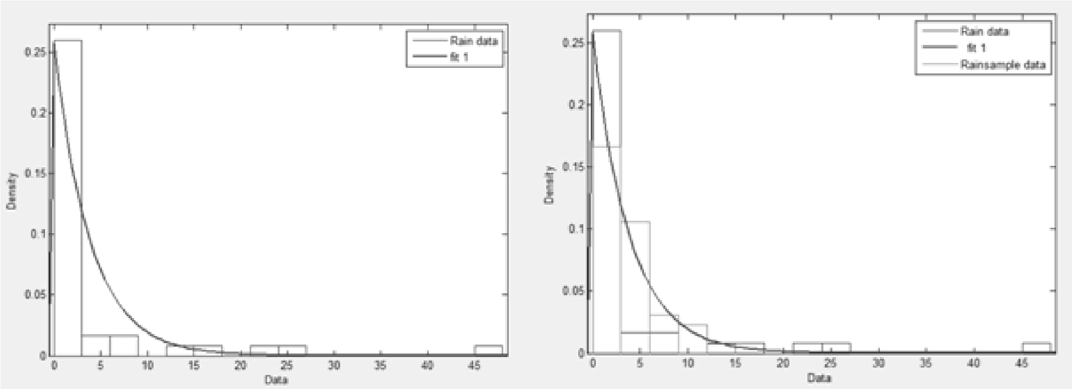


Figure 10-3 – Rain & Flooding Fit

Fire not due to faults - Exponential Distribution, 2>150, Mu = 9.75278

Table B-4 - Fire not due to faults Outages RTS Time Count

Company	With RTS Times	Without RTS Times
A	0	9
B	7	0
C	13	1
Total	20	10

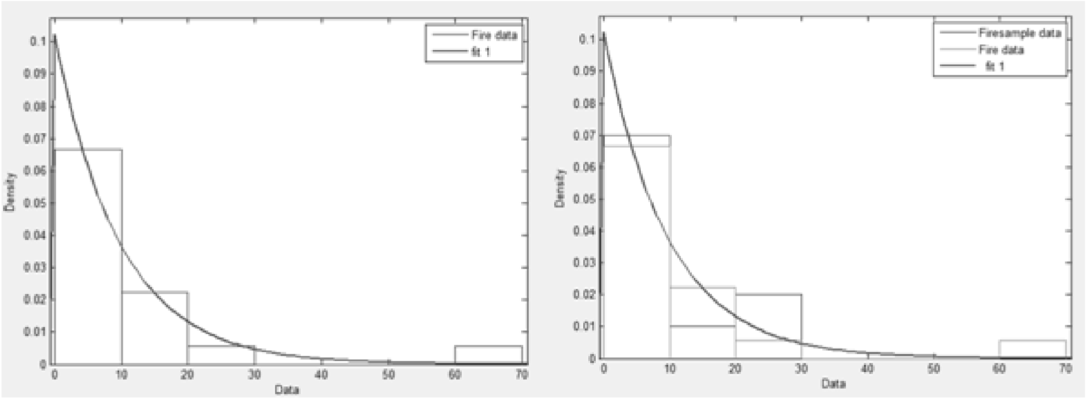


Figure 10-4 – Fire not due to faults Fit

Blanks & Unknowns - Exponential Distribution, 0>150, Mu = 1.204

Table B-5 - Blanks & Unknowns Outages RTS Time Count

Company	With RTS Times	Without RTS Times
A	44	234
B	13	0
C	3	1
Total	60	235

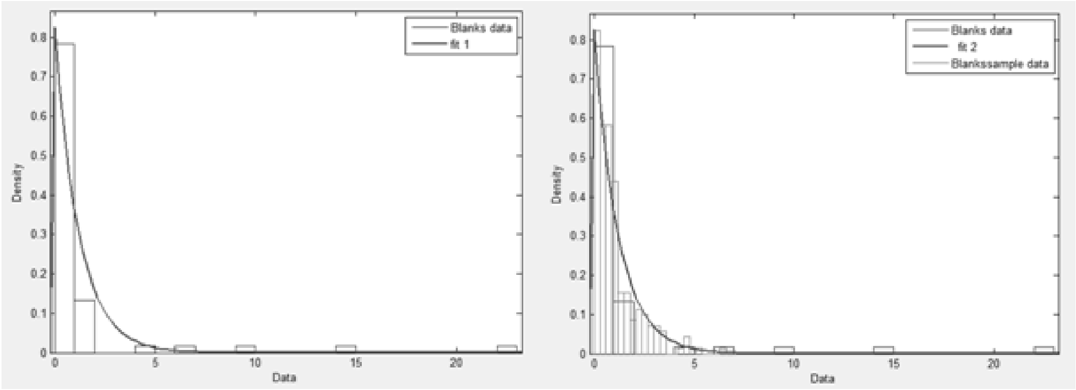


Figure 10-5 – Blanks & Unknowns Fit

Salt, Condensation & Corrosion - Parametric Distribution, 12>150, Bandwidth = 1

Table B-6 - Salt, Condensation & Corrosion Outages RTS Time Count

Company	With RTS Times	Without RTS Times
A	0	8
B	129	0
C	6	2
Total	135	10

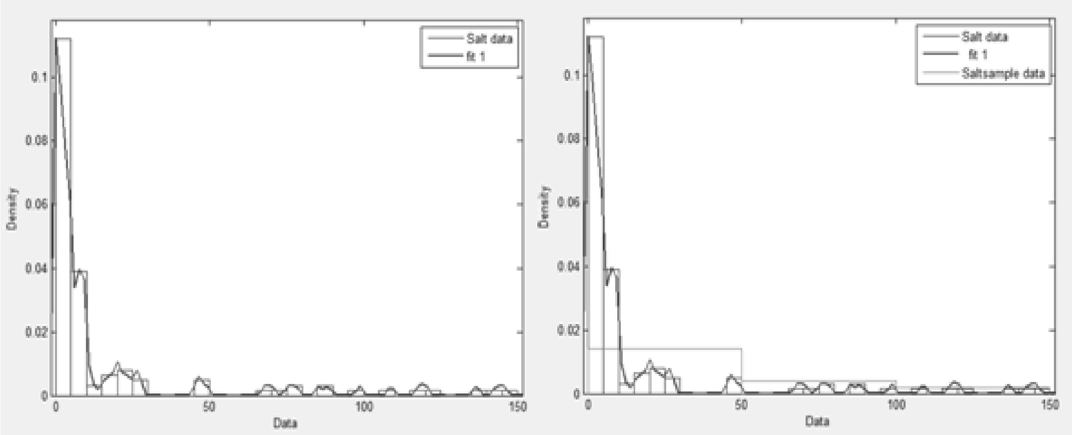


Figure 10-6 – Salt, Condensation & Corrosion Fit

Pollution, Mist & Freezing Fog - Parametric Distribution, 0>150, Bandwidth = 0.65

Table B-7 - Pollution, Mist & Freezing Fog Outages RTS Time Count

Company	With RTS Times	Without RTS Times
A	5	90
B	11	0
C	10	1
Total	26	91

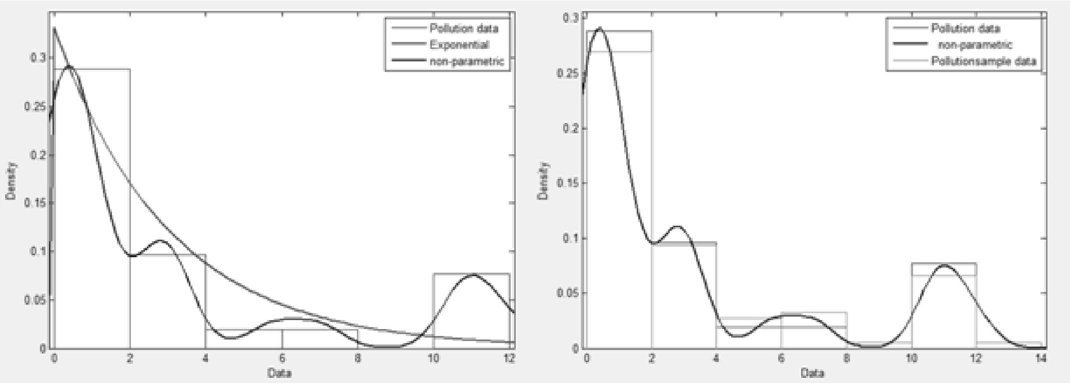


Figure 10-7 Pollution, Mist & Freezing Fog Fit

Other Weather Types - Parametric Distribution, 1>150, Bandwidth = 0.8

Table B-8 - Other Weather Types Outages RTS Time Count

Company	With RTS Times	Without RTS Times
B	12	0
C	34	1
A	1	6
Total	47	7

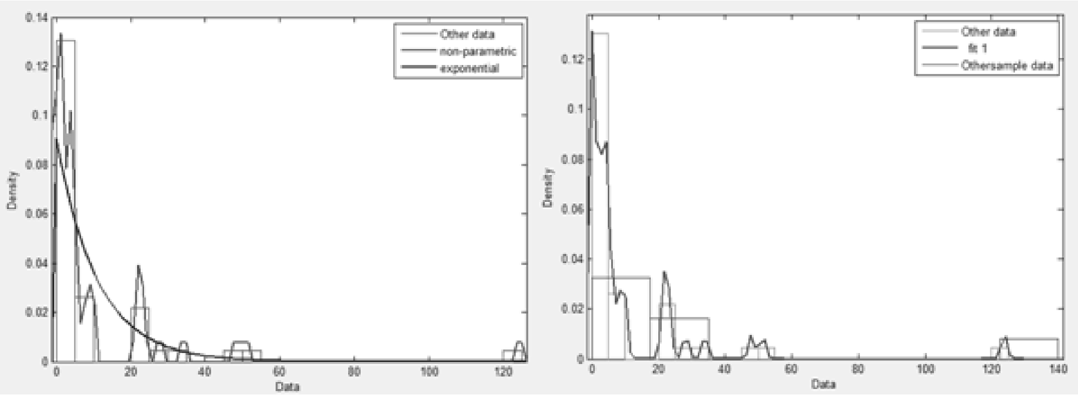


Figure 10-8 - Other Weather Types Fit

B-2 Non-Weather

Transformers

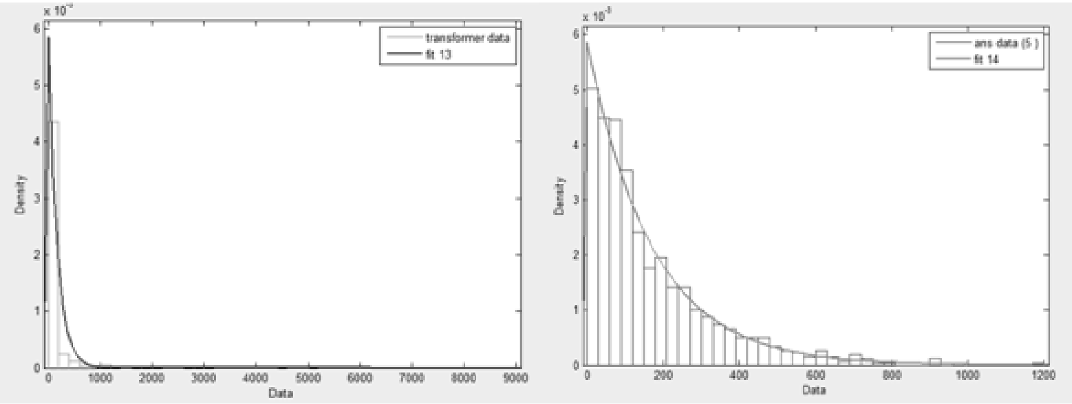


Figure 10-9 - Transformers Fit

Switchgear

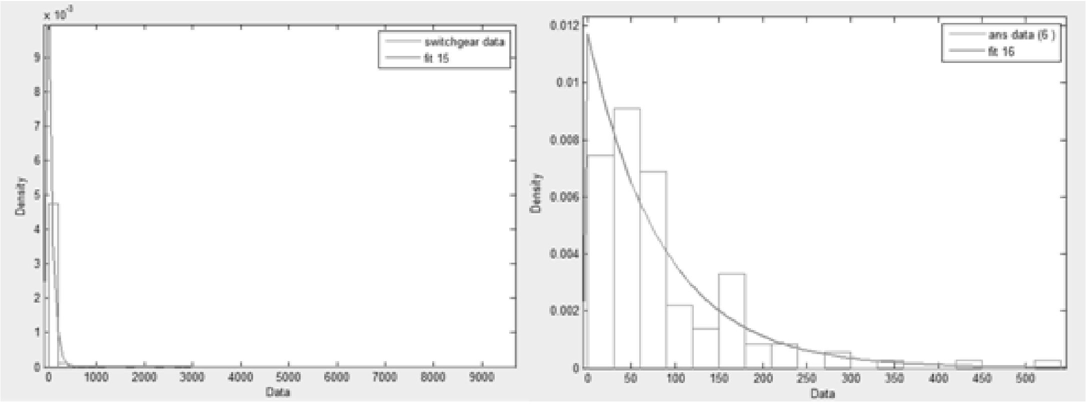


Figure 10-10 – Switchgear Fit

Protection

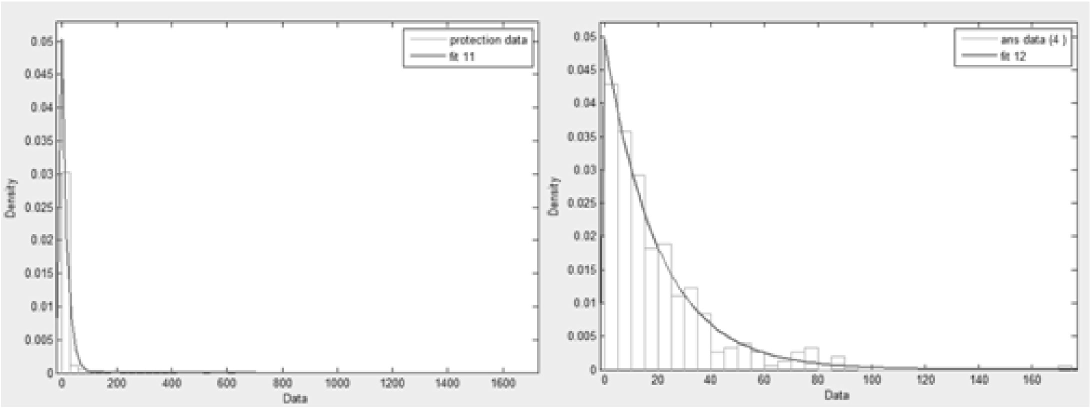


Figure 10-11 – Protection Fit

OHL

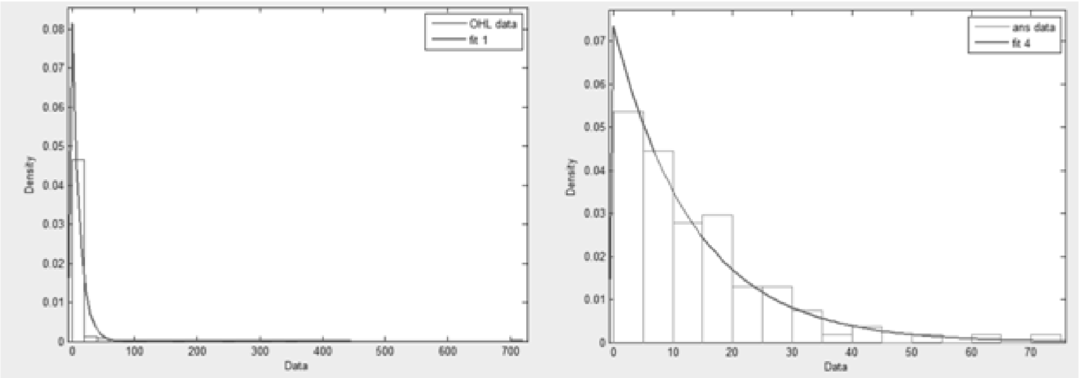


Figure 10-12 – OHL Fit

Miscellaneous

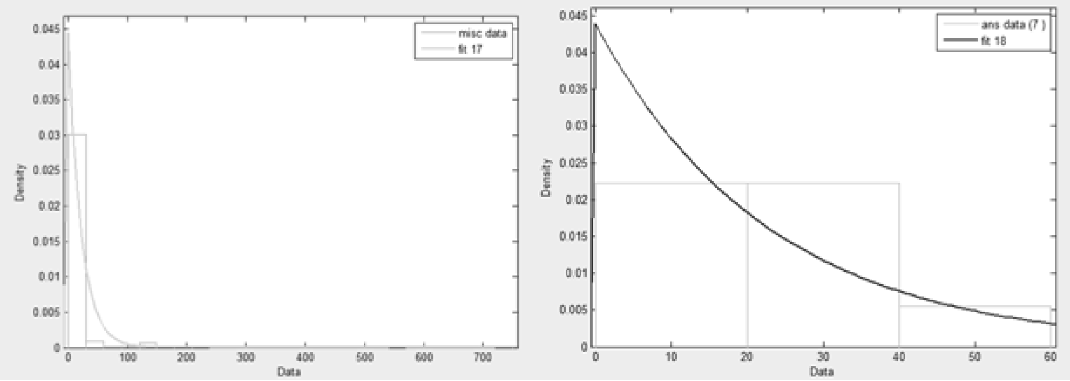


Figure 10-13 – Miscellaneous Fit

Circuit Breakers

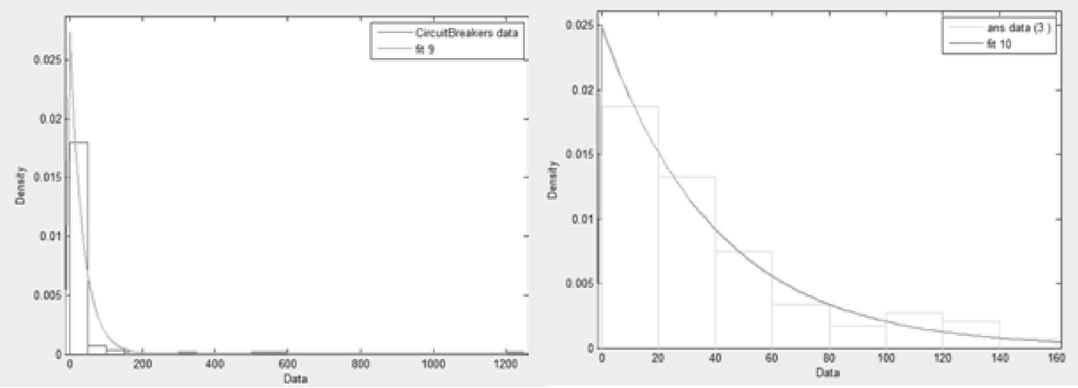


Figure 10-14 – Circuit Breakers Fit

Cables

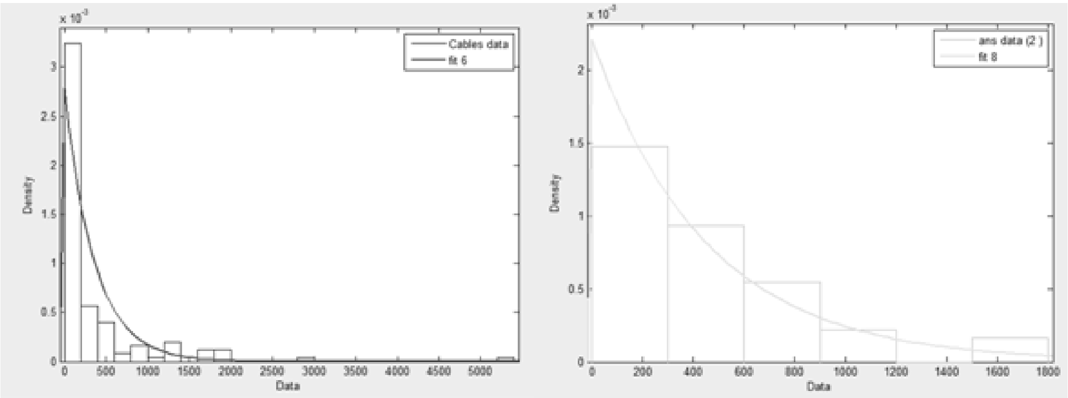


Figure 10-15 – Cables Fit

Equipment Blanks

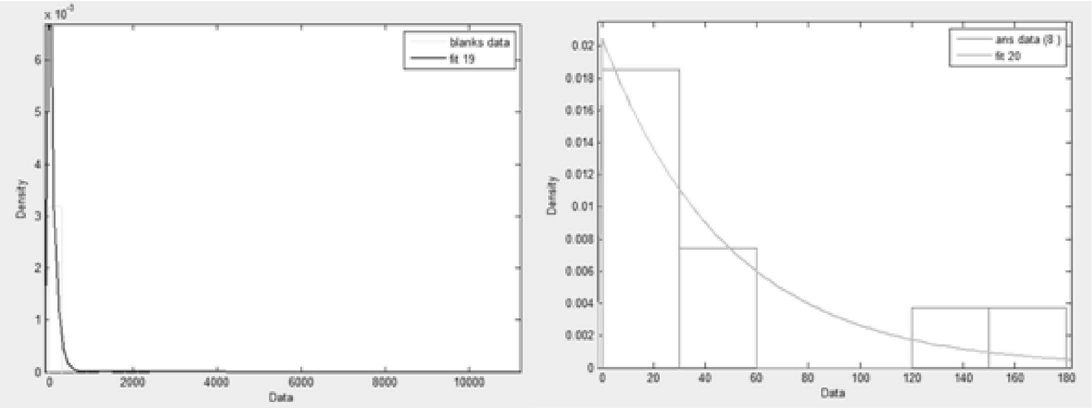


Figure 10-16 – Equipment Blanks Fit

Appendix C: Initial Weather and Outage Analysis – Further Statistics

This appendix shows the standard error, the upper and lower confidence limits of outages per weather, per company, per year, per 100km of circuit length for the statistics shown in Section 4.3.1.

Table C-1 - Standard Error, Upper and Lower Confidence Limits per year per 100km of Weather Related Outages

Category	**Standard Error per year per 100 km**			**Upper Confidence Limit per year per 100 km**			**Lower Confidence Limit per year per 100 km**		
Company	A	B	C	A	B	C	A	B	C
Lightning	0.04	0.03	0.05	0.43	0.33	0.52	0.26	0.20	0.31
SSB & Ice	0.04	0.14	0.10	0.15	0.67	0.63	0.00	0.11	0.25
Wind, Gales & Windborne Objects	0.03	0.16	0.08	0.20	0.88	0.53	0.06	0.24	0.20
Other Weather Types	0.02	0.05	0.02	0.12	0.25	0.10	0.05	0.06	0.04
Blanks and Unknowns	0.03	0.01	0.00	0.16	0.02	0.01	0.05	0.00	0.00
Total	0.08	0.25	0.14	0.90	1.88	1.56	0.57	0.88	1.03

Appendix D: Correlation Analysis for South Scotland, North England and North Wales and South England and South Wales

This appendix contains the frequency distributions, cumulative frequency distributions and finally correlations for the top weather-related outages classes for the GB transmission network and their weather variables for South Scotland, North England and North Wales, and South England and South Wales. As displayed in Chapter 5 - for North Scotland.

D-1 Wind Gusts

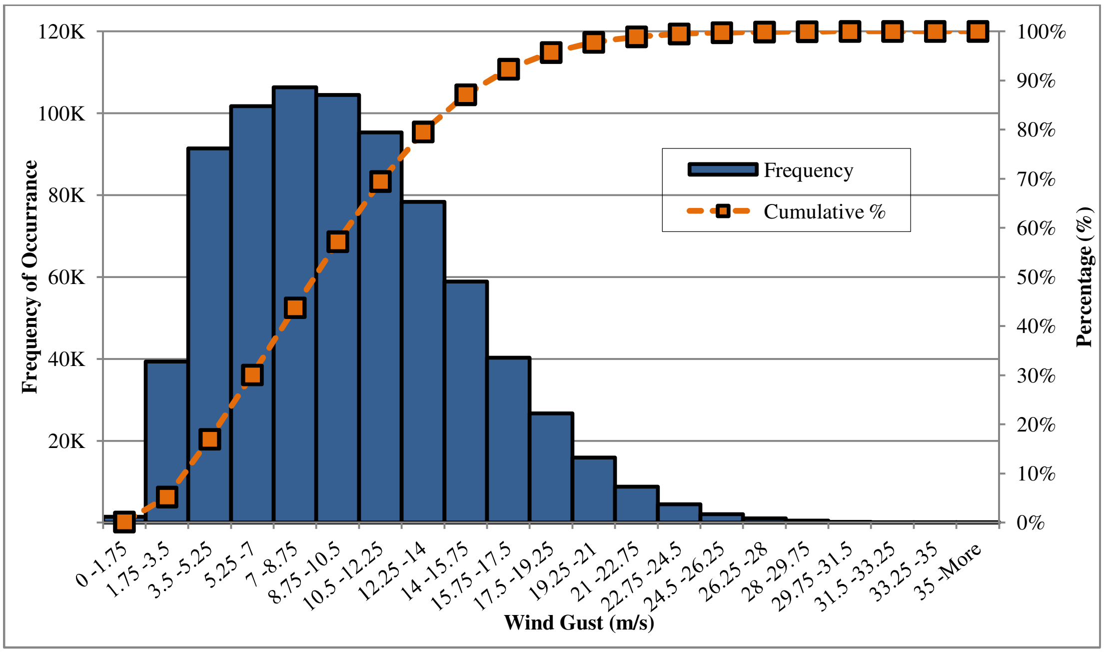


Figure 10-17 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Gust Occurrences, South Scotland

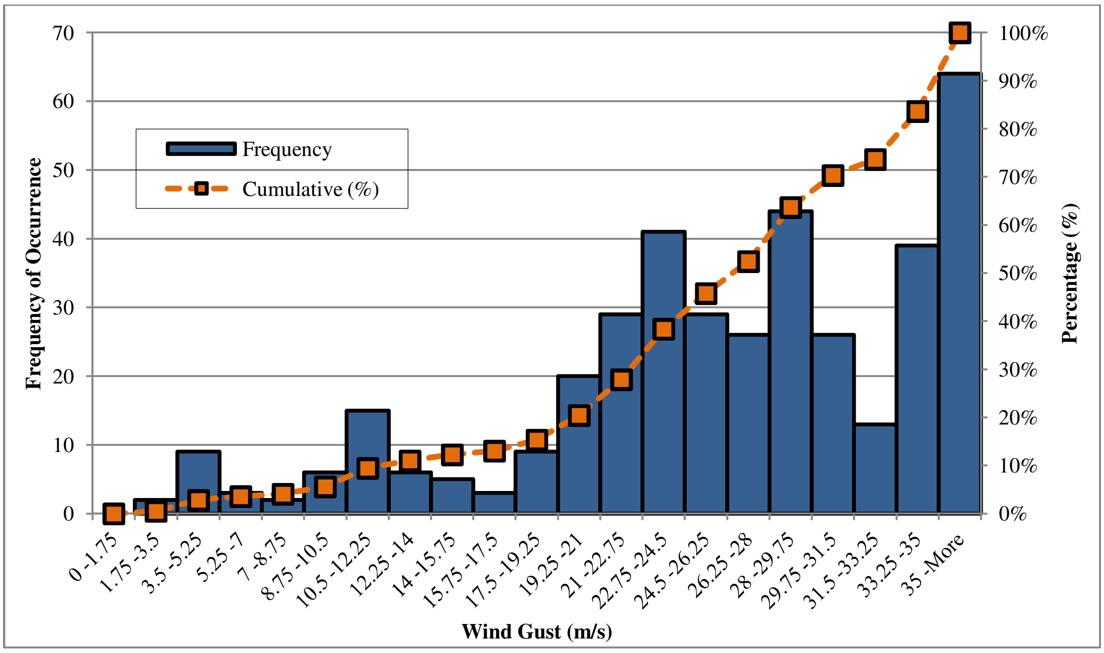


Figure 10-18 – Wind Gust Frequency Distribution and Cumulative Frequency Distribution for Wind-Related Outages, South Scotland

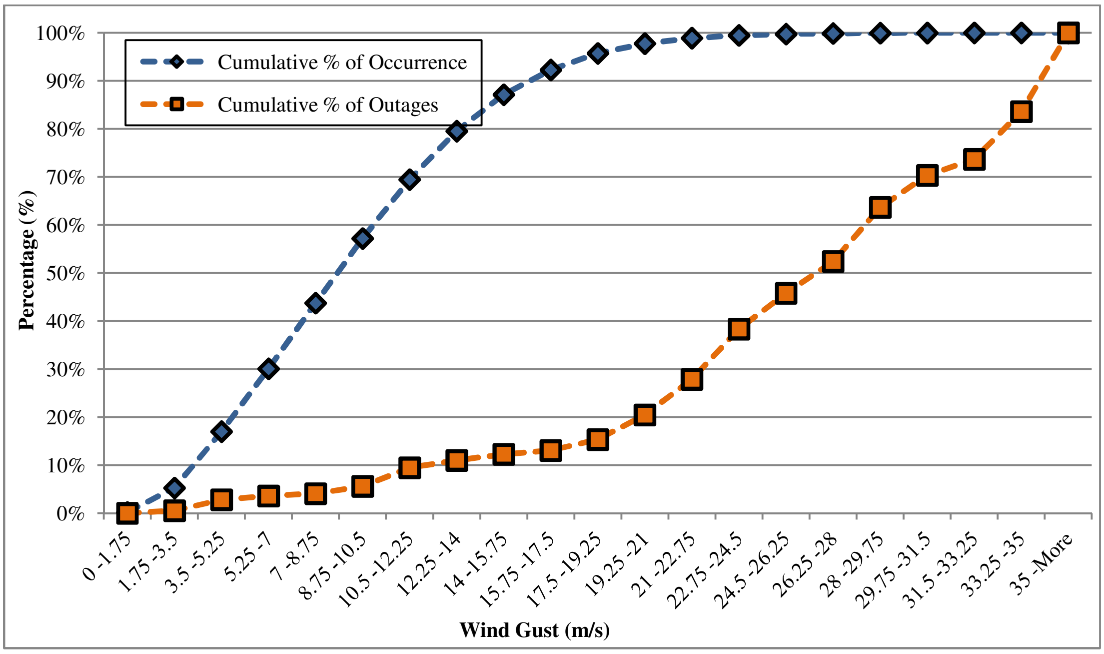


Figure 10-19 - Cumulative Distribution Function for Wind Faults and 10m Wind Gust Occurrences, South Scotland

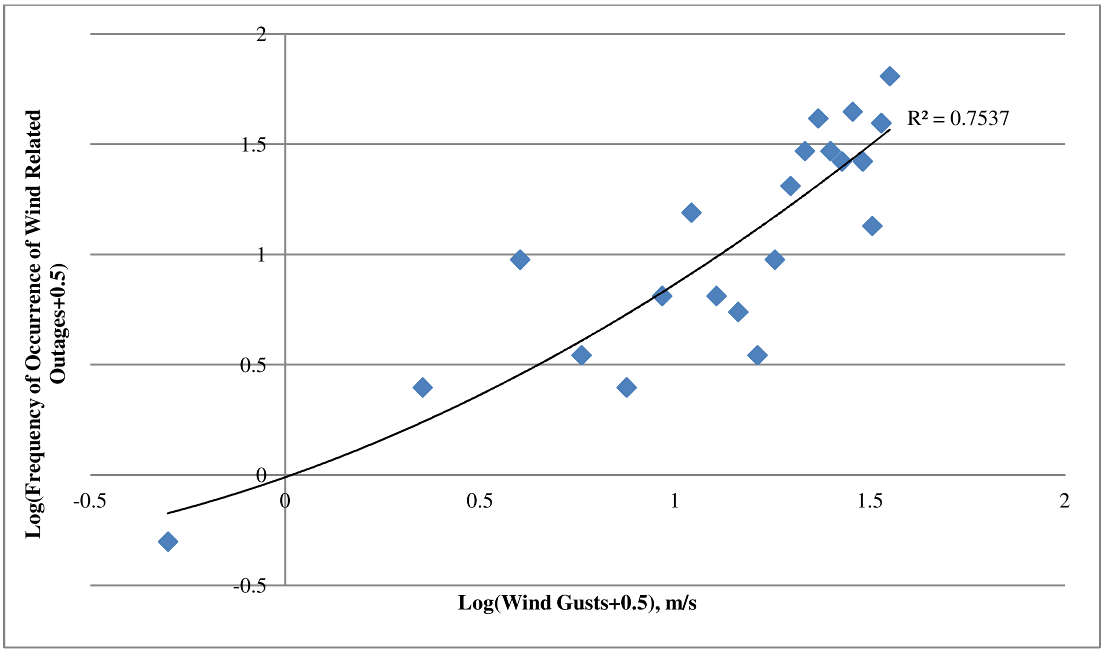


Figure 10-20 - Relationship between Wind-Related Outages and 10meter Wind Gusts, South Scotland

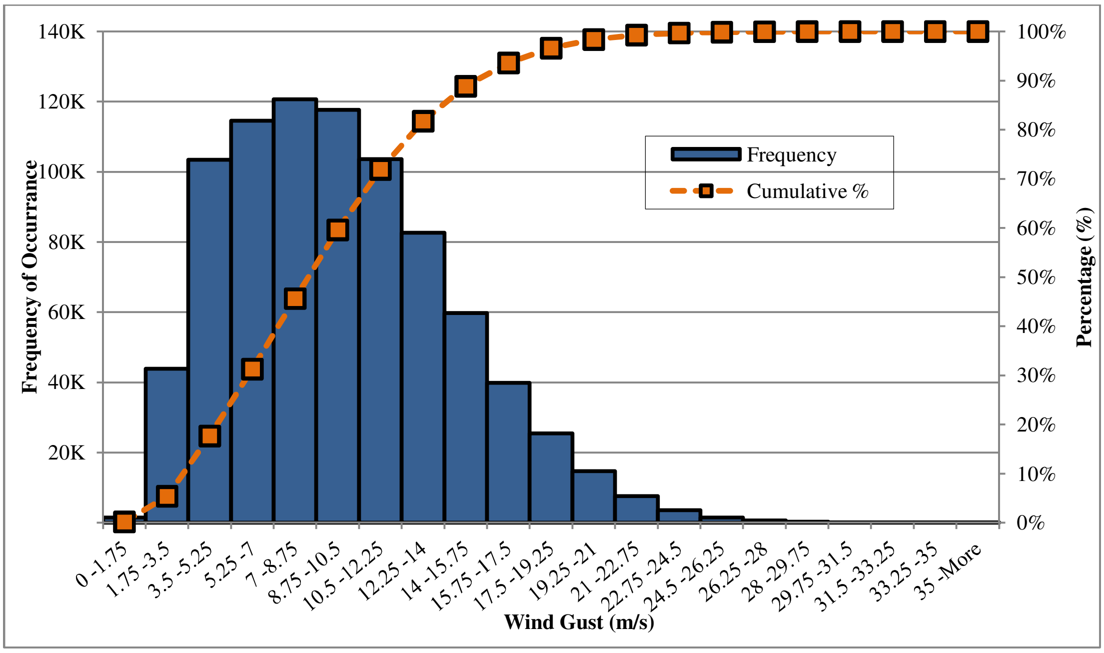


Figure 10-21 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Gust Occurrences, North England and North Wales

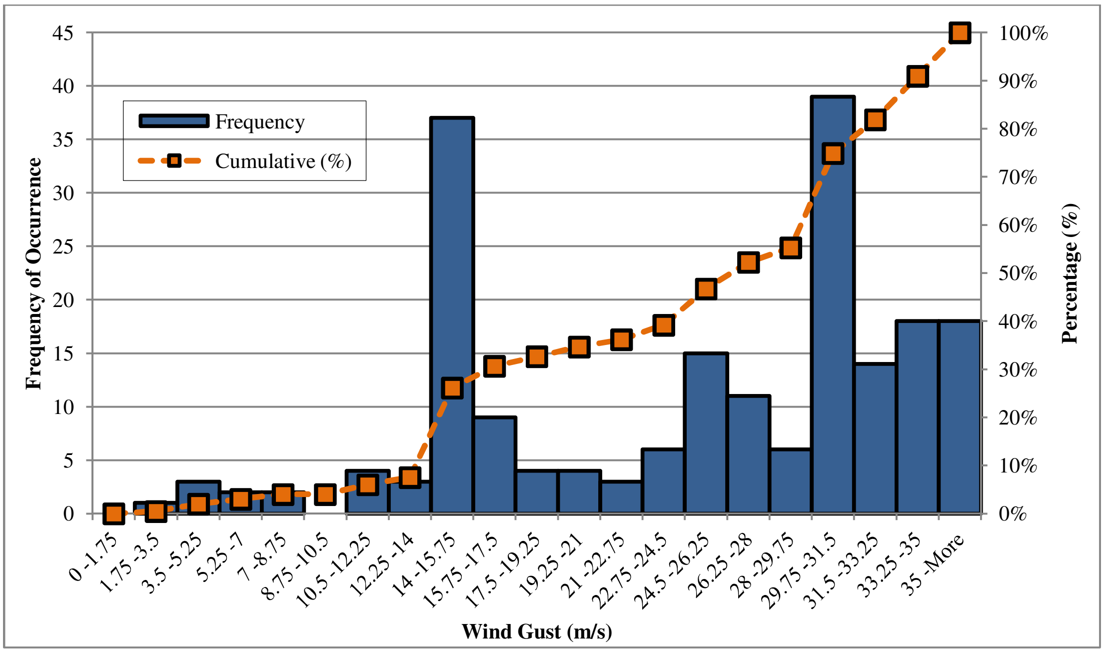


Figure 10-22 – Wind Gust Frequency Distribution and Cumulative Frequency Distribution for Wind-Related Outages, North England and North Wales

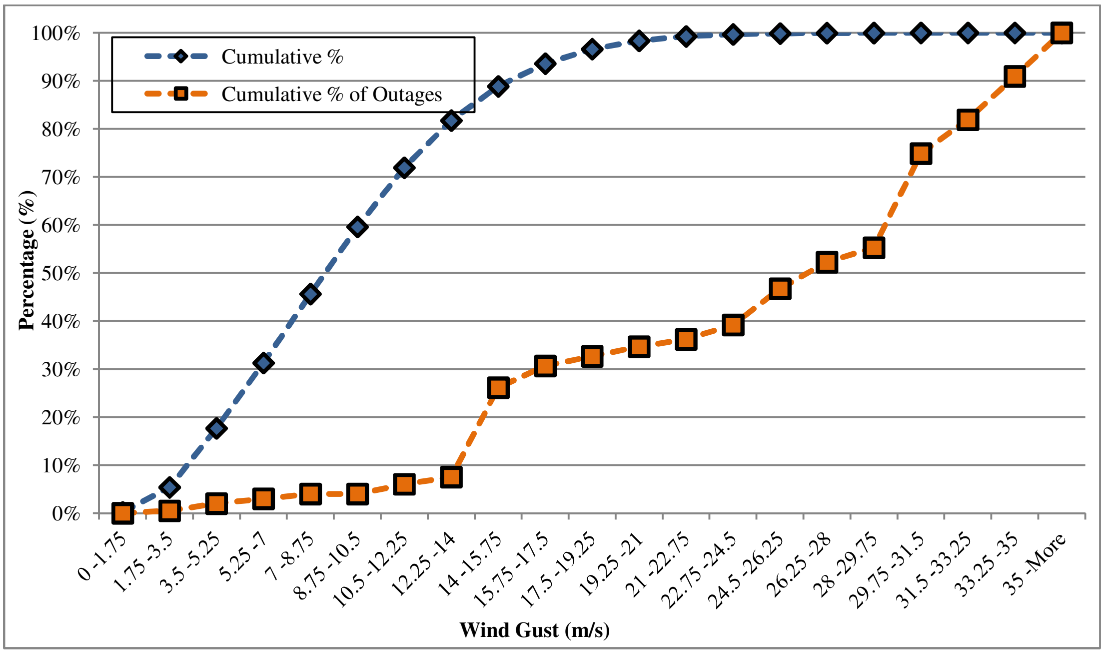


Figure 10-23 - Cumulative Distribution Function for Wind Faults and 10m Wind Gust Occurrences, North England and North Wales

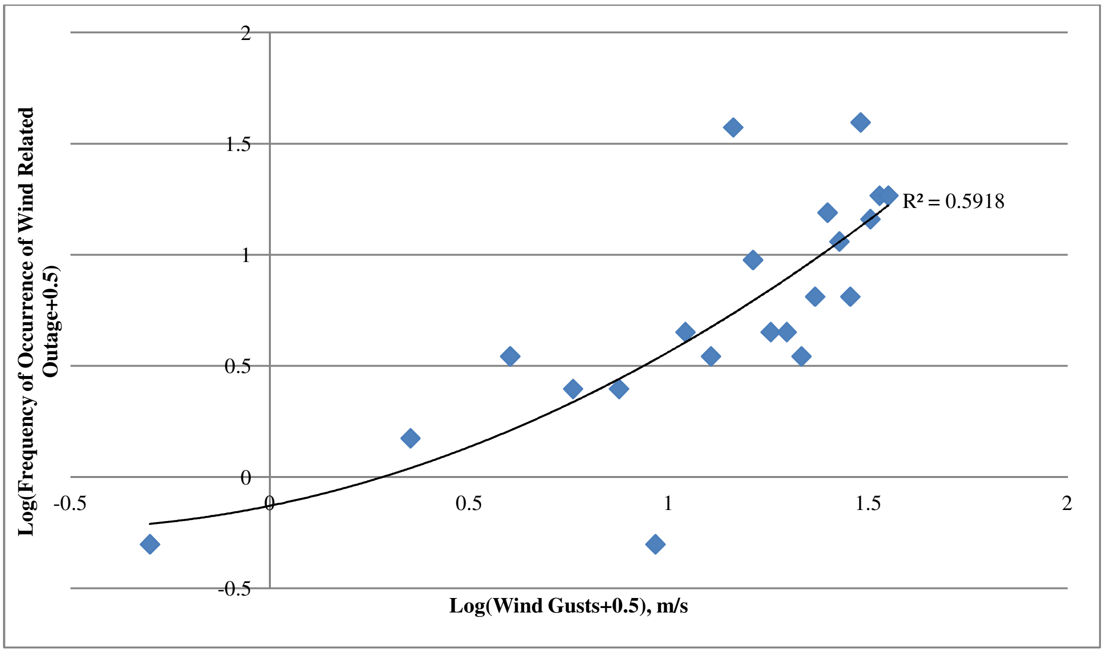


Figure 10-24 - Relationship between Wind-Related Outages and 10meter Wind Gusts, North England and North Wales

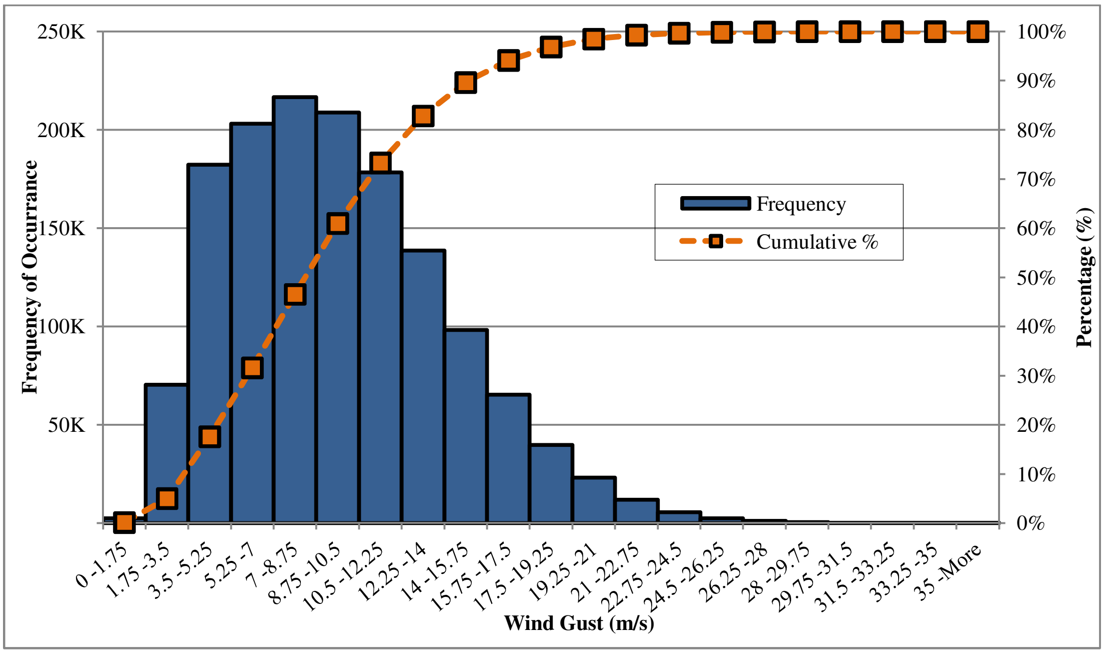


Figure 10-25 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Gust Occurrences, South England and South Wales

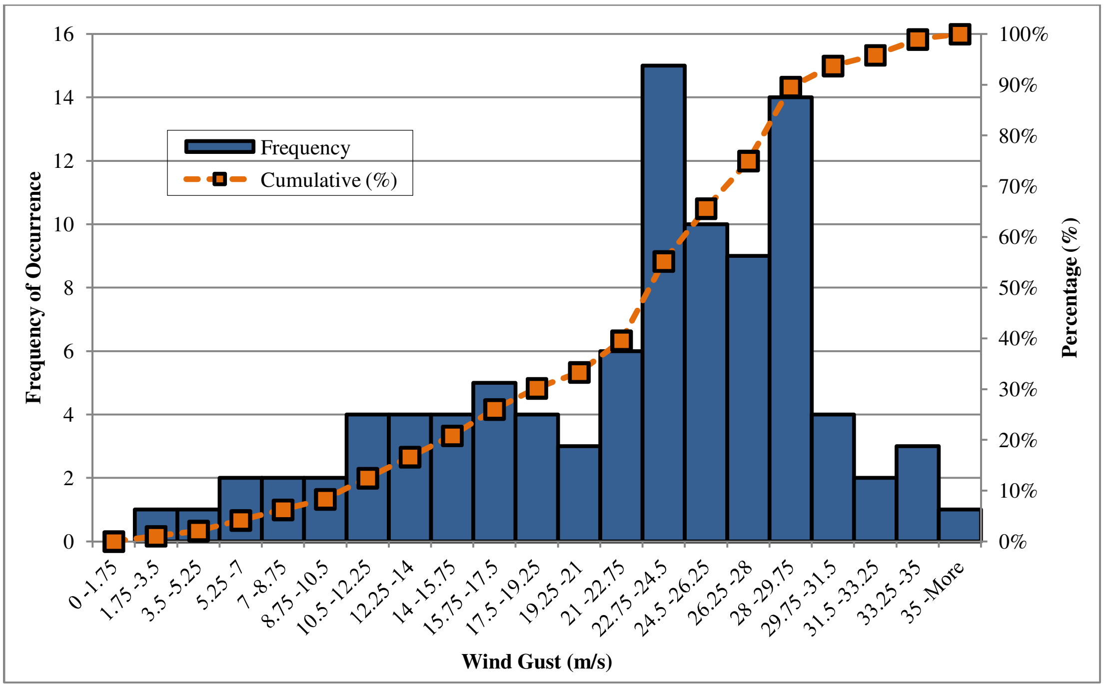


Figure 10-26– Wind Gust Frequency Distribution and Cumulative Frequency Distribution for Wind-Related Outages, South England and South Wales

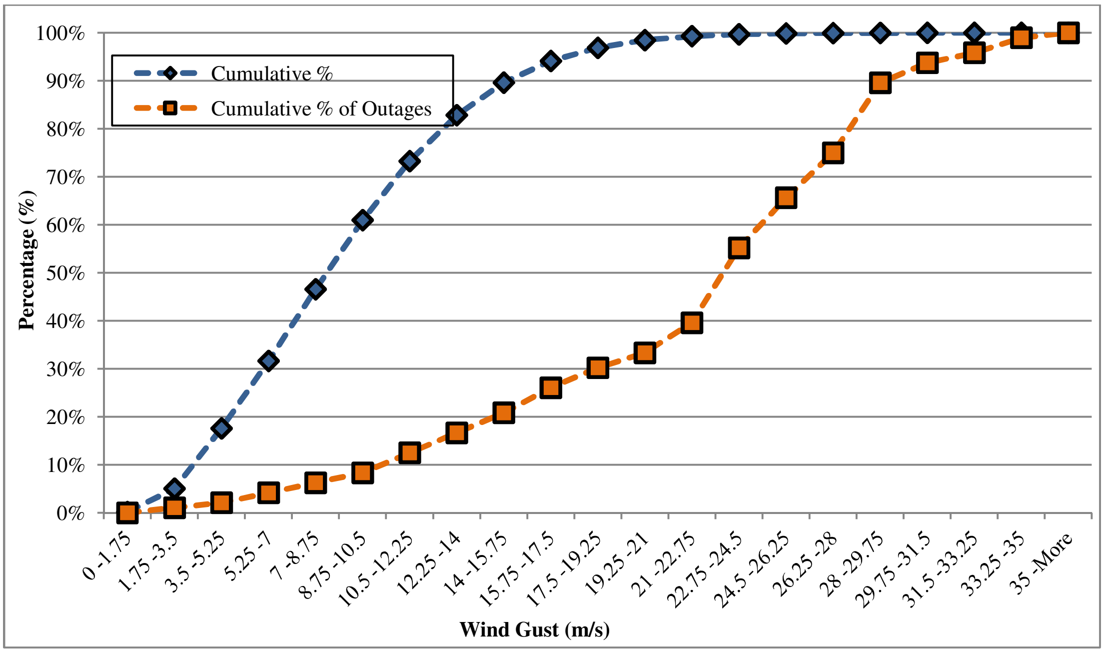


Figure 10-27 - Cumulative Distribution Function for Wind Faults and 10m Wind Gust Occurrences, South England and South Wales

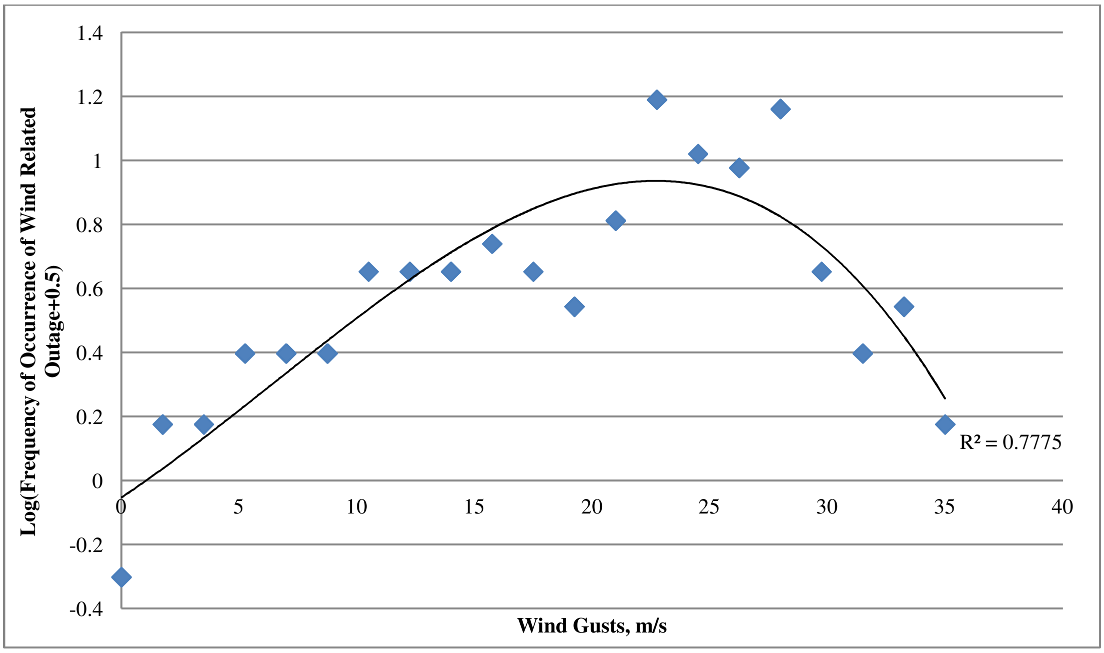


Figure 10-28- Relationship between Wind-Related Outages and 10meter Wind Gusts, South England and South Wales

D-2 Wind Speeds

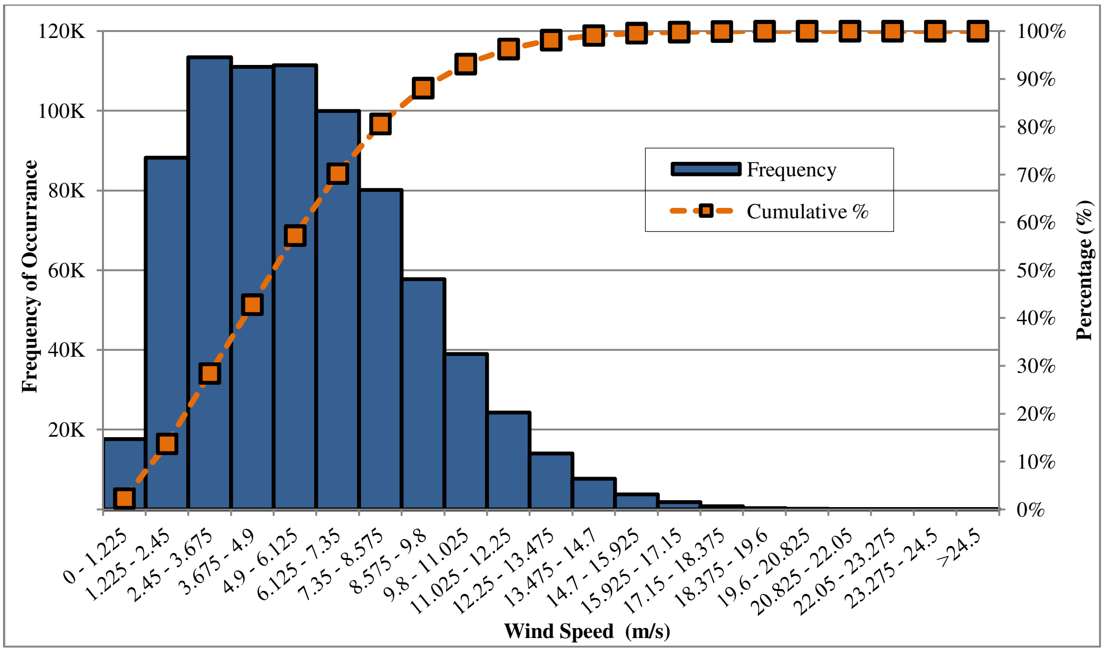


Figure 10-29 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Speed Occurrences, South Scotland

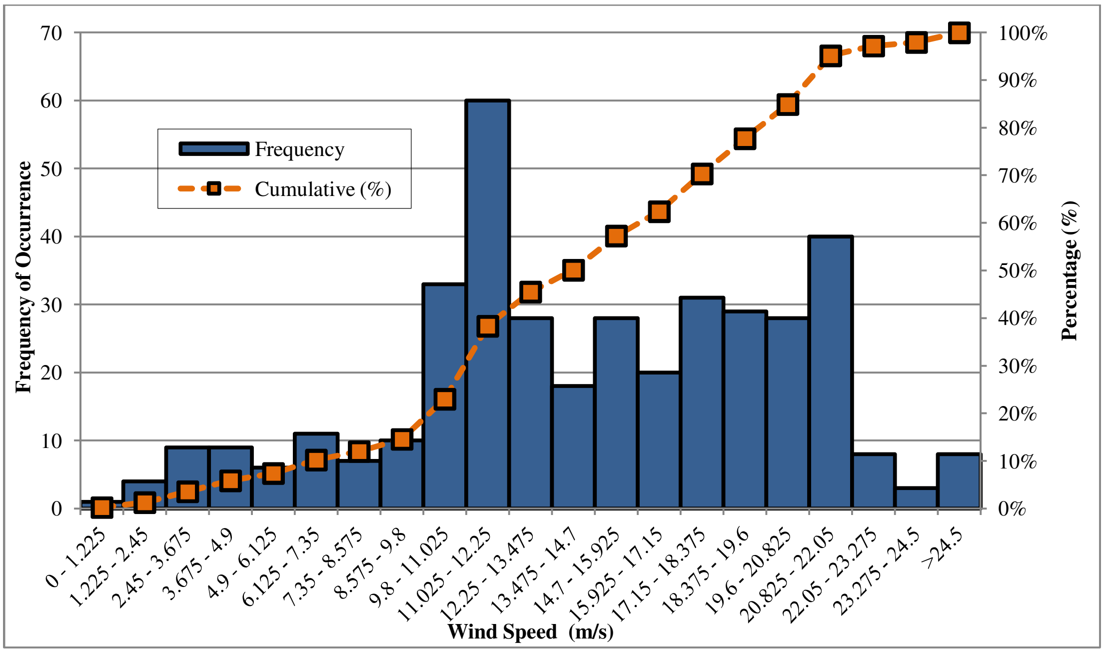


Figure 10-30 – Wind Speed Frequency Distribution and Cumulative Frequency Distribution for Wind-Related Outages, South Scotland

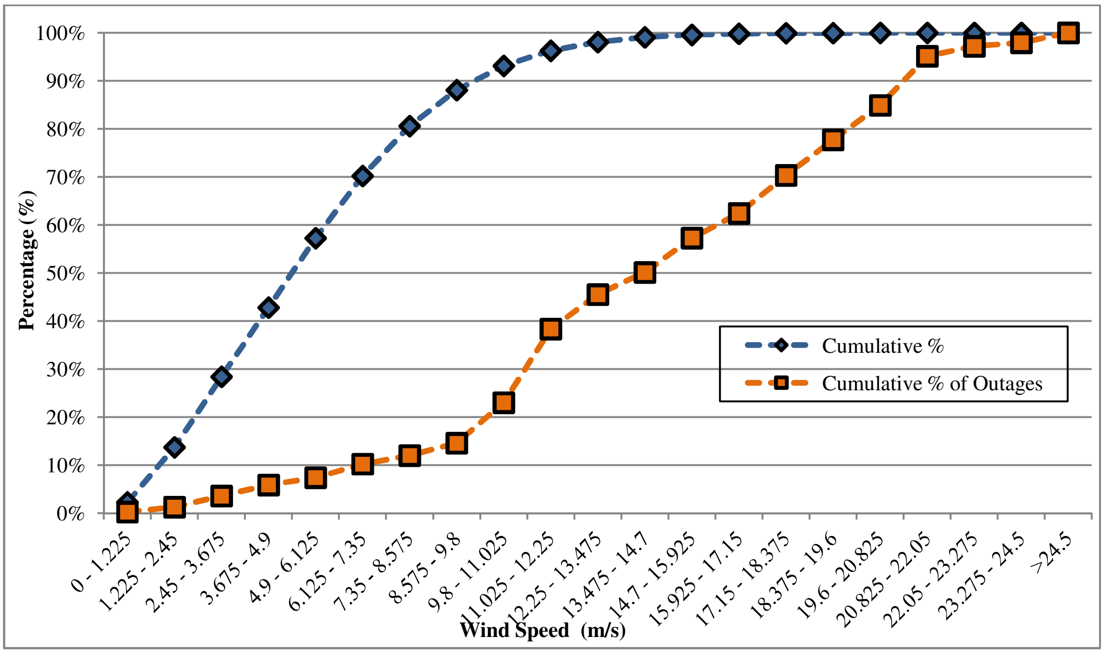


Figure 10-31 - Cumulative Distribution Function for Wind Faults and 10m Wind Speed Occurrences, South Scotland

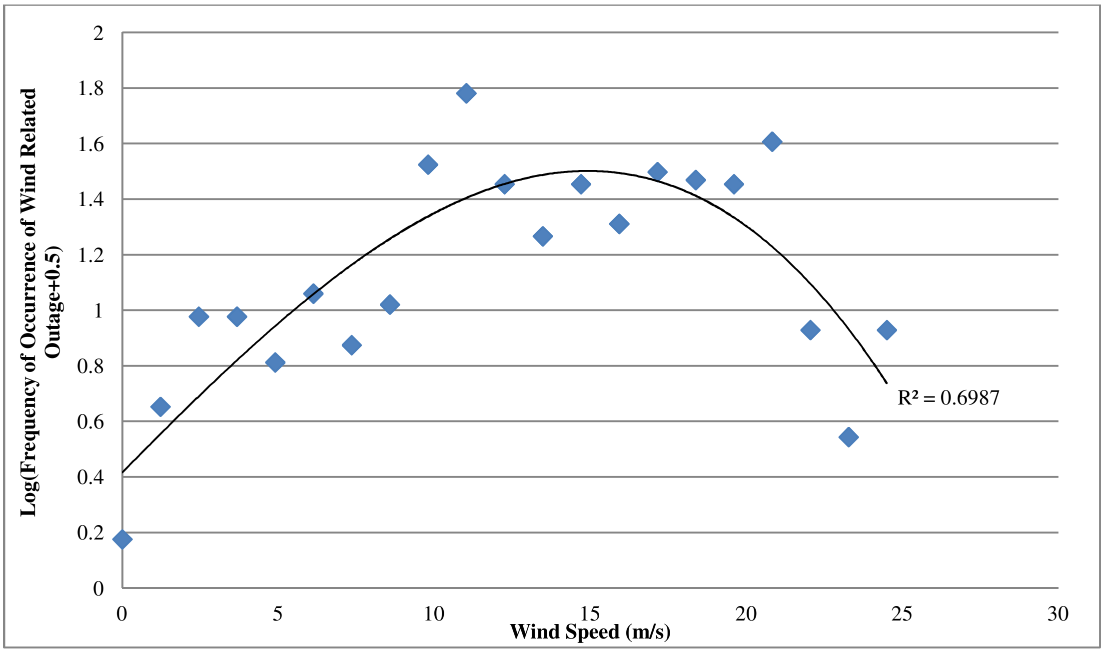


Figure 10-32 - Relationship between Wind-Related Outages and 10meter Wind Speeds, South Scotland

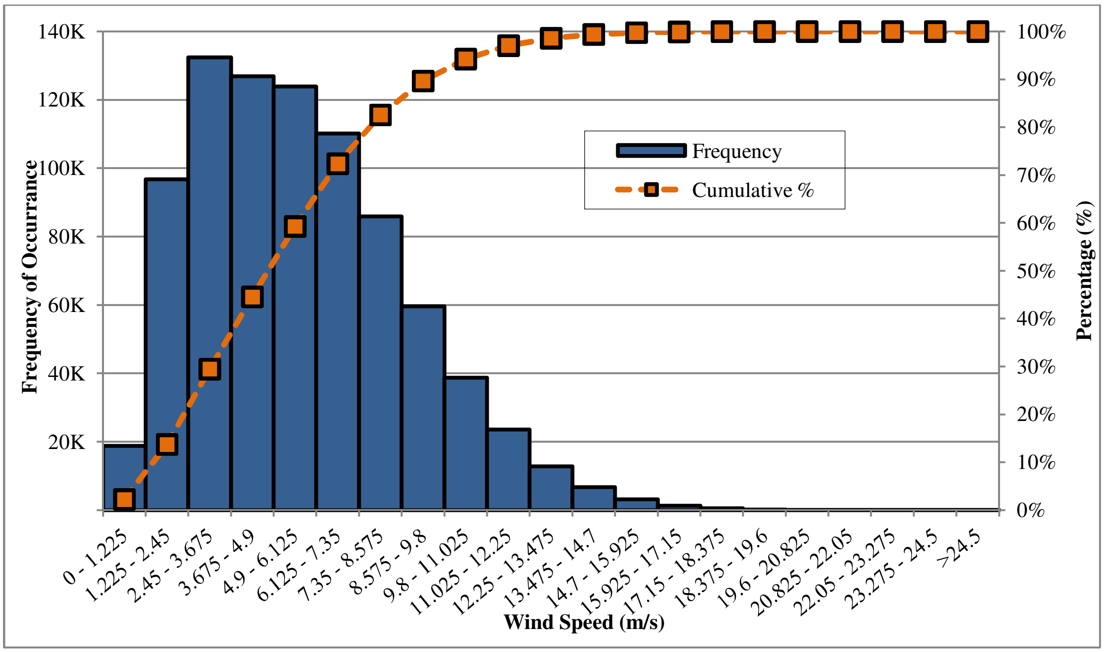


Figure 10-33 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Speed Occurrences, North England and North Wales

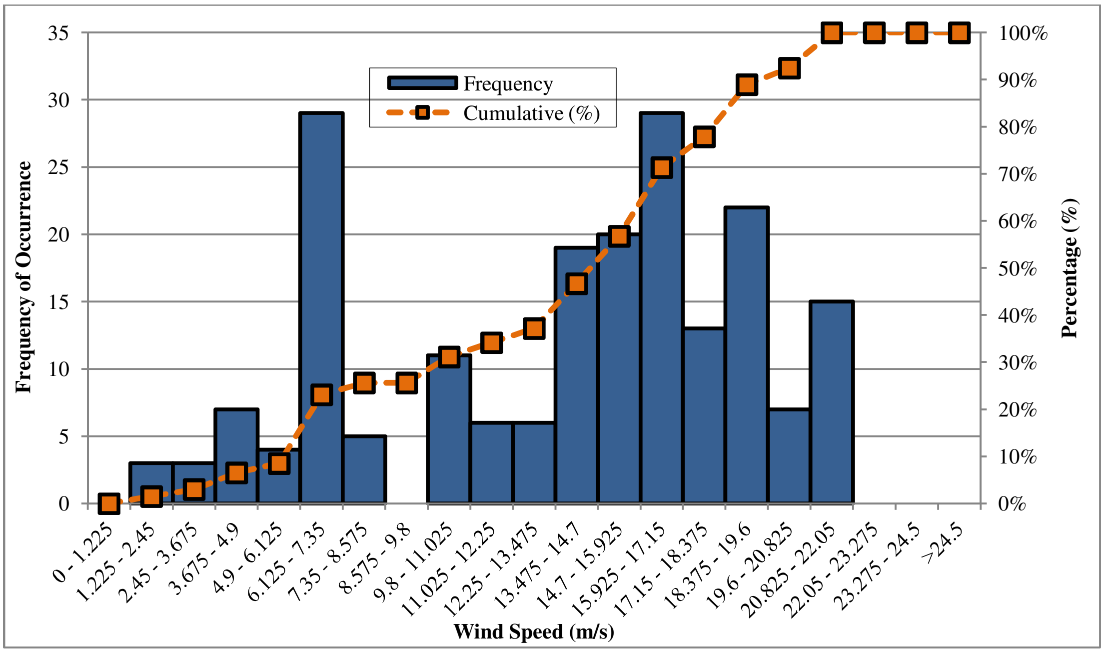


Figure 10-34 – Wind Speed Frequency Distribution and Cumulative Frequency Distribution for Wind-Related Outages, North England and North Wales

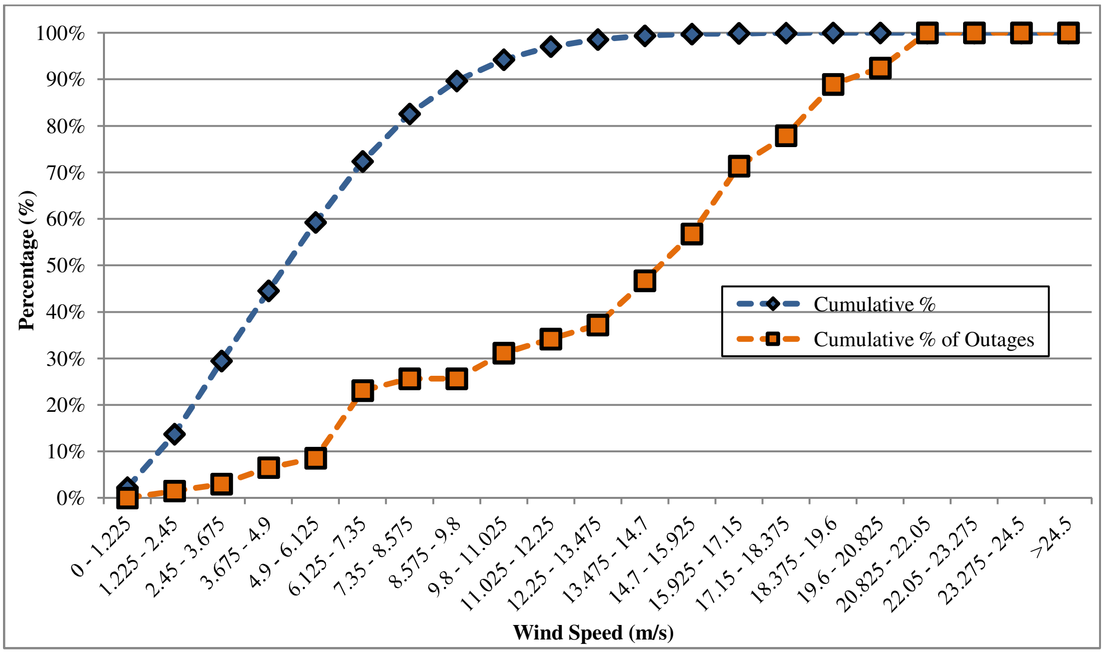


Figure 10-35 - Cumulative Distribution Function for Wind Faults and 10m Wind Speed Occurrences, North England and North Wales

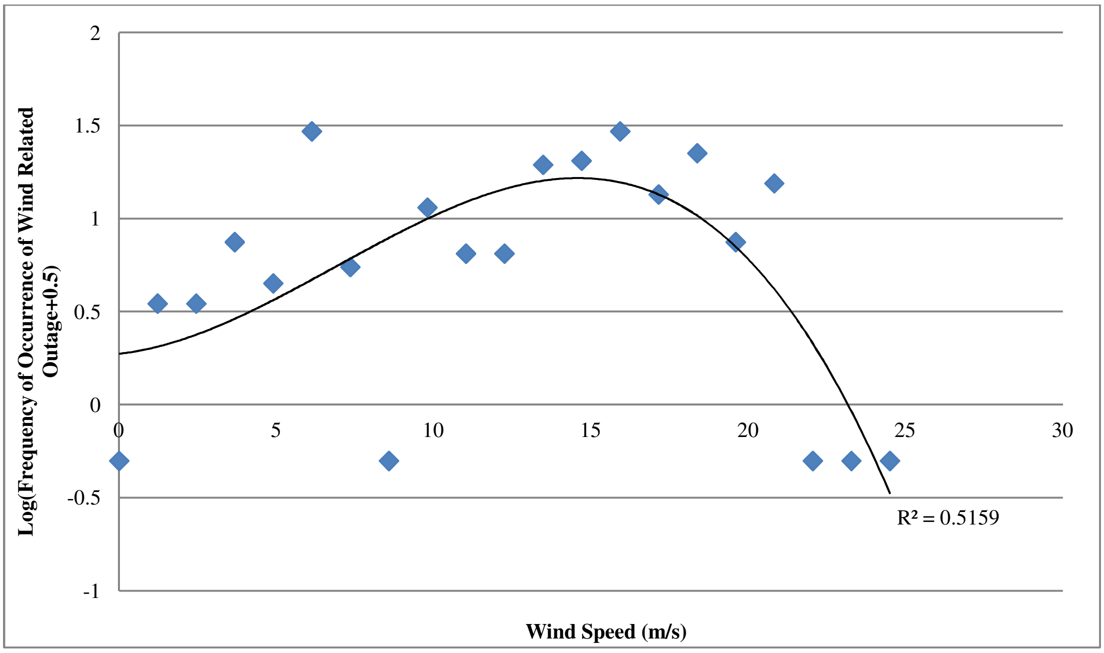


Figure 10-36 - Relationship between Wind-Related Outages and 10meter Wind Speeds, North England and North Wales

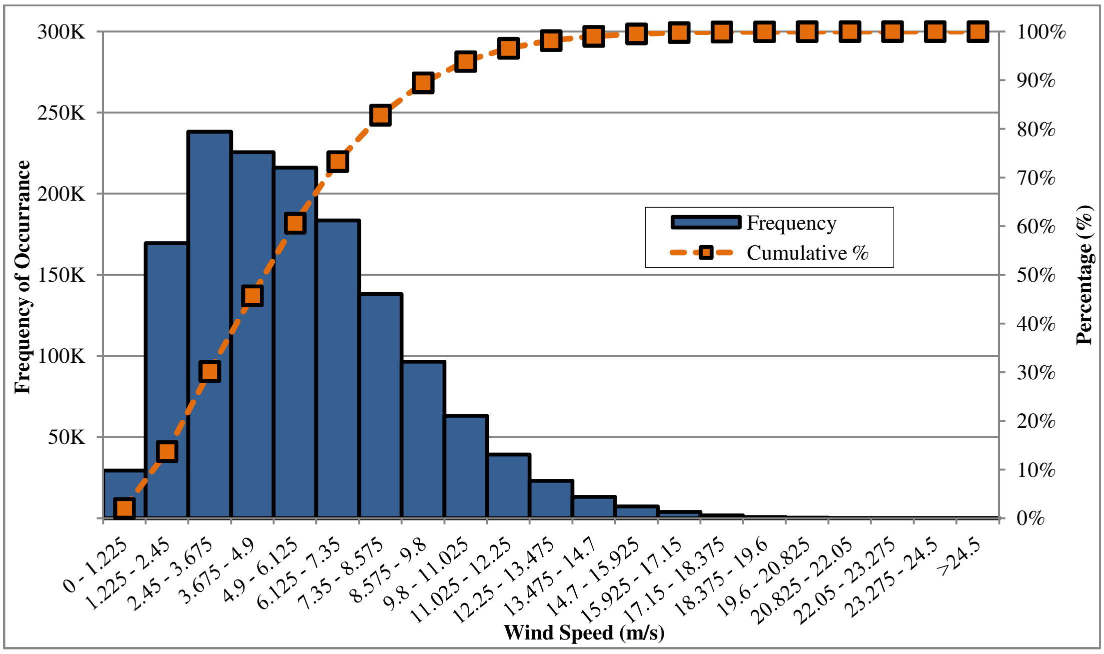


Figure 10-37 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Speed Occurrences, South England and South Wales

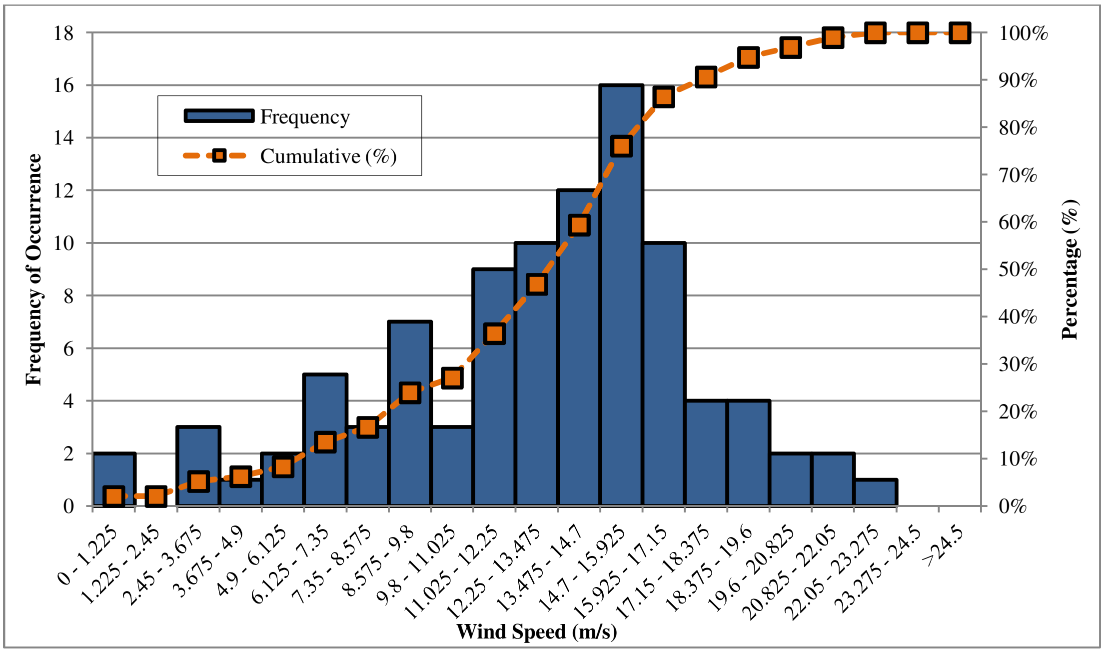


Figure 10-38 – Wind Speed Frequency Distribution and Cumulative Frequency Distribution for Wind-Related Outages, South England and South Wales

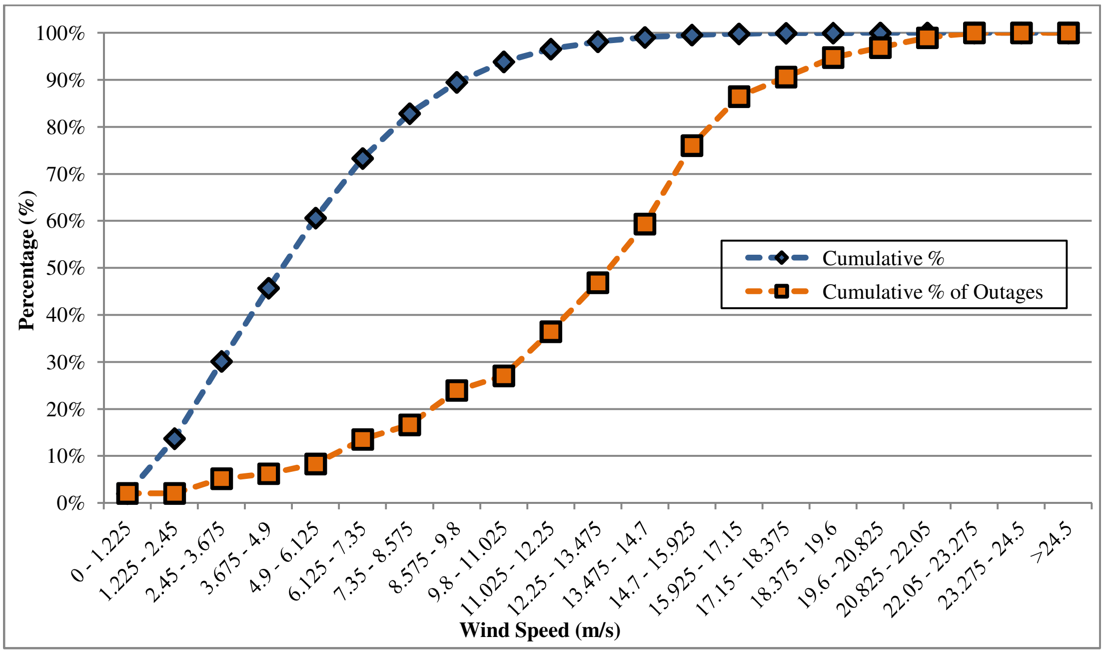


Figure 10-39 - Cumulative Distribution Function for Wind Faults and 10m Wind Speed Occurrences, South England and South Wales

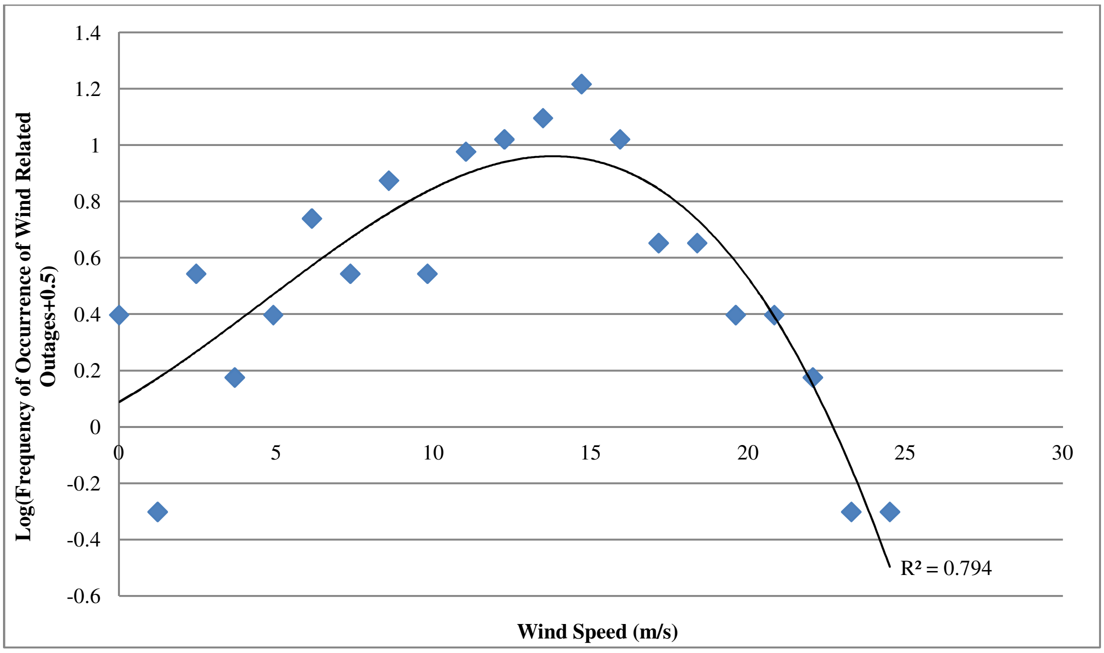


Figure 10-40 - Relationship between Wind-Related Outages and 10meter Wind Speeds, South England and South Wales

D-3 Snowfall

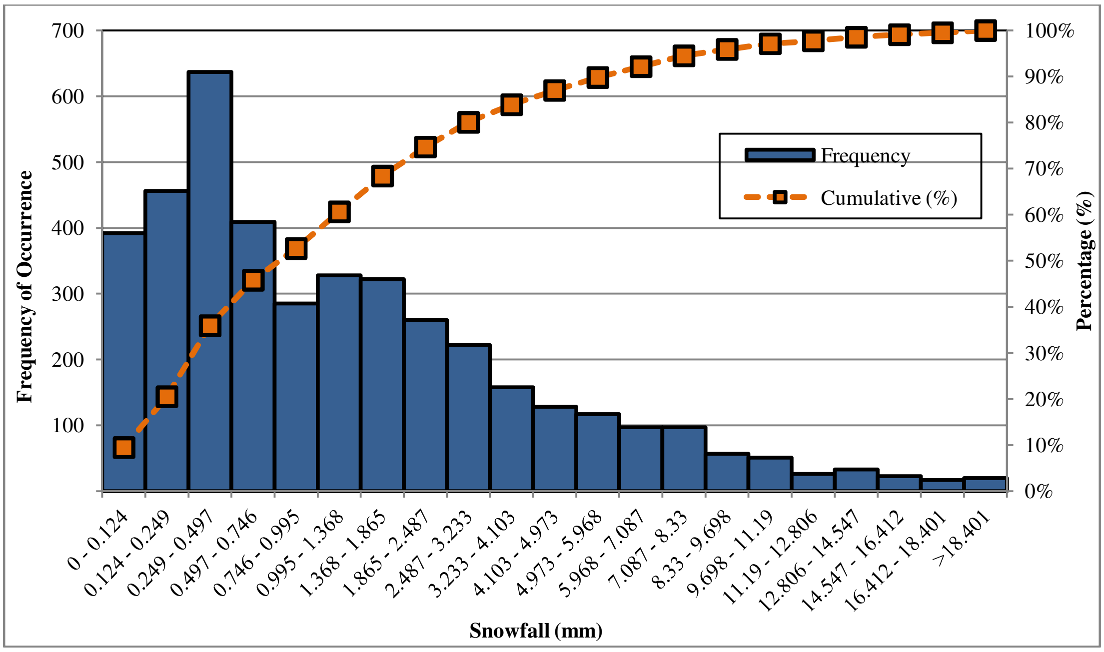


Figure 10-41 - Frequency Distribution and Cumulative Frequency Distribution for Snowfall Occurrences, South Scotland

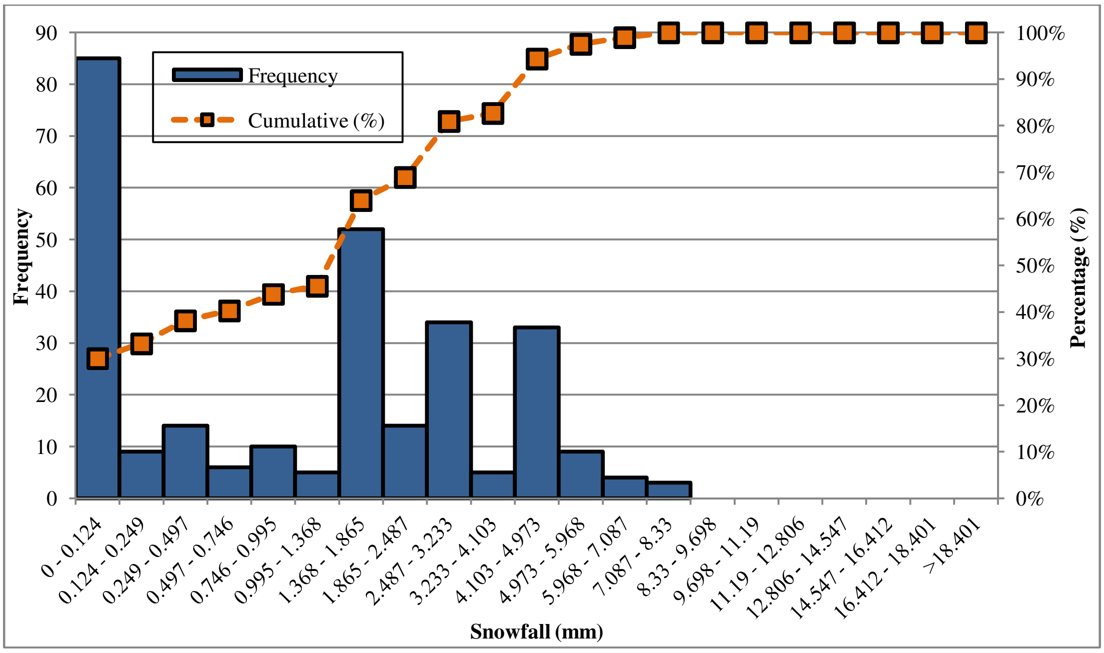


Figure 10-42 – Snowfall Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, South Scotland

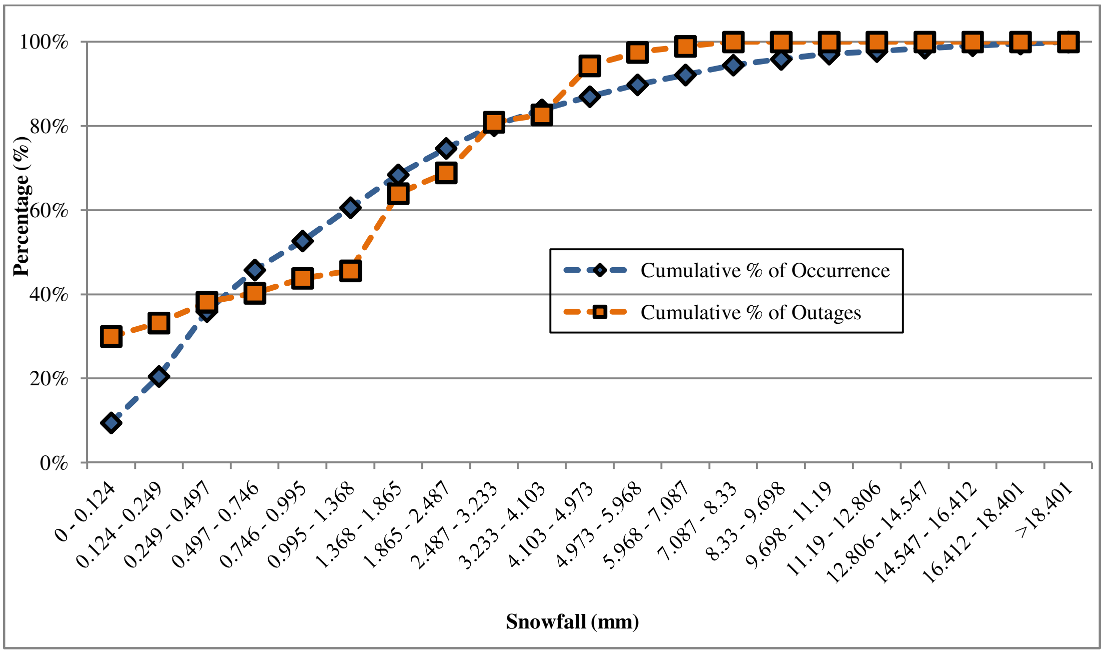


Figure 10-43 - Cumulative Distribution Function for Snow-Related Outages and Snowfall (mm) Occurrences, South Scotland

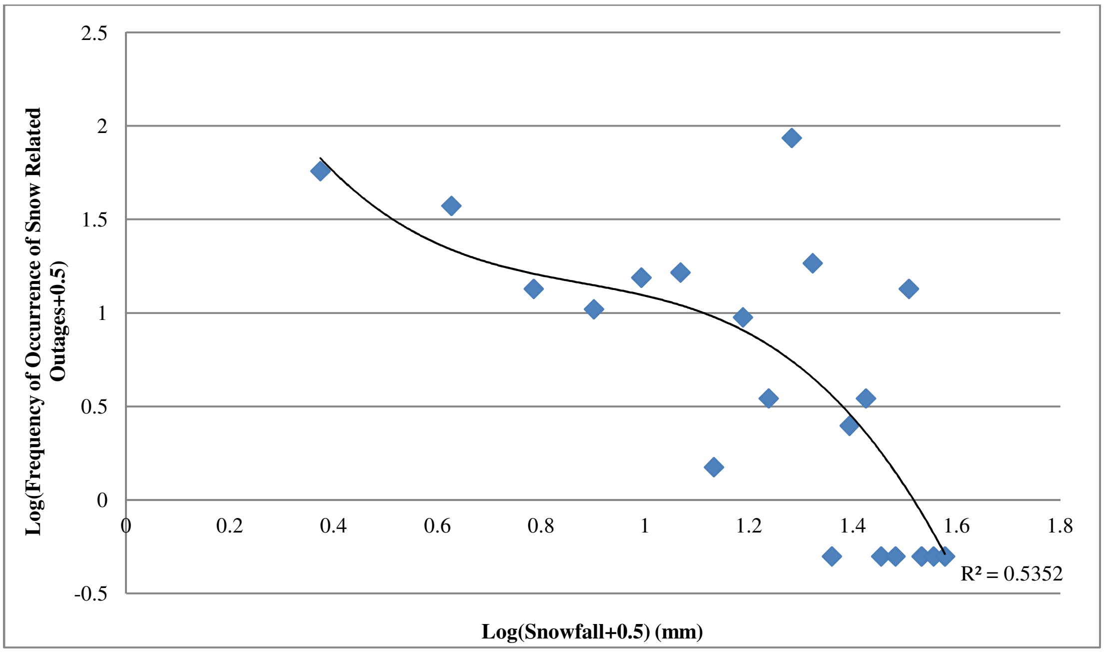


Figure 10-44 - Relationship between Snow-Related Outages and Snowfall (mm), South Scotland

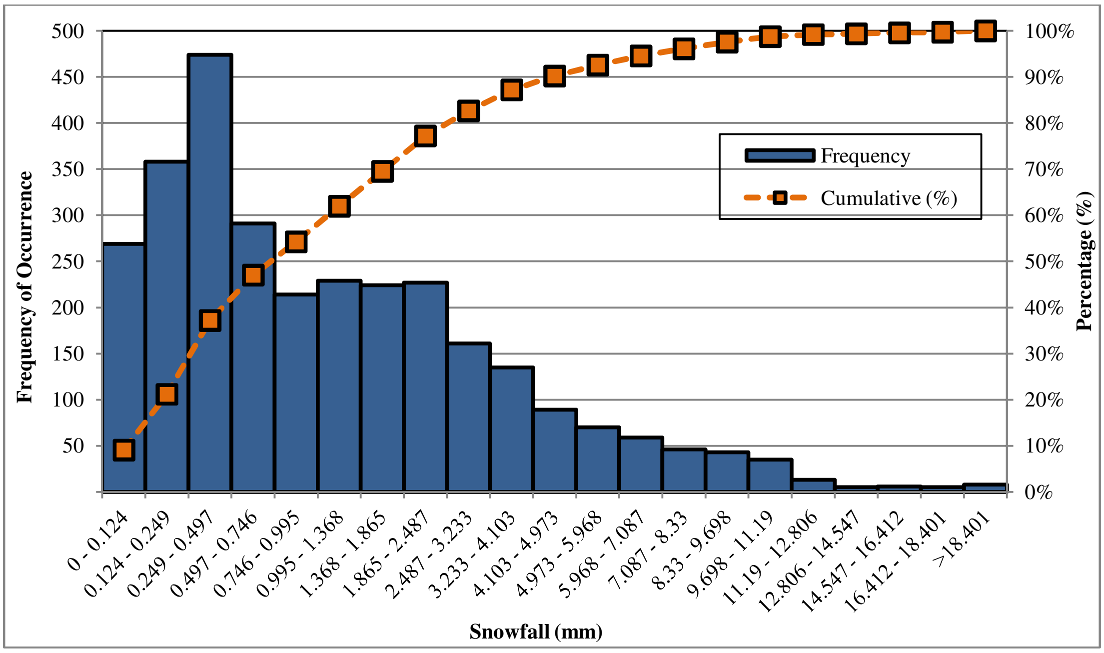


Figure 10-45- Frequency Distribution and Cumulative Frequency Distribution for Snowfall Occurrences, North England and North Wales

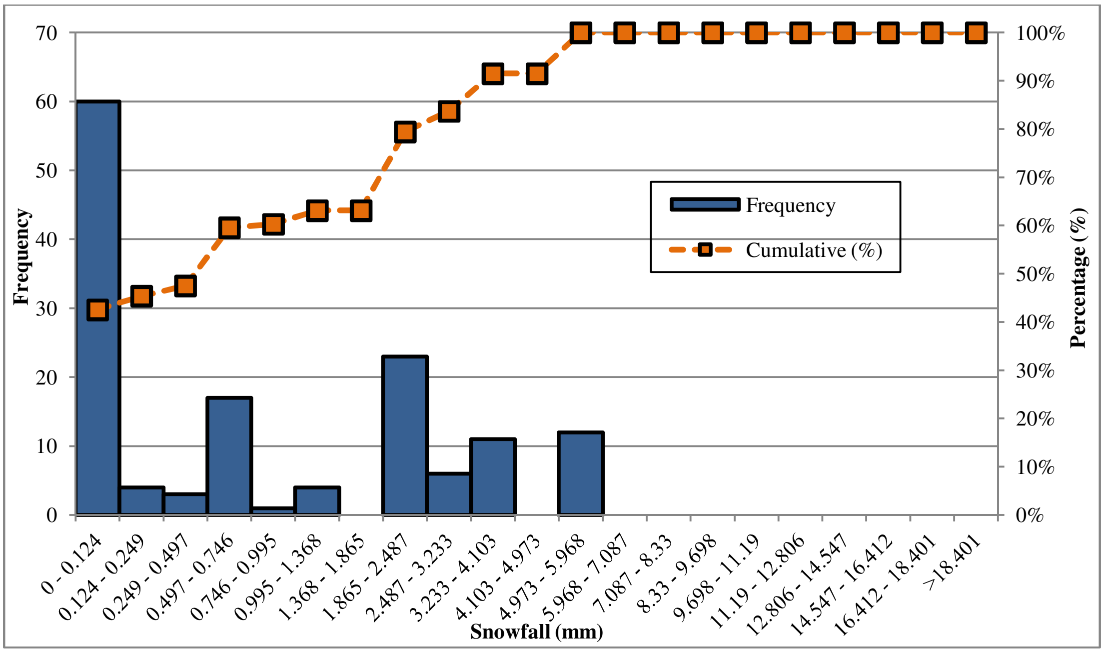


Figure 10-46– Snowfall Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, North England and North Wales

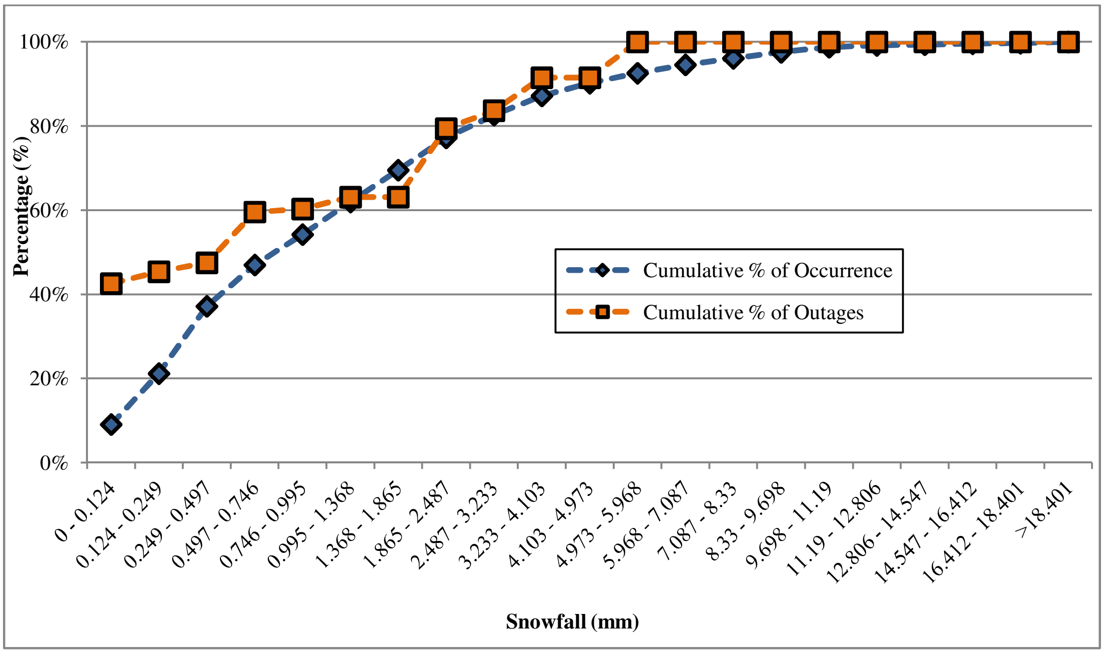


Figure 10-47- Cumulative Distribution Function for Snow-Related Outages and Snowfall (mm) Occurrences, North England and North Wales

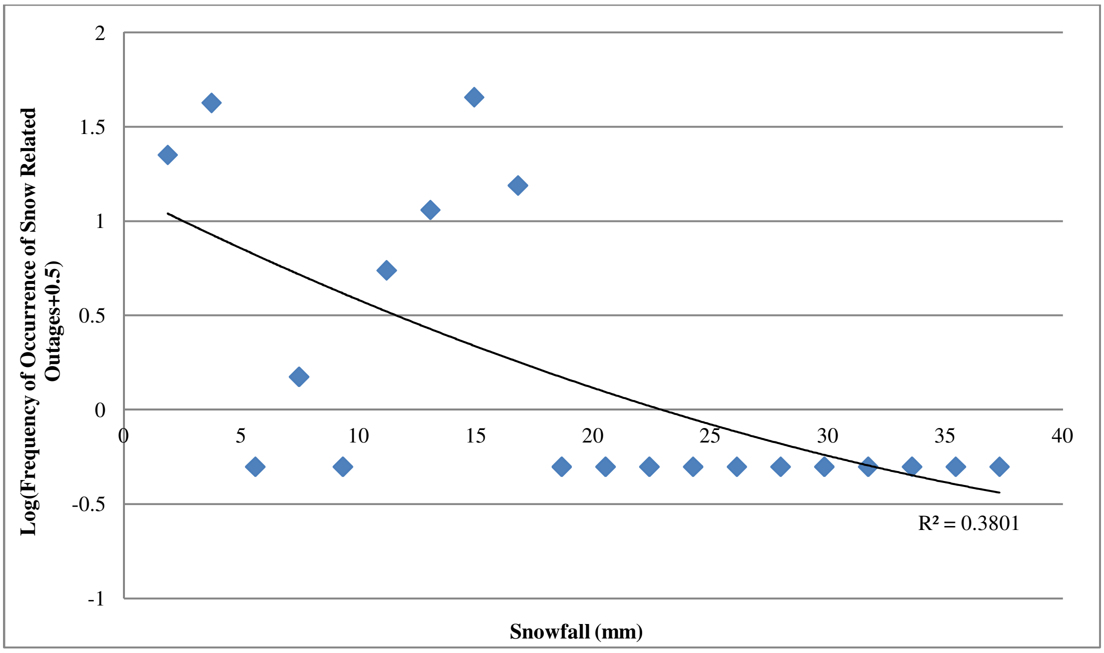


Figure 10-48- Relationship between Snow-Related Outages and Snowfall (mm), North England and North Wales

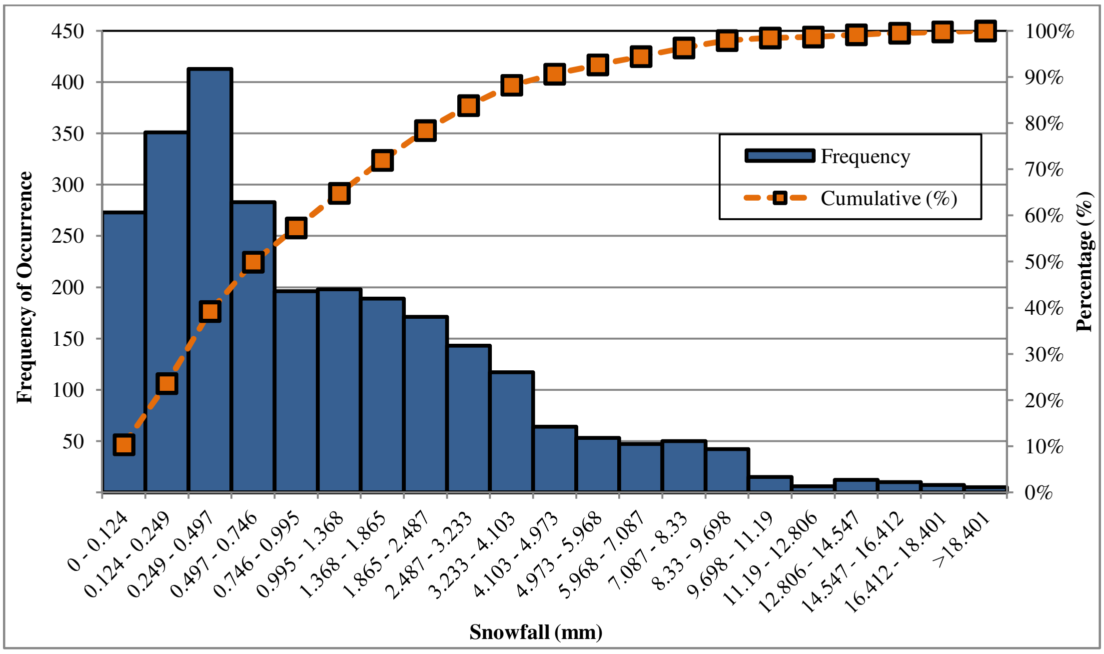


Figure 10-49- Frequency Distribution and Cumulative Frequency Distribution for Snowfall Occurrences, South England and South Wales

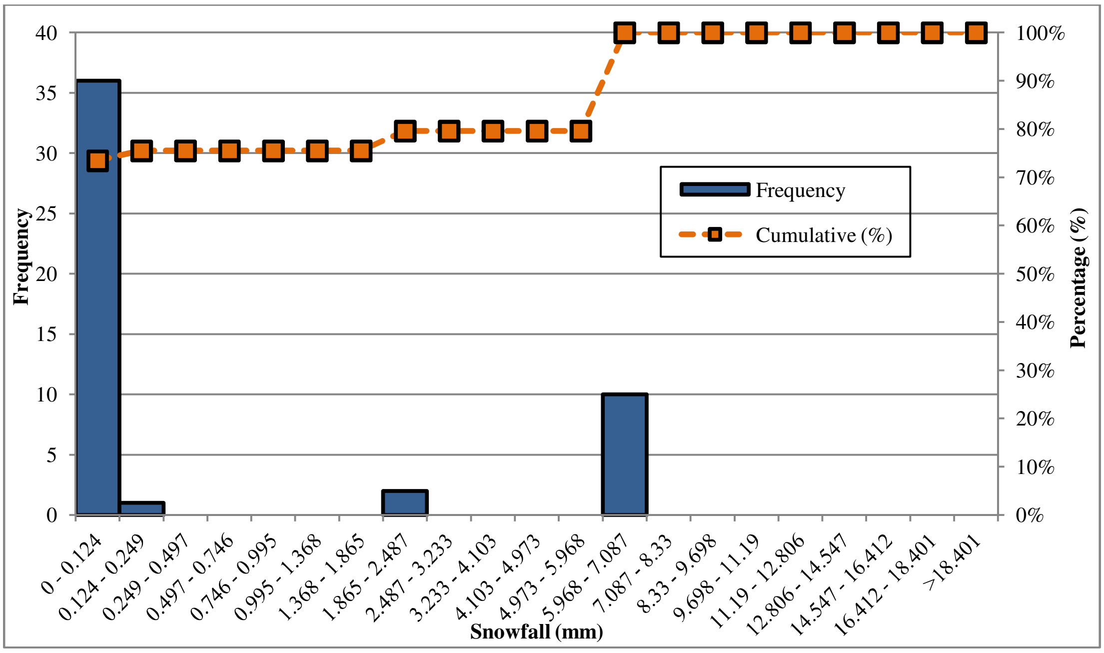


Figure 10-50– Snowfall Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, South England and South Wales

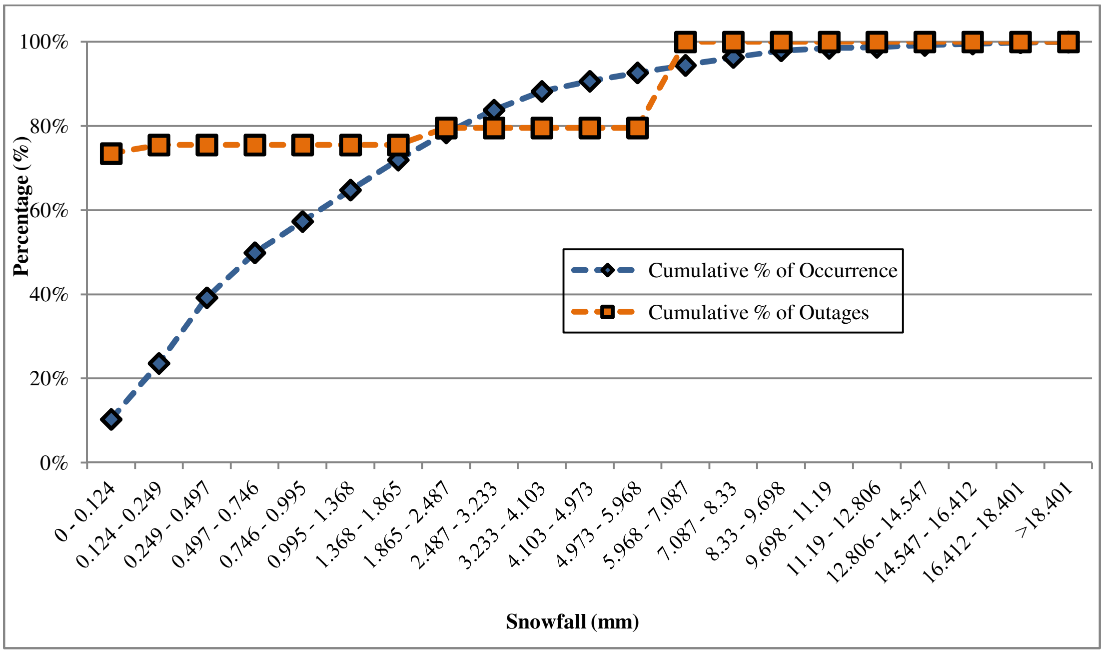


Figure 10-51- Cumulative Distribution Function for Snow-Related Outages and Snowfall (mm) Occurrences, South England and South Wales

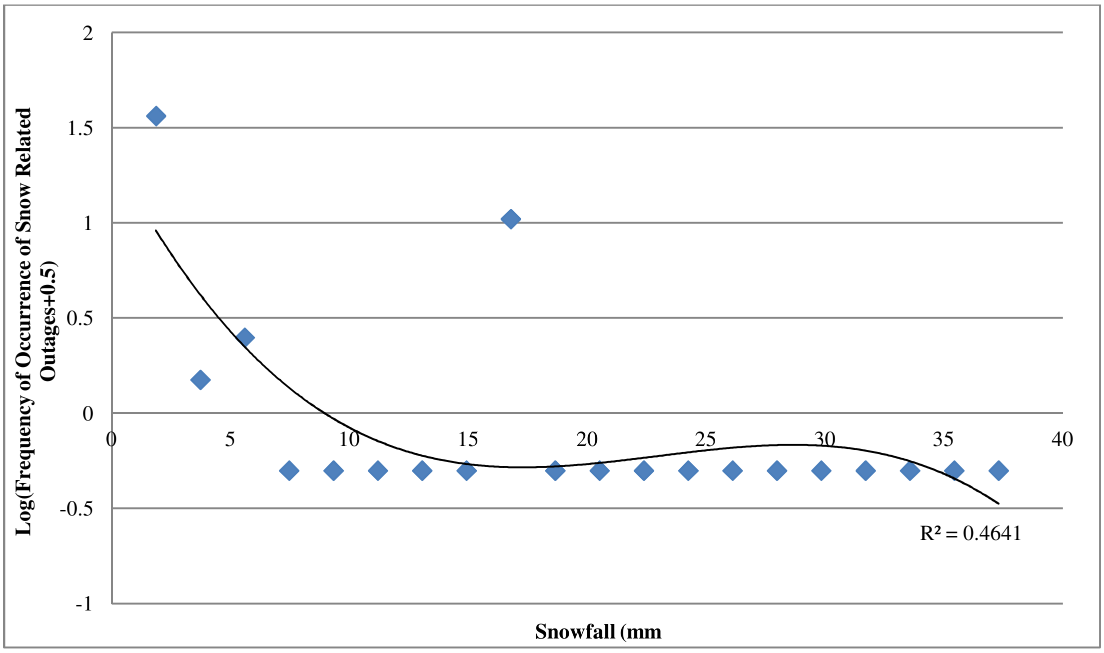


Figure 10-52- Relationship between Snow-Related Outages and Snowfall (mm), South England and South Wales

D-4 Snow Depth

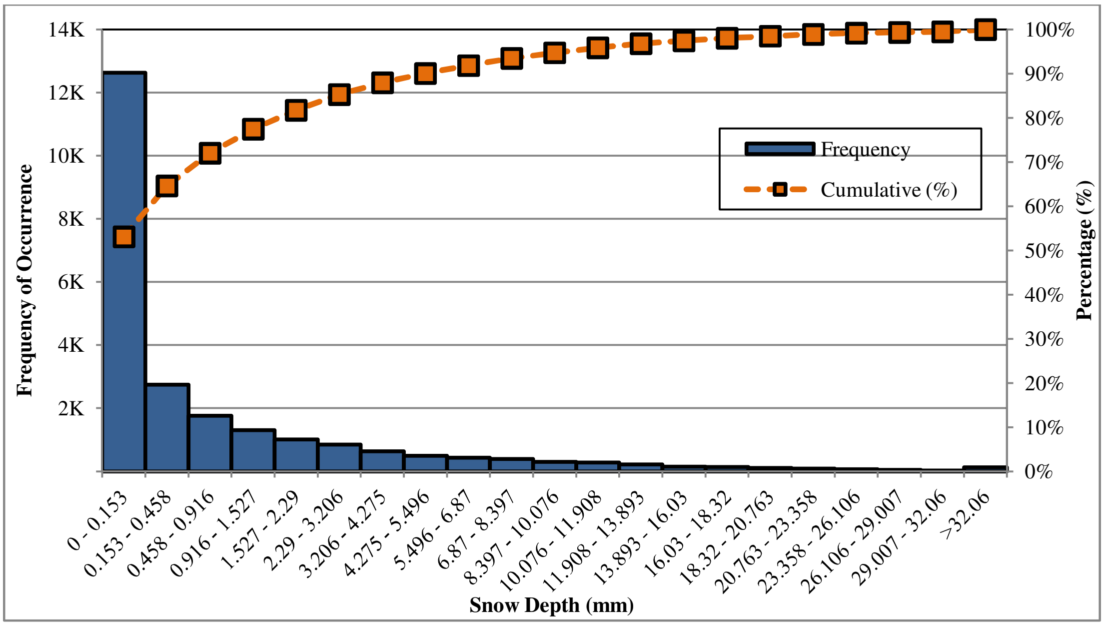


Figure 10-53 - Frequency Distribution and Cumulative Frequency Distribution for Snow Depth Occurrences, South Scotland

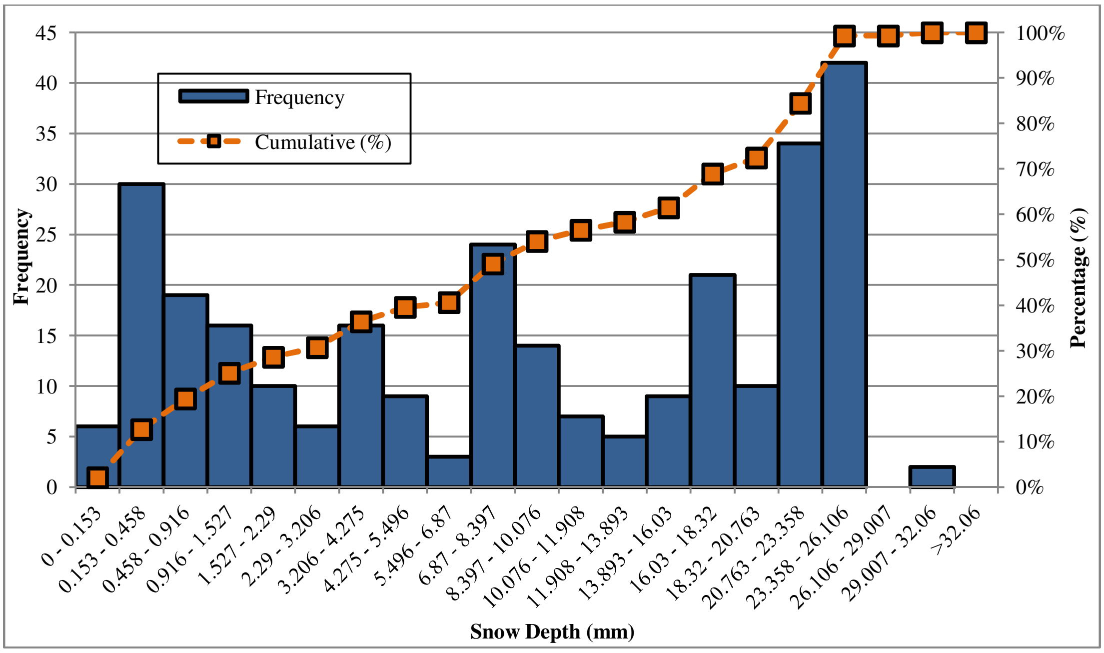


Figure 10-54 – Snow Depth Frequency Distribution and Cumulative Frequency Distribution for Snow Outages, South Scotland

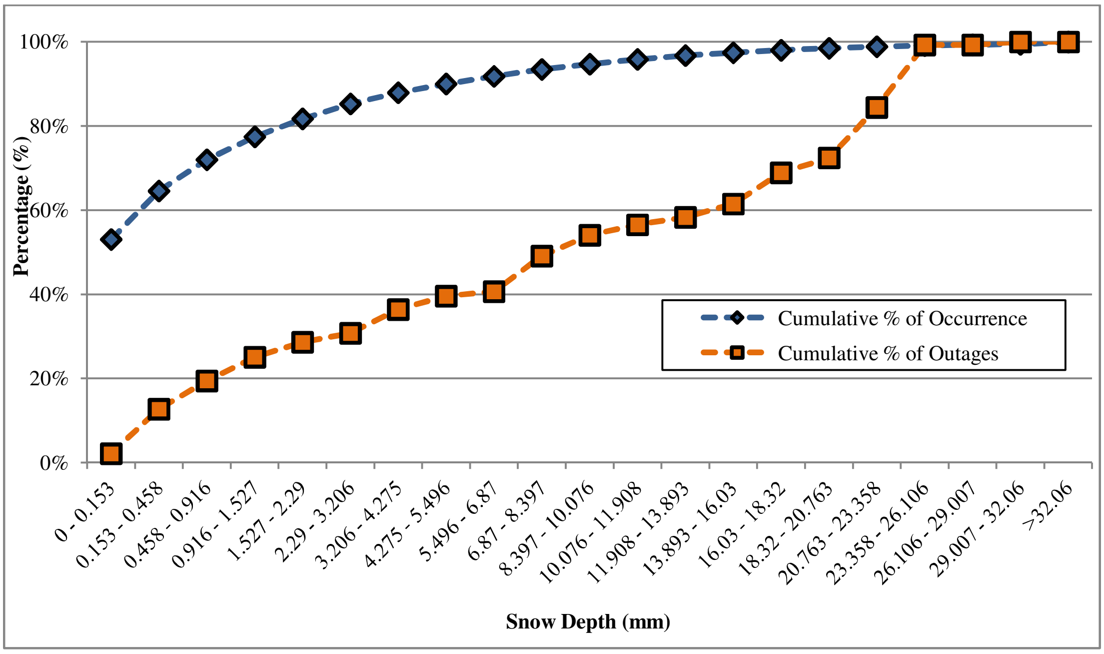


Figure 10-55 - Cumulative Distribution Function for Snow-Related Outages and Snow Depth (mm) Occurrences, South Scotland

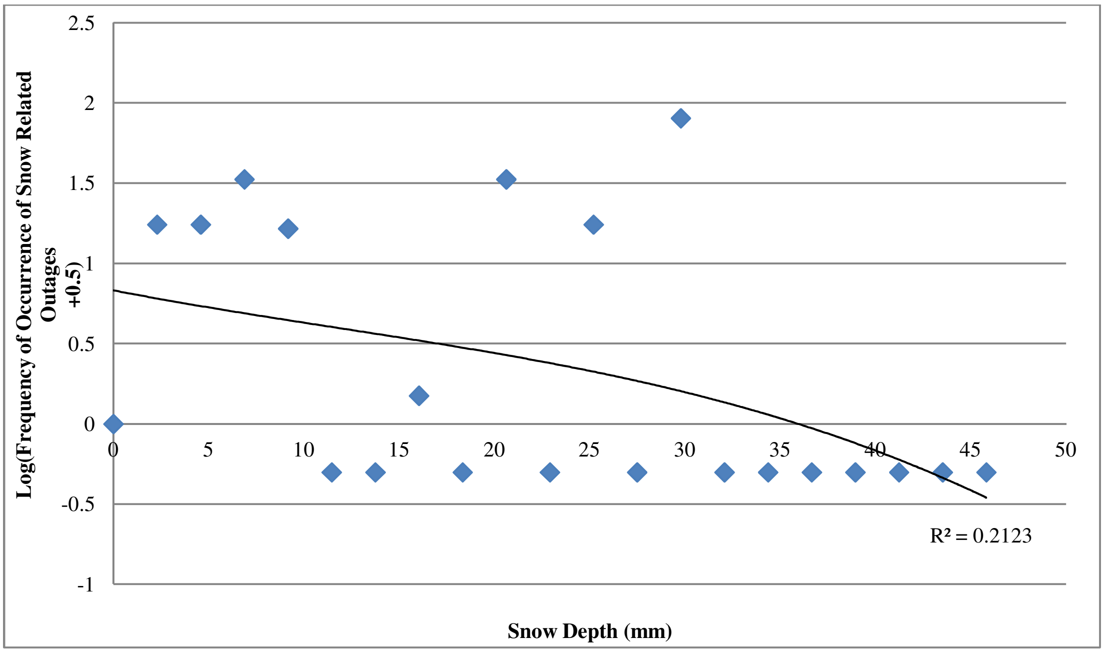


Figure 10-56 - Relationship between Snow-Related Outages and Snow Depth (mm), South Scotland

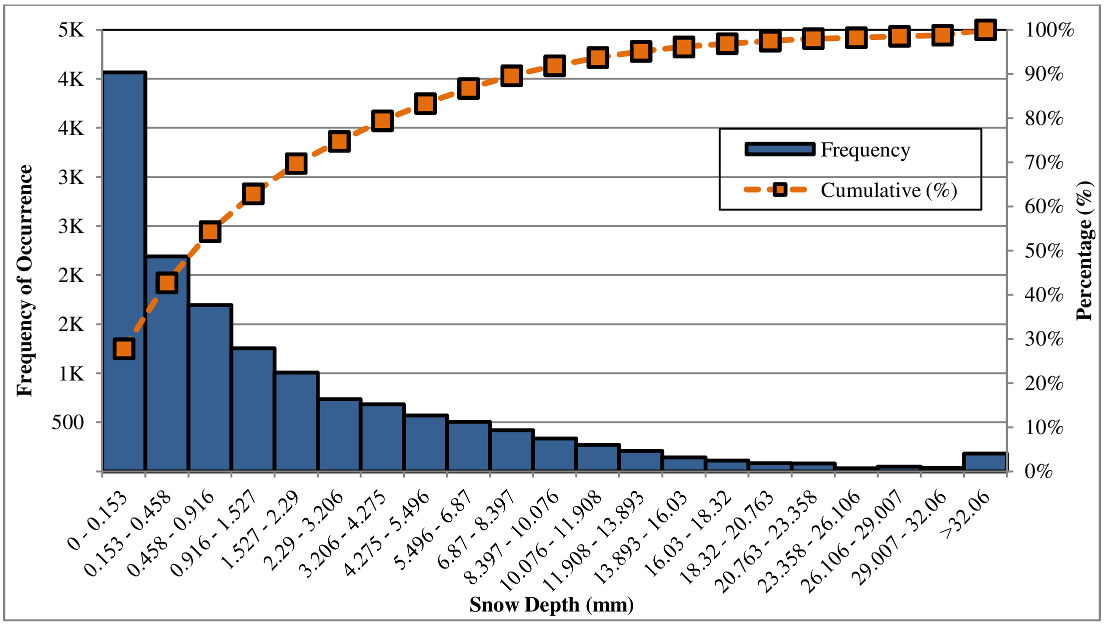


Figure 10-57 - Frequency Distribution and Cumulative Frequency Distribution for Snow Depth Occurrences, North England and North Wales

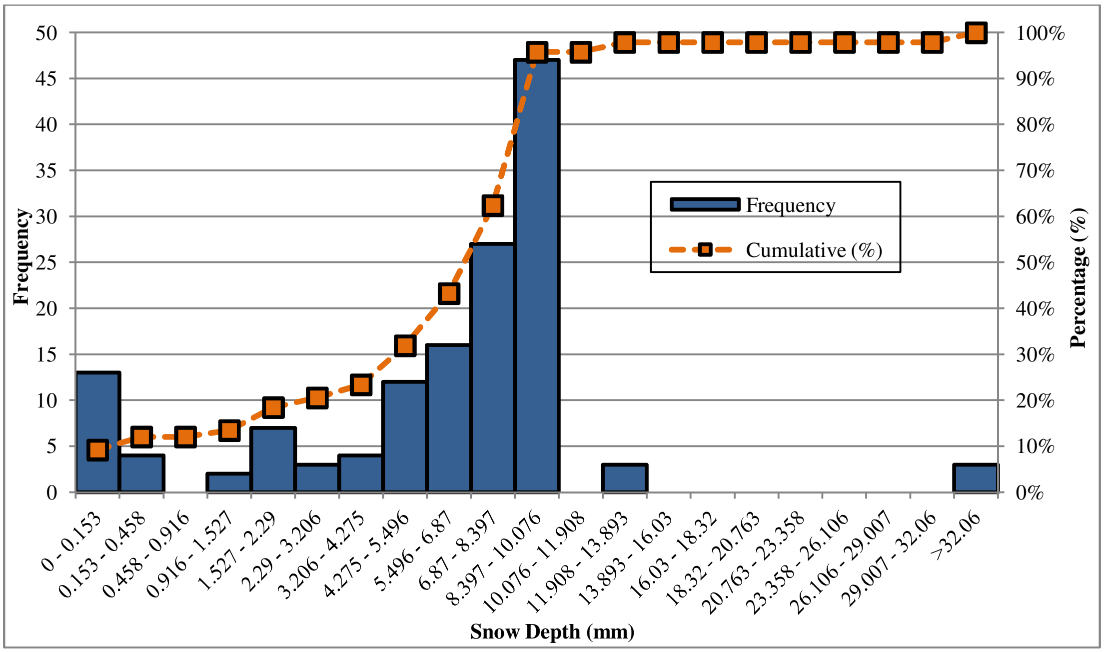


Figure 10-58 – Snow Depth Frequency Distribution and Cumulative Frequency Distribution for Snow Outages, North England and North Wales

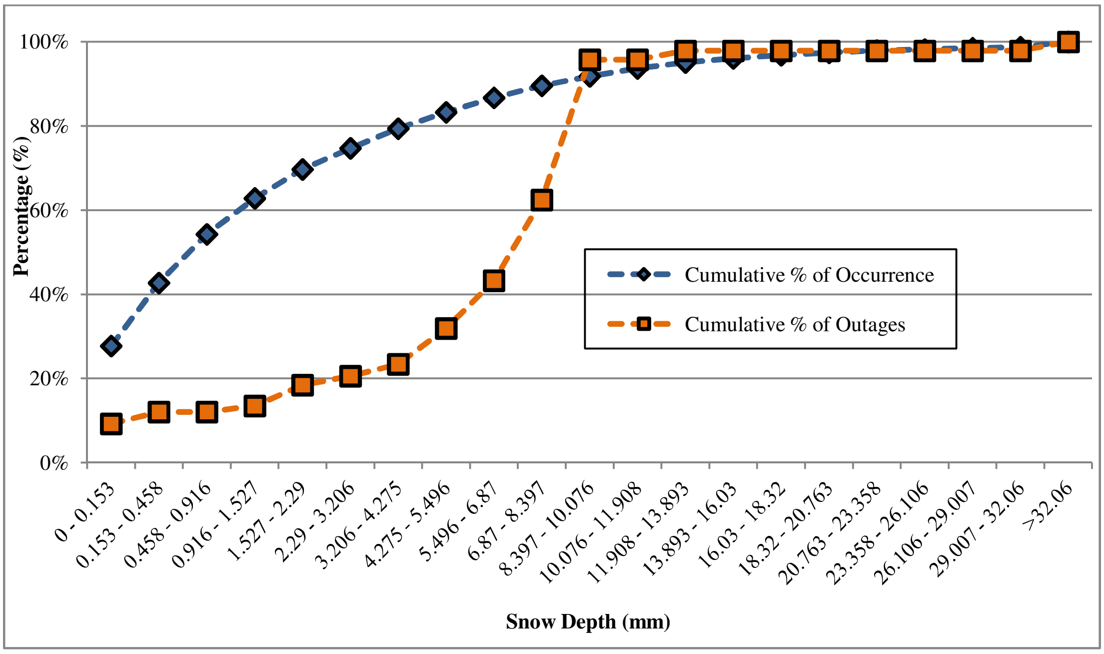


Figure 10-59 - Cumulative Distribution Function for Snow-Related Outages and Snow Depth (mm) Occurrences, North England and North Wales

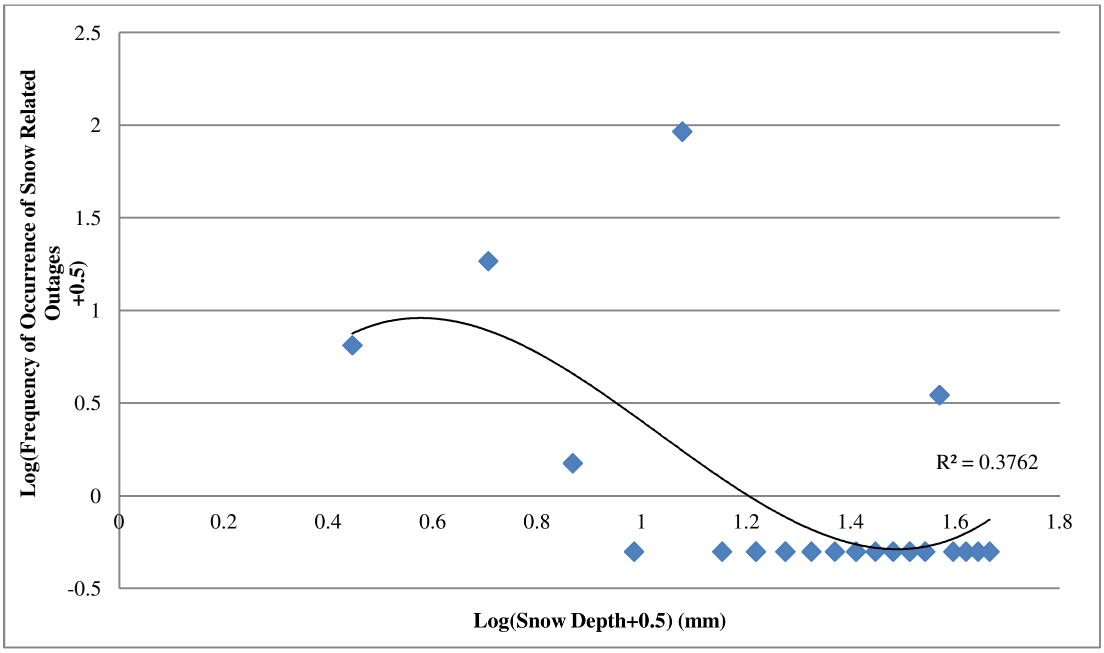


Figure 10-60 - Relationship between Snow-Related Outages and Snow Depth (mm), North England and North Wales

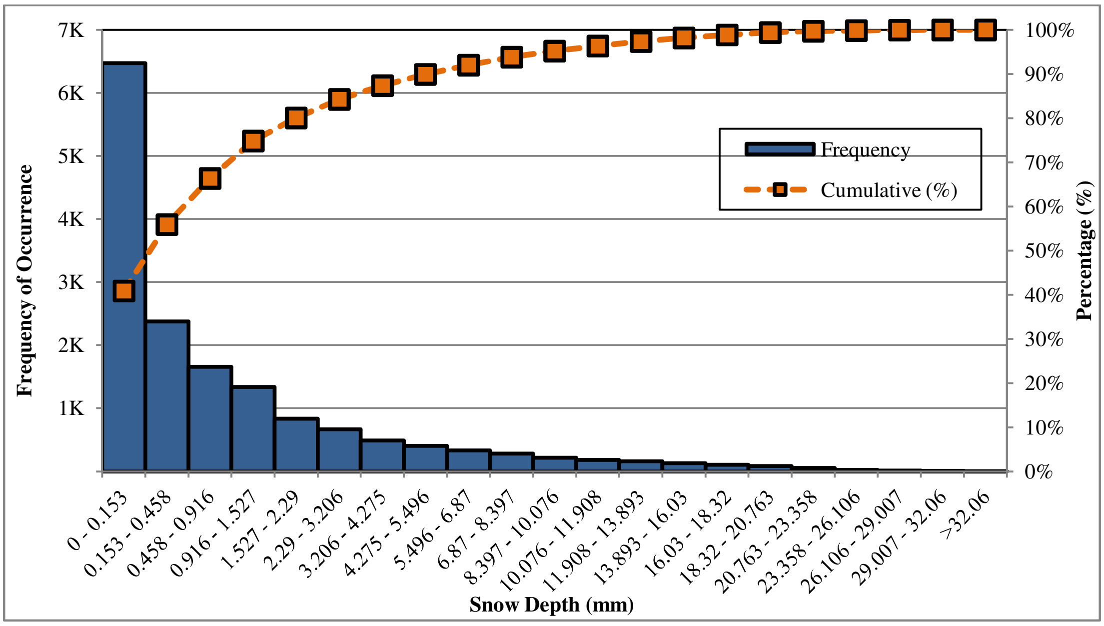


Figure 10-61 - Frequency Distribution and Cumulative Frequency Distribution for Snow Depth Occurrences, South England and South Wales

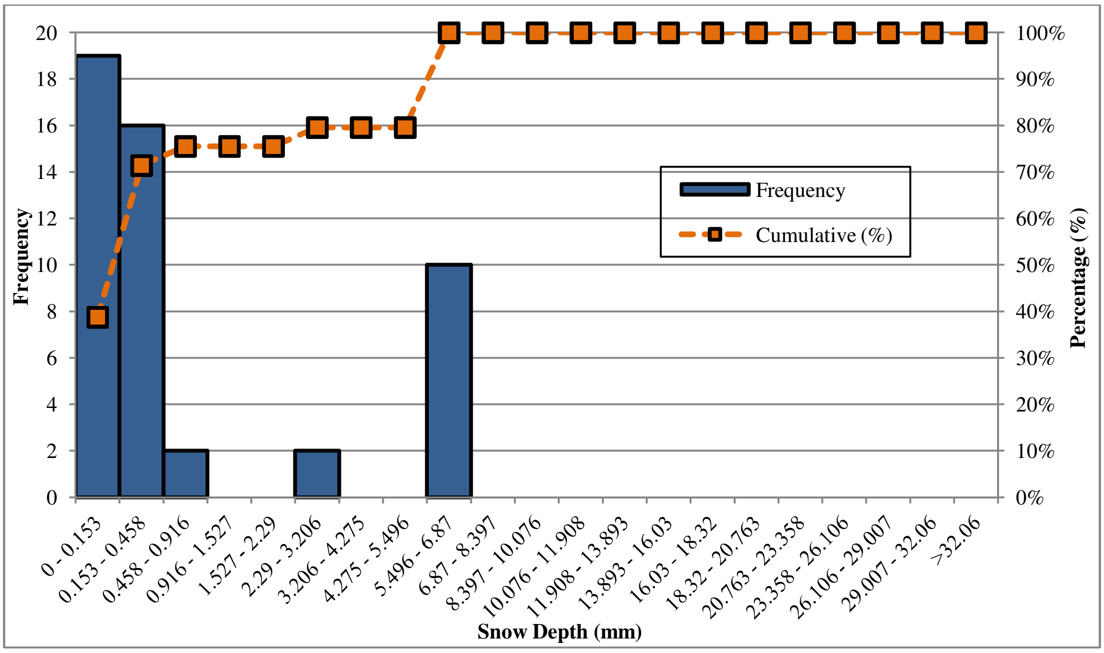


Figure 10-62 – Snow Depth Frequency Distribution and Cumulative Frequency Distribution for Snow Outages, South England and South Wales

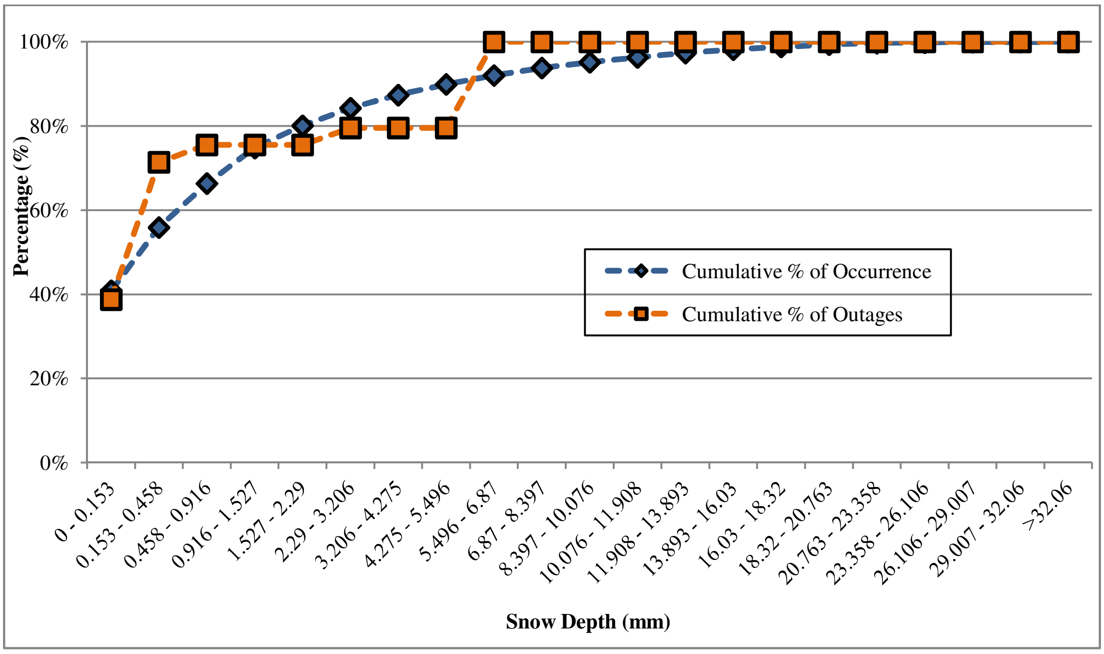


Figure 10-63 - Cumulative Distribution Function for Snow-Related Outages and Snow Depth (mm) Occurrences, South England and South Wales

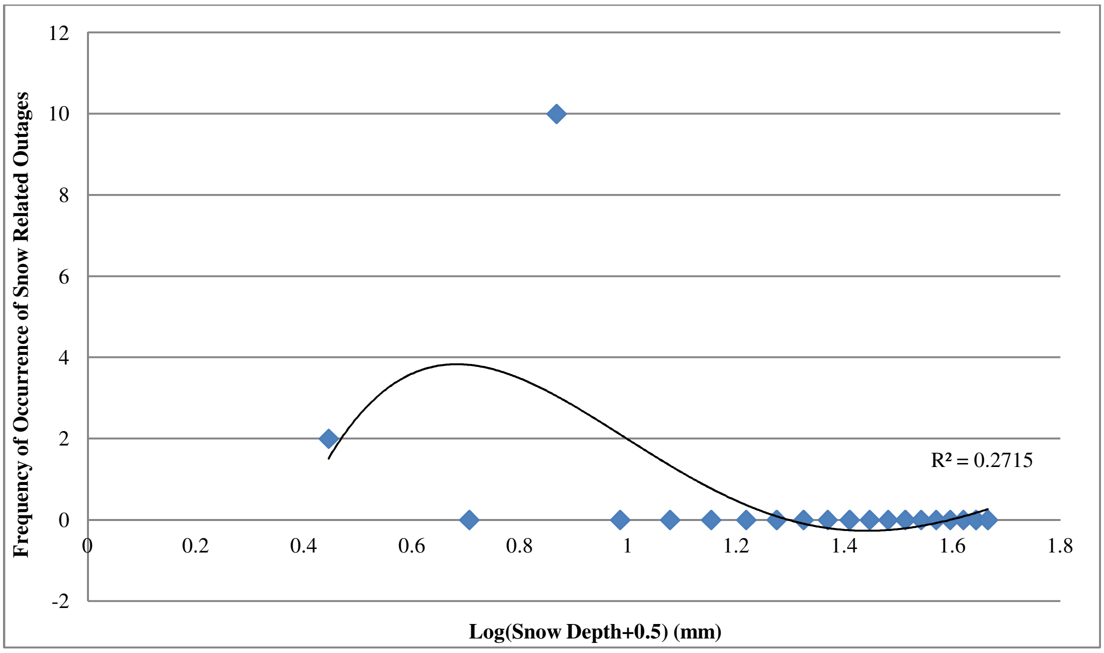


Figure 10-64 - Relationship between Snow-Related Outages and Snow Depth (mm), South England and South Wales

D-5 Minimum Temperature

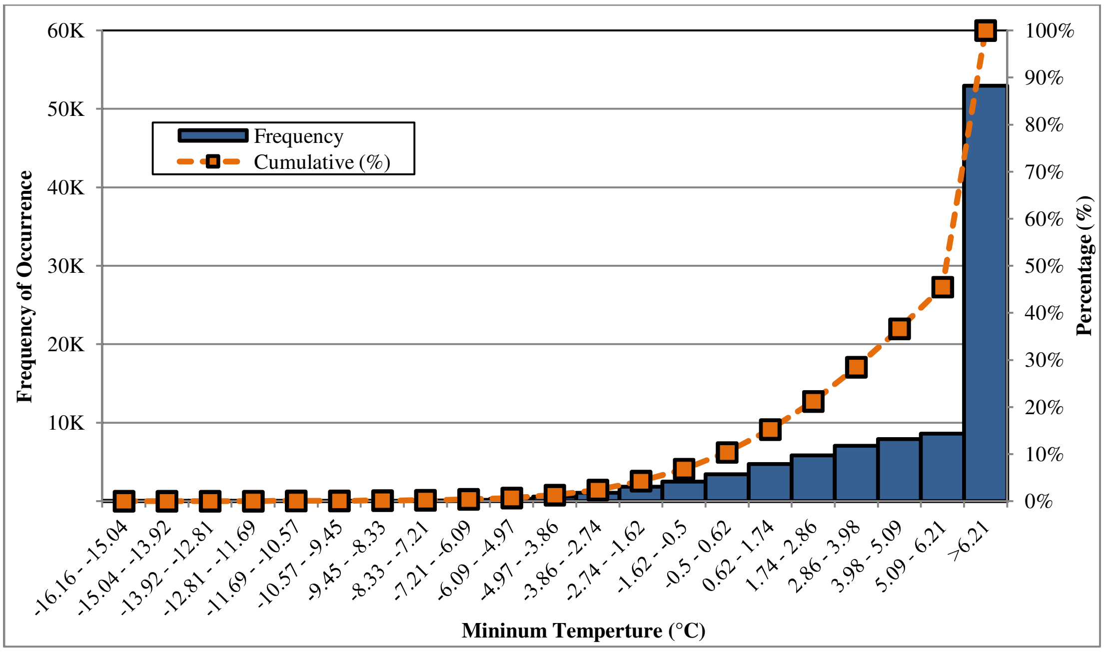


Figure 10-65 - Frequency Distribution and Cumulative Frequency Distribution for Minimum Temperature (°C) Occurrences, South Scotland

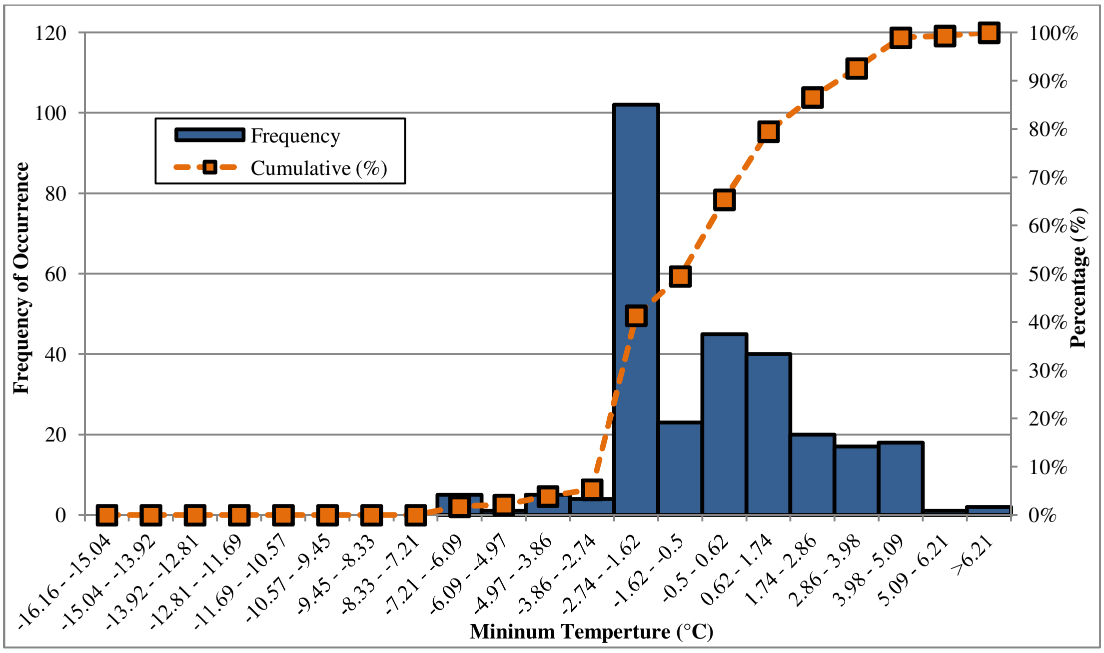


Figure 10-66 – Minimum Temperature Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, South Scotland

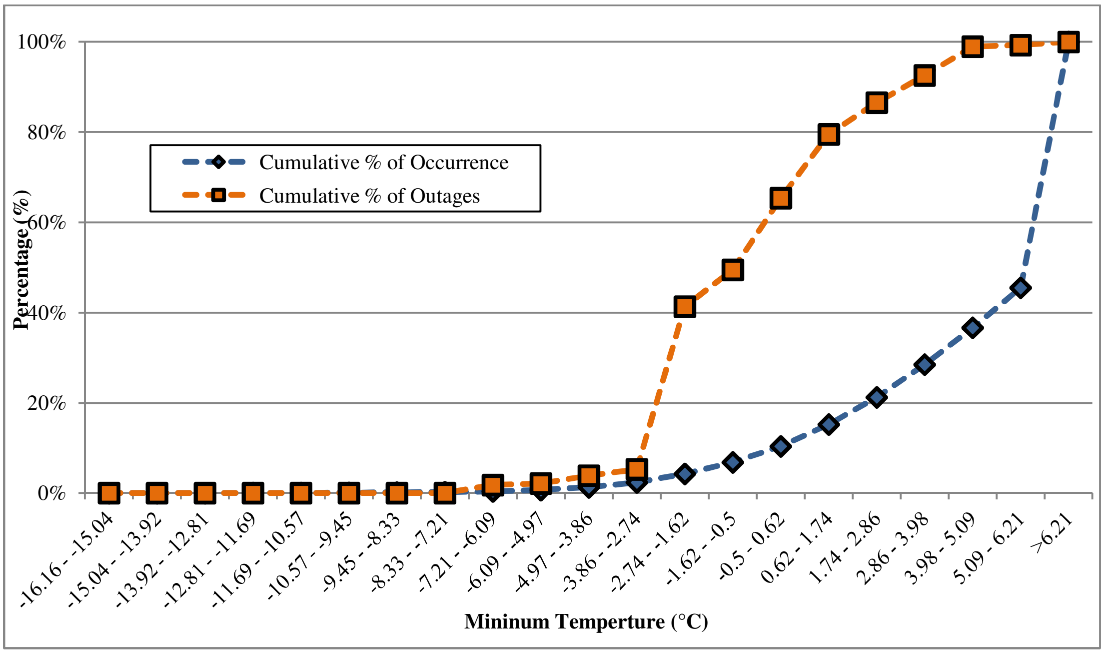


Figure 10-67 - Cumulative Distribution Function for Snow-Related Outages and Minimum Temperature (°C) Occurrences, South Scotland

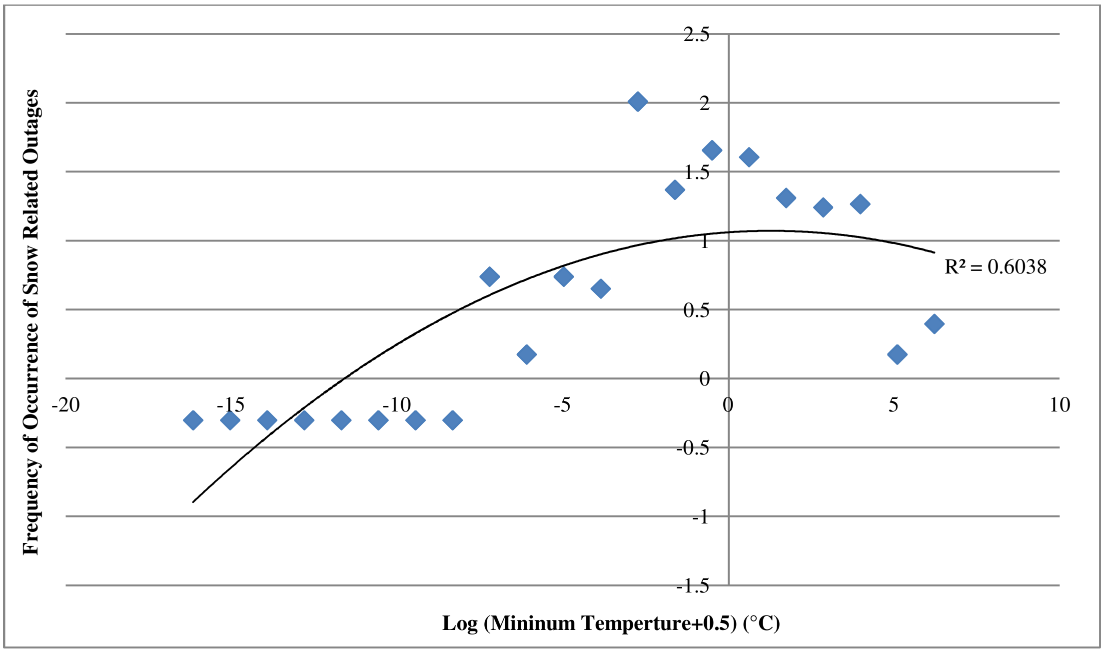


Figure 10-68 - Relationship between Snow-Related Outages and Minimum Temperature (°C), South Scotland

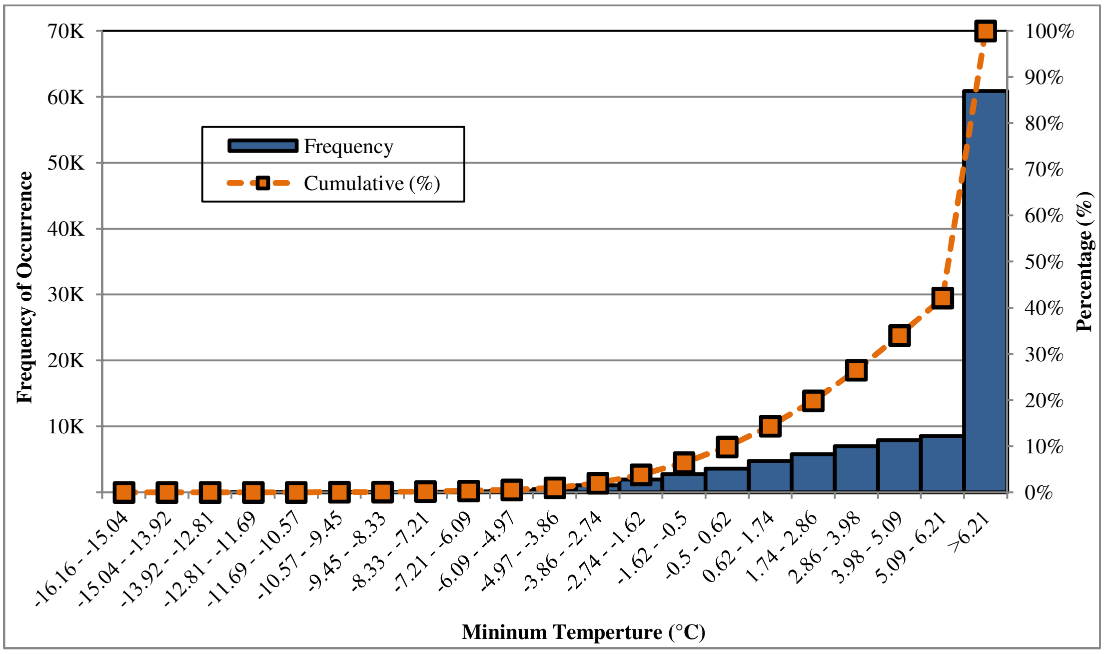


Figure 10-69 - Frequency Distribution and Cumulative Frequency Distribution for Minimum Temperature (°C) Occurrences, North England and North Wales

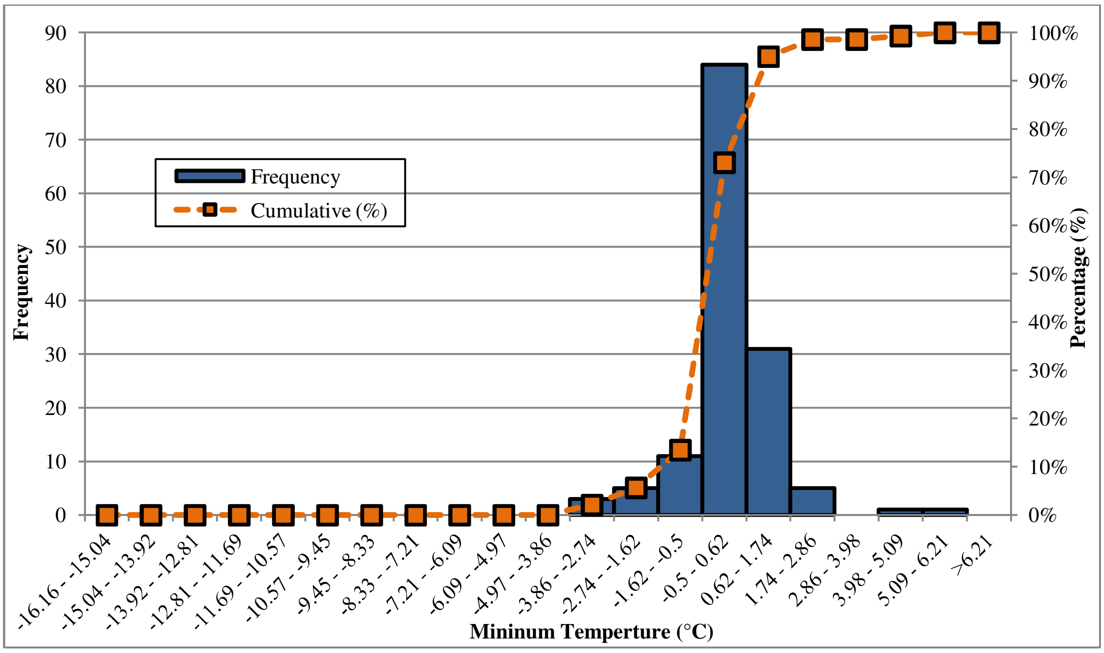


Figure 10-70 – Minimum Temperature Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, North England and North Wales

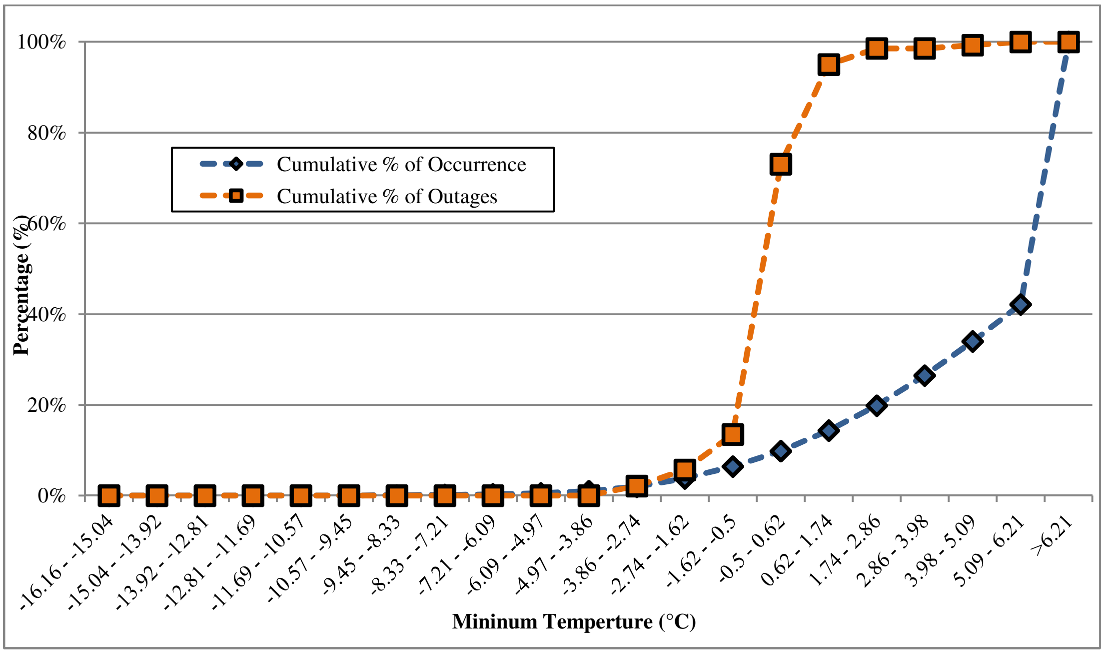


Figure 10-71 - Cumulative Distribution Function for Snow-Related Outages and Minimum Temperature (°C) Occurrences, North England and North Wales

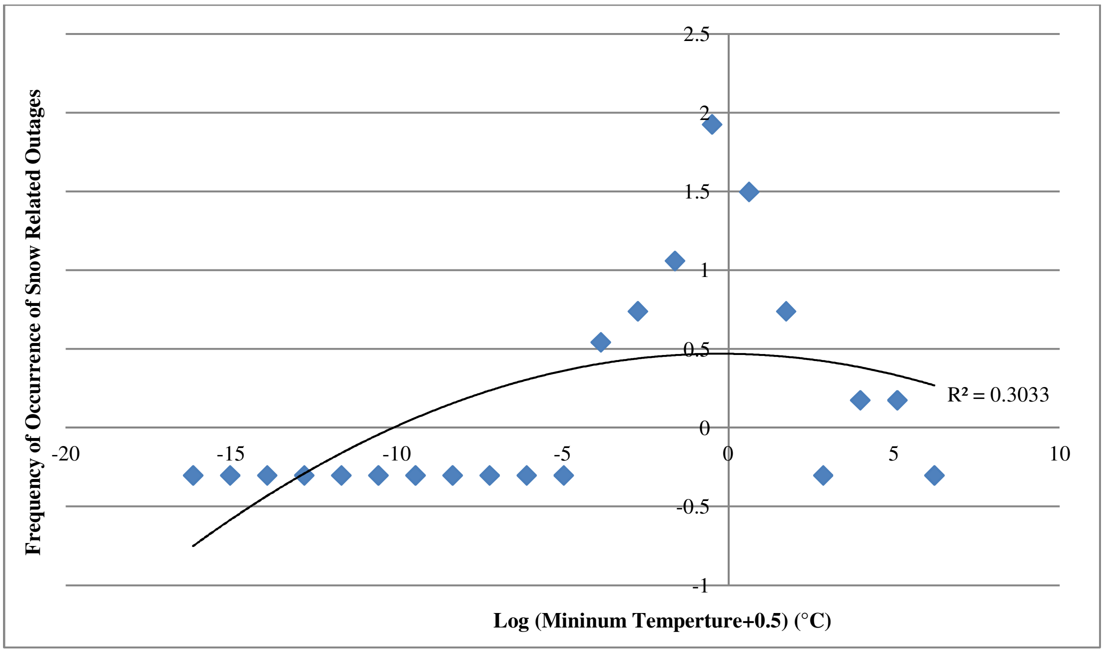


Figure 10-72 - Relationship between Snow-Related Outages and Minimum Temperature (°C), North England and North Wales

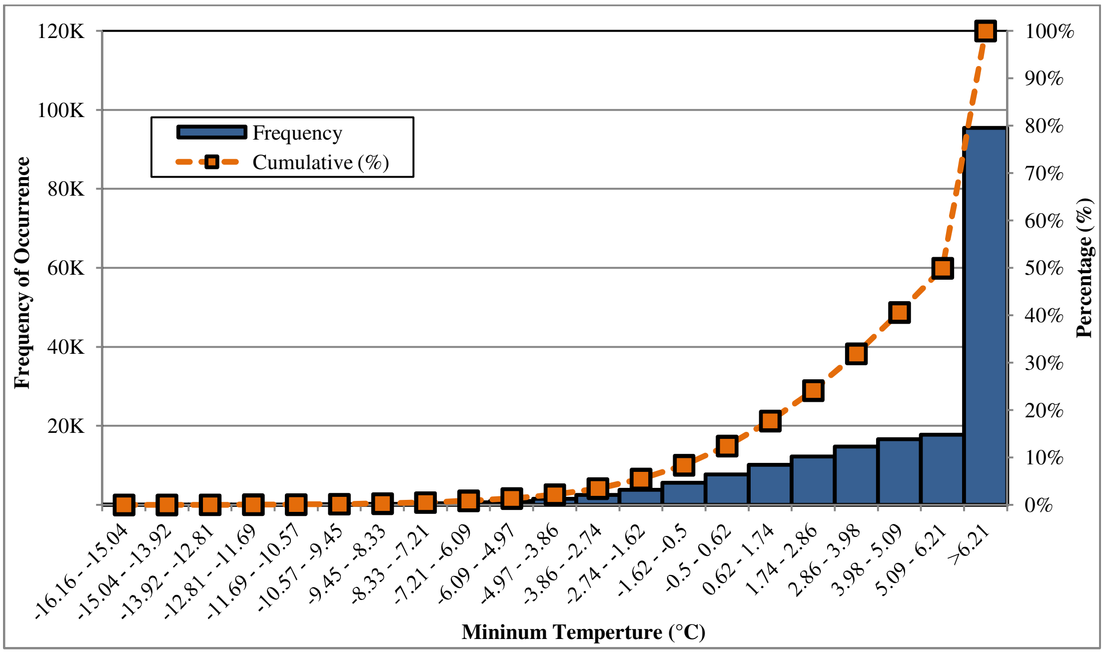


Figure 10-73 - Frequency Distribution and Cumulative Frequency Distribution for Minimum Temperature (°C) Occurrences, South England and South Wales

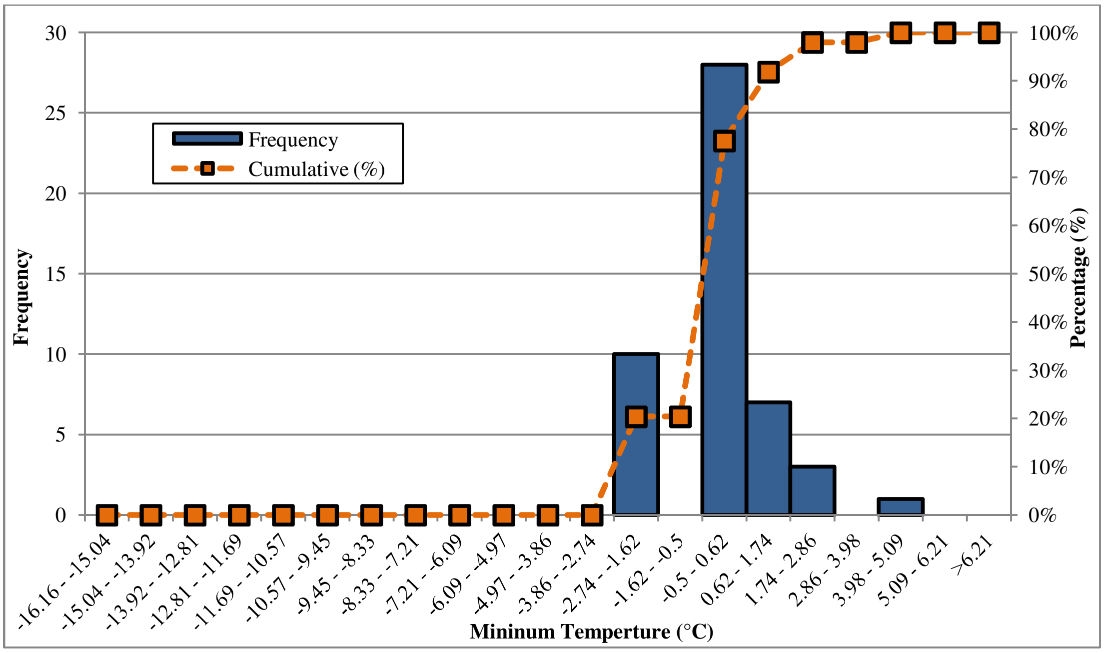


Figure 10-74 – Minimum Temperature Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, South England and South Wales

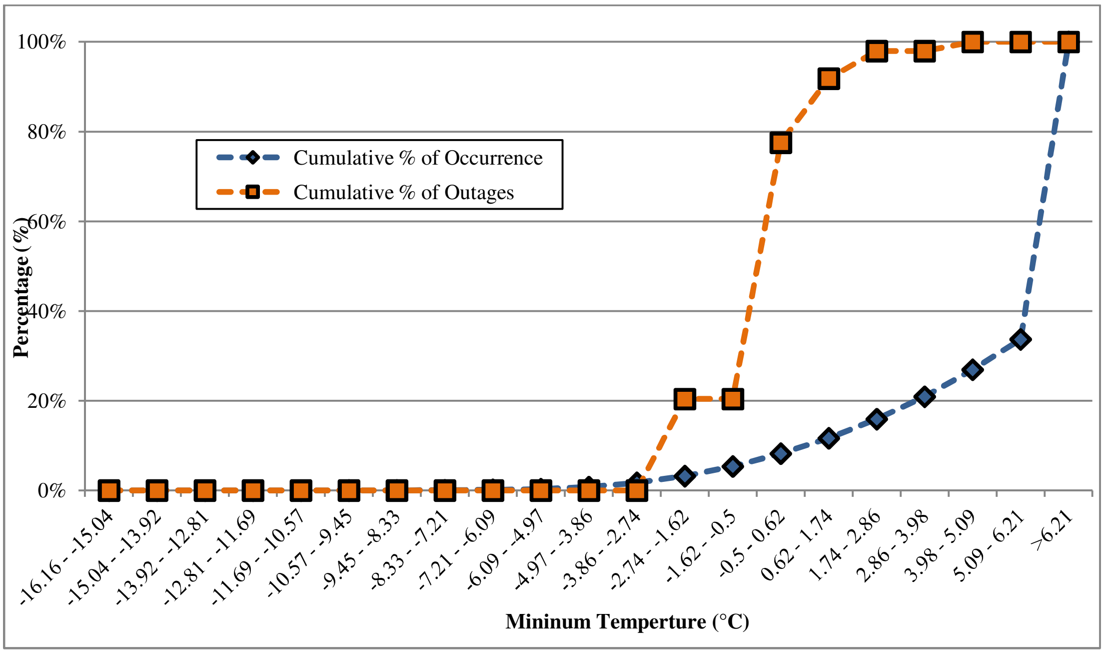


Figure 10-75 - Cumulative Distribution Function for Snow-Related Outages and Minimum Temperature (°C) Occurrences, South England and South Wales

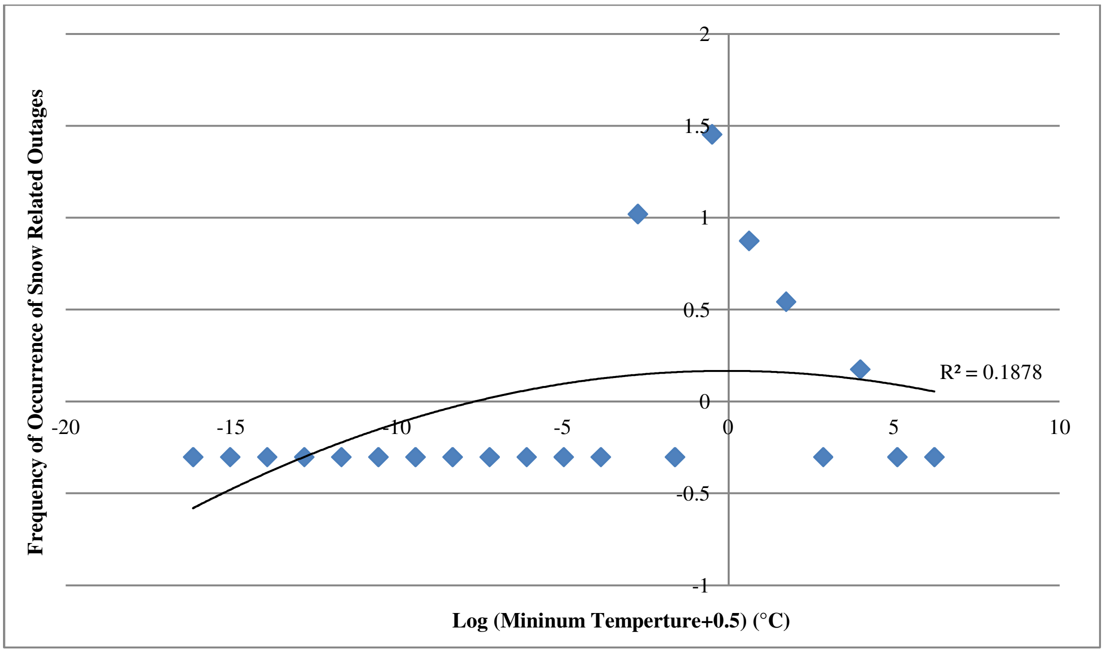


Figure 10-76 - Relationship between Snow-Related Outages and Minimum Temperature (°C), South England and South Wales

D-6 Wind Gusts on Snow Days

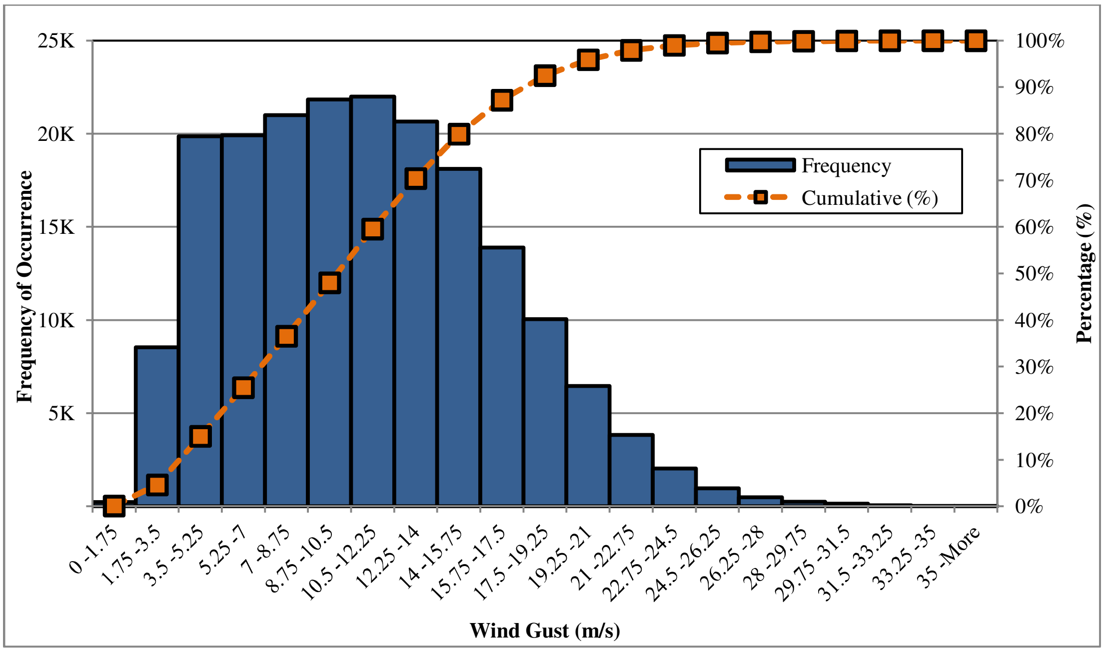


Figure 10-77 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Gusts on Snow Days Occurrences, South Scotland

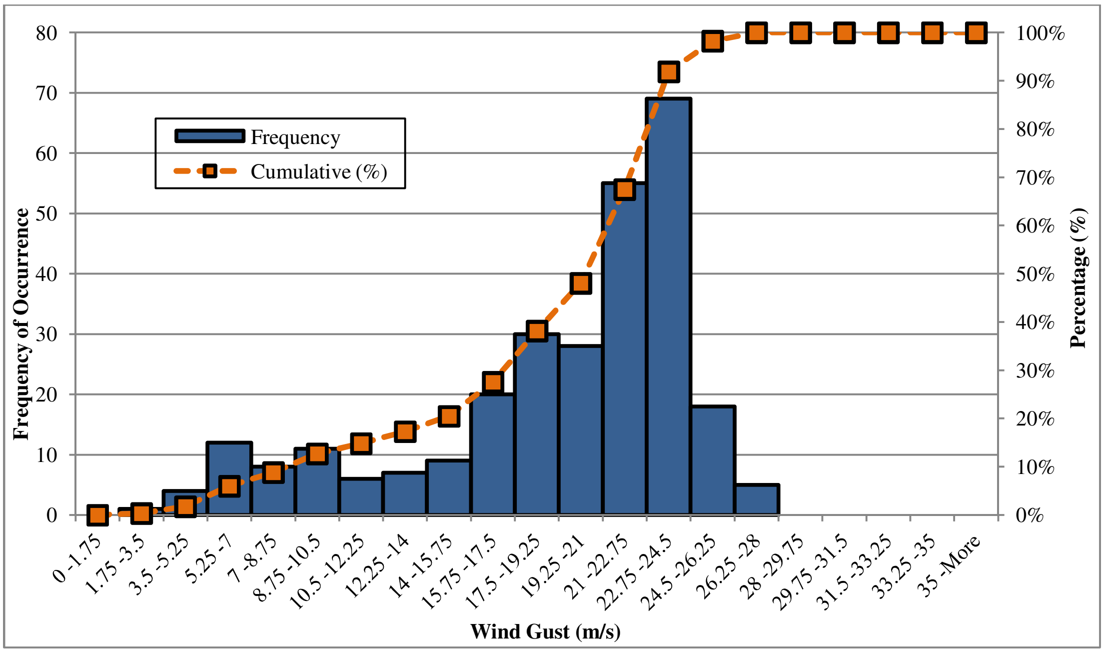


Figure 10-78 – Wind Gusts on Snow Days Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, South Scotland

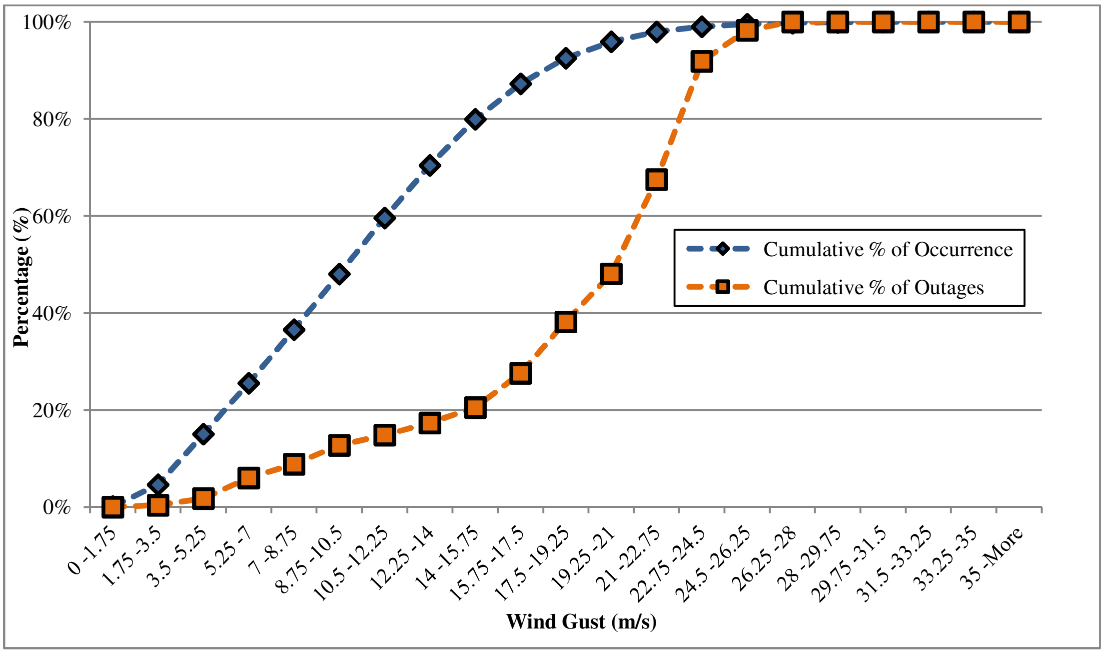


Figure 10-79 - Cumulative Distribution Function for Snow-Related Outages and Wind Gusts on Snow Days (m/s) Occurrences, South Scotland

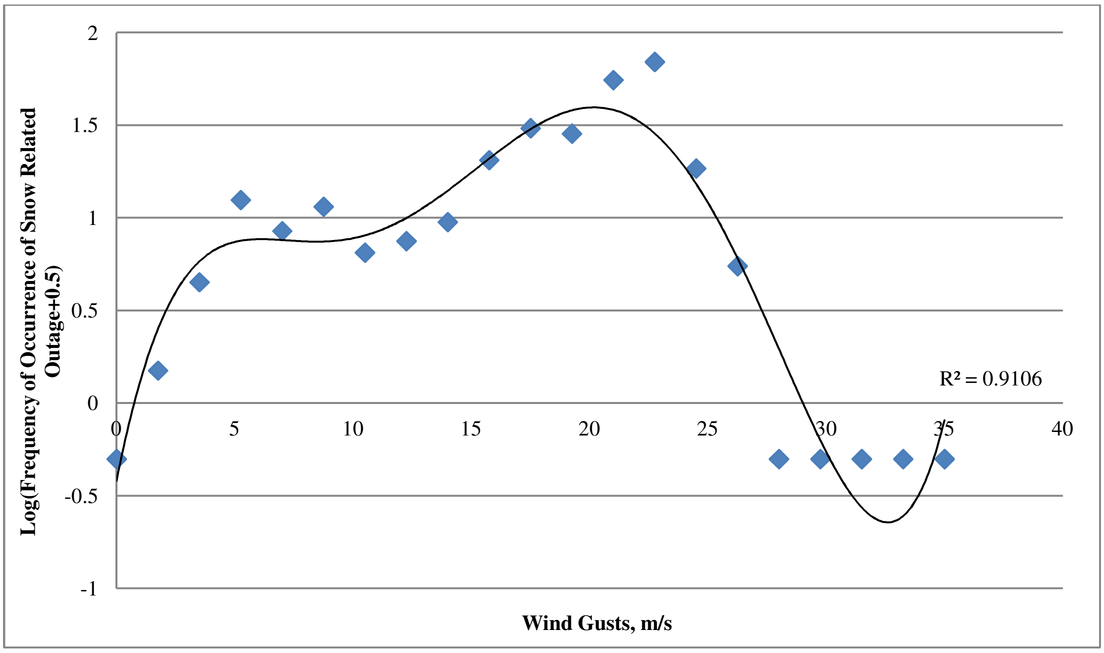


Figure 10-80 - Log Relationship between Snow-Related Outages and 10meter Wind Gusts on Snow Days (m/s), South Scotland

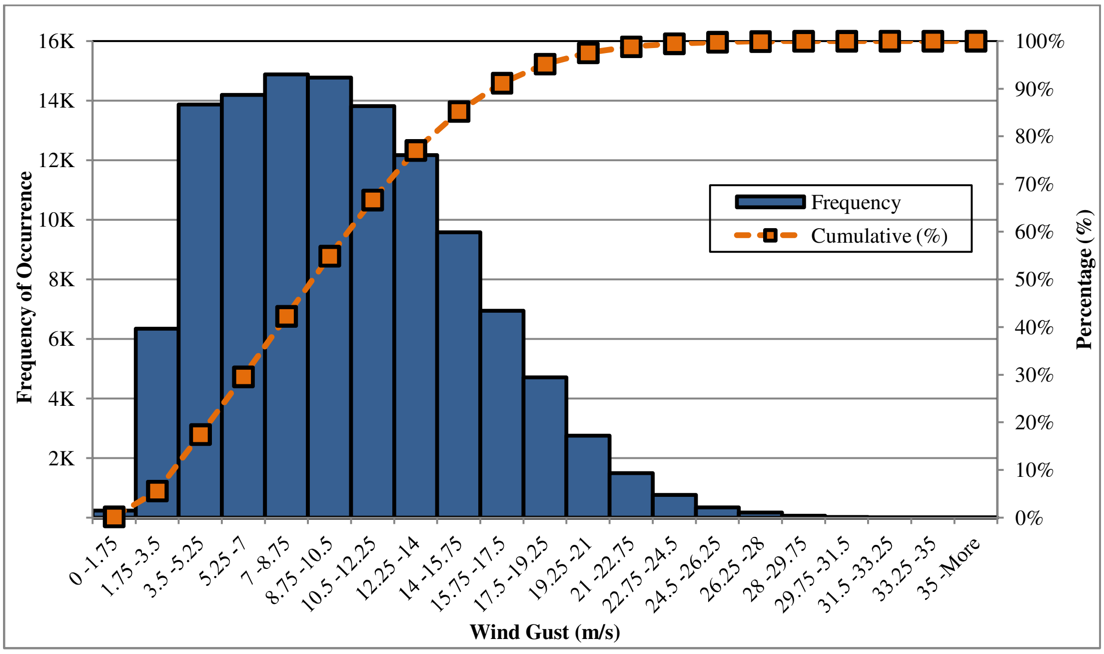


Figure 10-81 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Gusts on Snow Days Occurrences, North England and North Wales

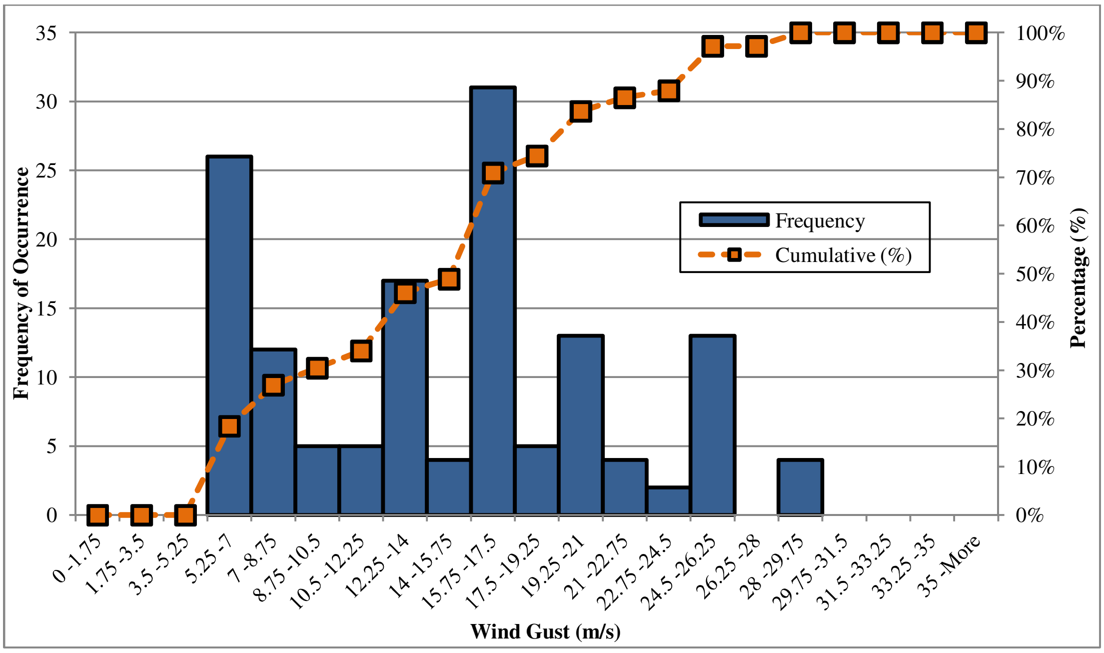


Figure 10-82 – Wind Gusts on Snow Days Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, North England and North Wales

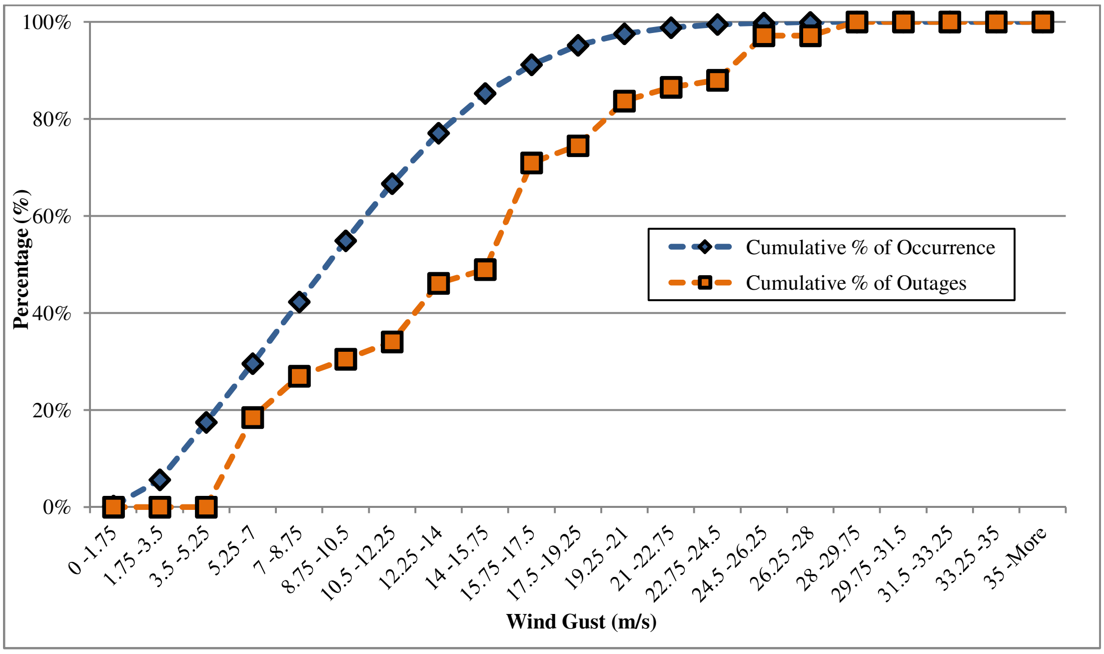


Figure 10-83 - Cumulative Distribution Function for Snow-Related Outages and Wind Gusts on Snow Days (m/s) Occurrences, North England and North Wales

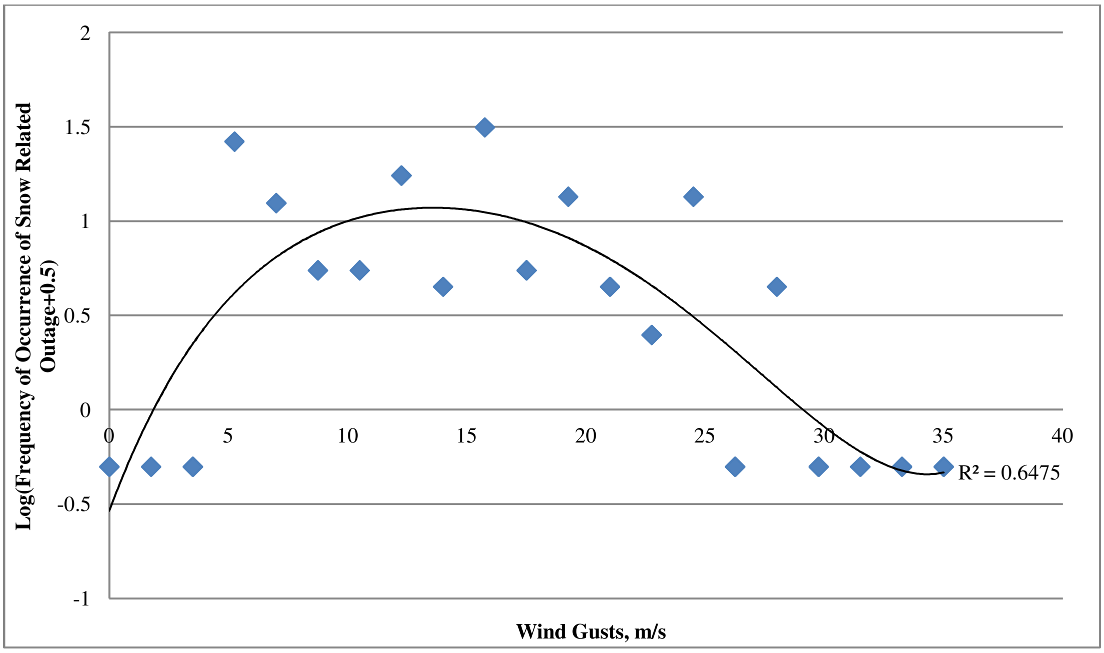


Figure 10-84 - Log Relationship between Snow-Related Outages and 10meter Wind Gusts on Snow Days (m/s), North England and North Wales

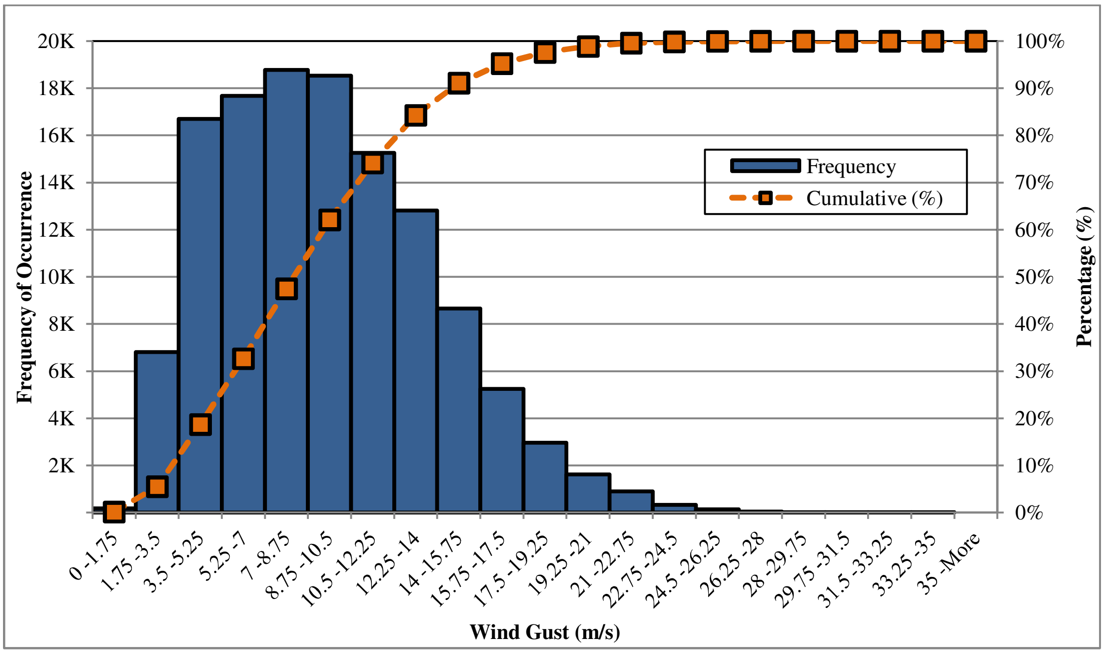


Figure 10-85 - Frequency Distribution and Cumulative Frequency Distribution for 10m Wind Gusts on Snow Days Occurrences, South England and South Wales

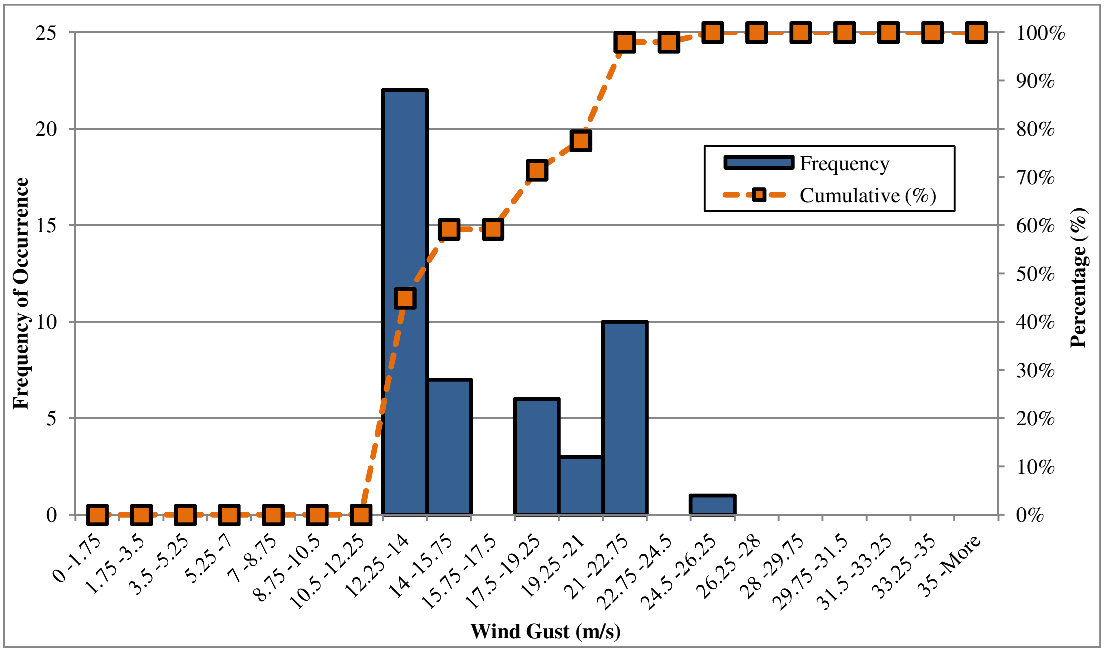


Figure 10-86 – Wind Gusts on Snow Days Frequency Distribution and Cumulative Frequency Distribution for Snow-Related Outages, South England and South Wales

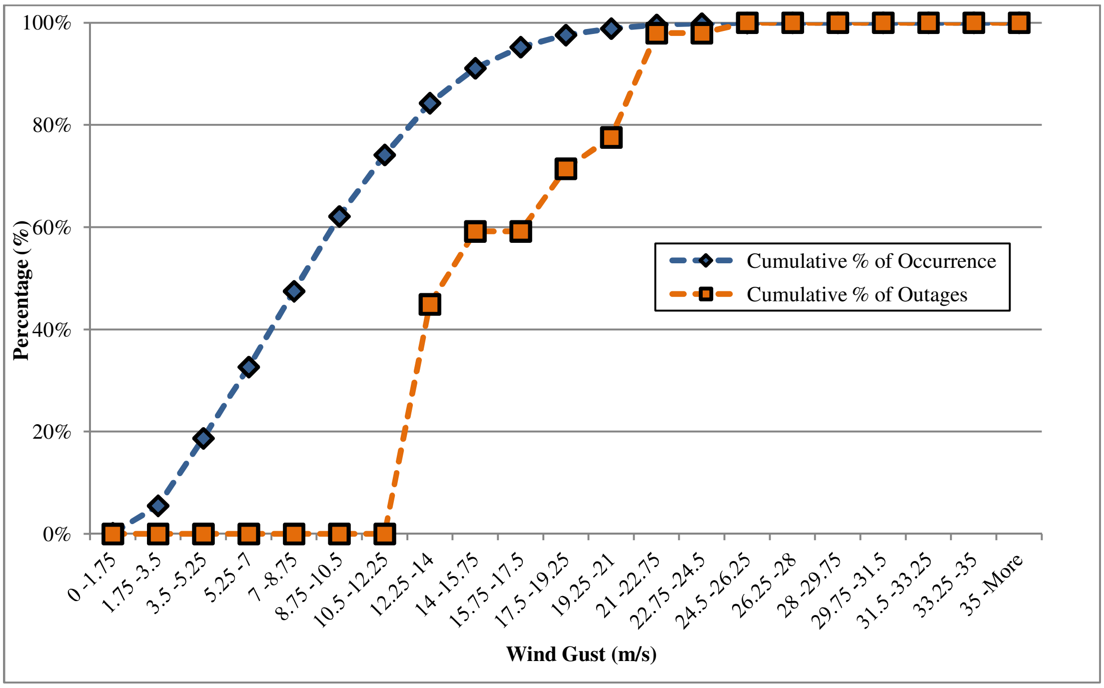


Figure 10-87 - Cumulative Distribution Function for Snow-Related Outages and Wind Gusts on Snow Days (m/s) Occurrences, South England and South Wales

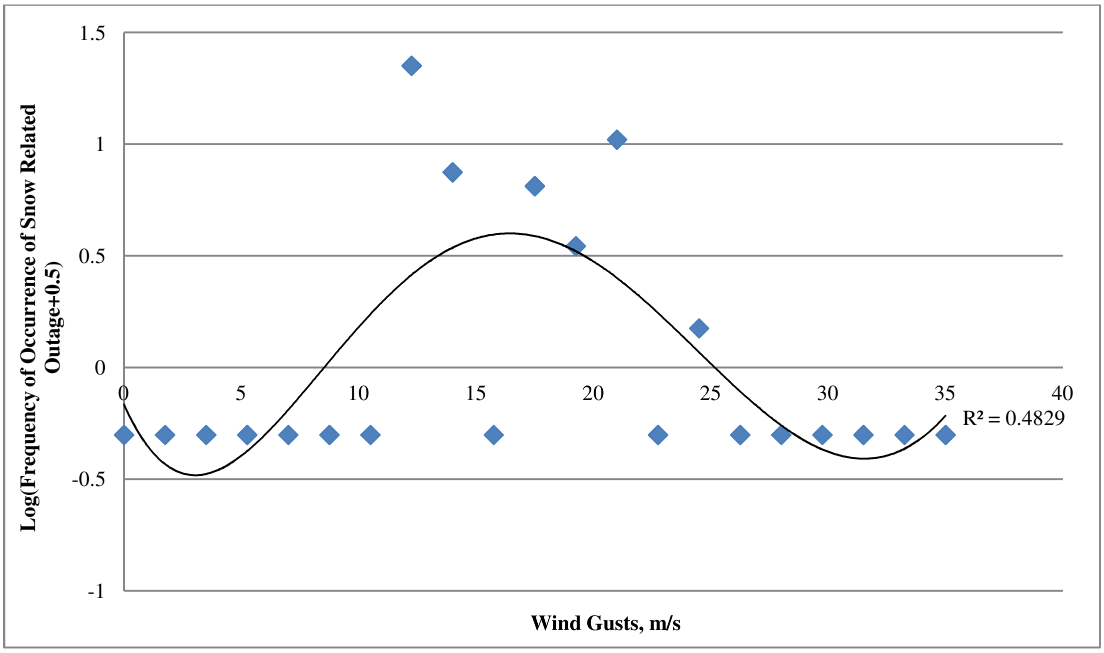


Figure 10-88 - Log Relationship between Snow-Related Outages and 10meter Wind Gusts on Snow Days (m/s), South England and South Wales

D-7 Lightning Strikes

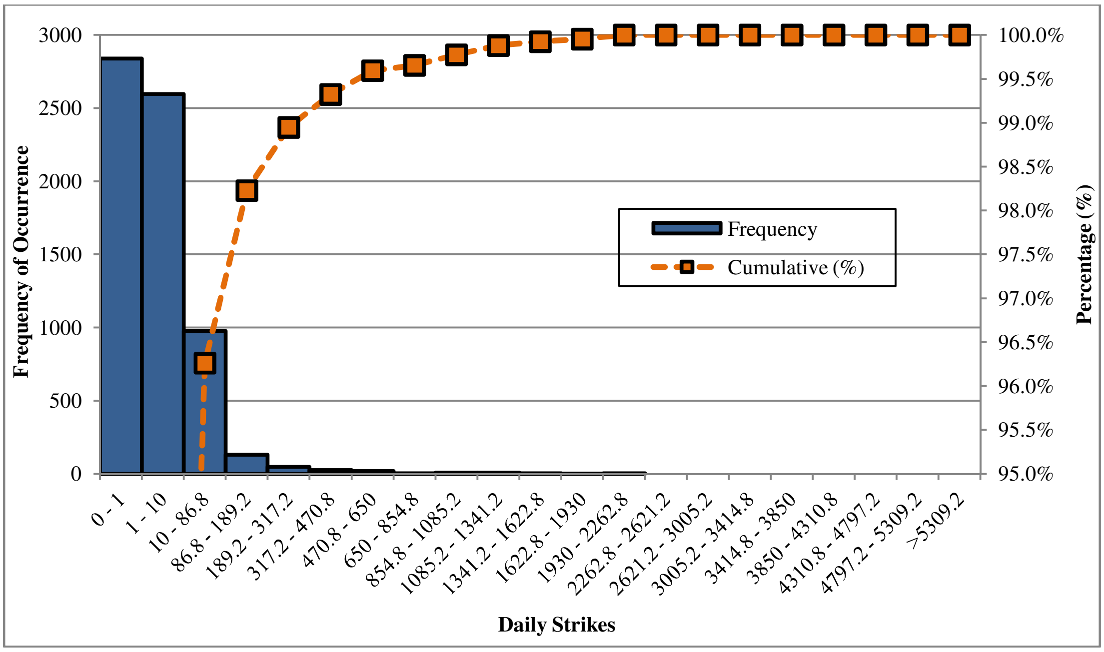


Figure 10-89 - Frequency Distribution and Cumulative Frequency Distribution for Daily Lightning Strikes, South Scotland

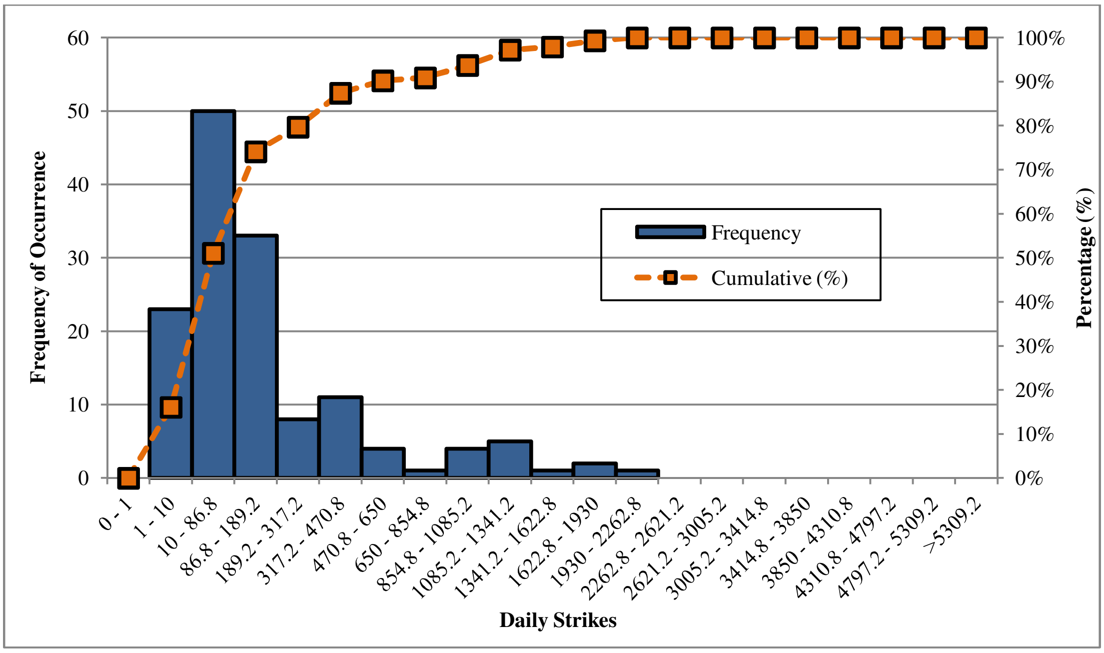


Figure 10-90 - Daily Lightning Strikes Frequency Distribution and Cumulative Frequency Distribution for Lightning-Related Outages, South Scotland

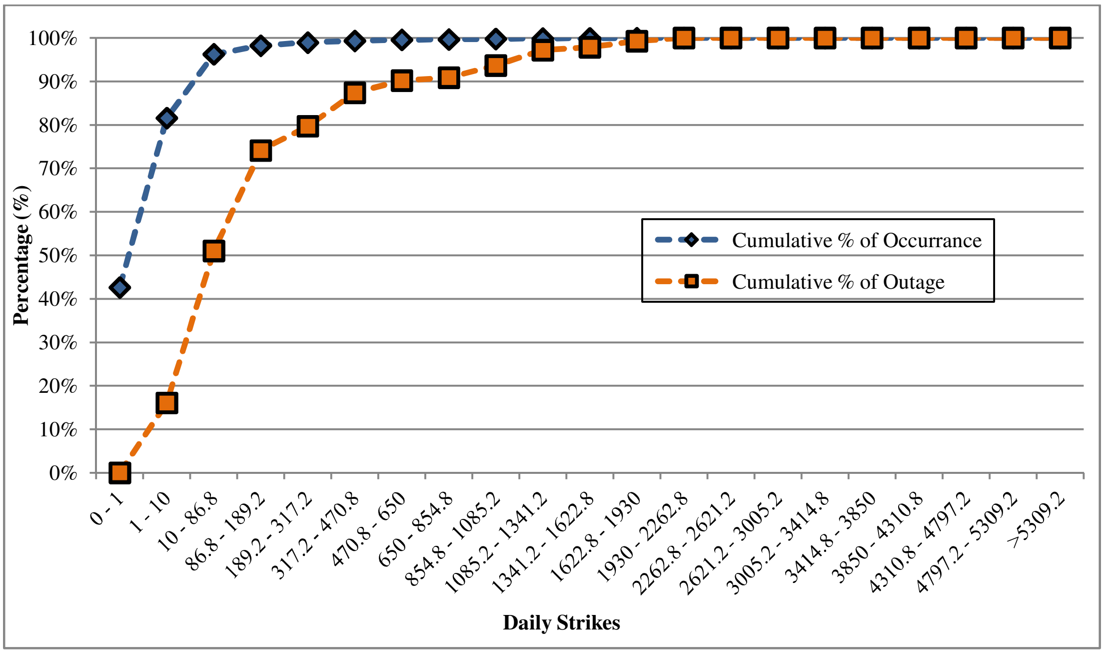


Figure 10-91 - Cumulative Distribution Function for Lightning-Related Outages and Daily Lightning Strikes, South Scotland

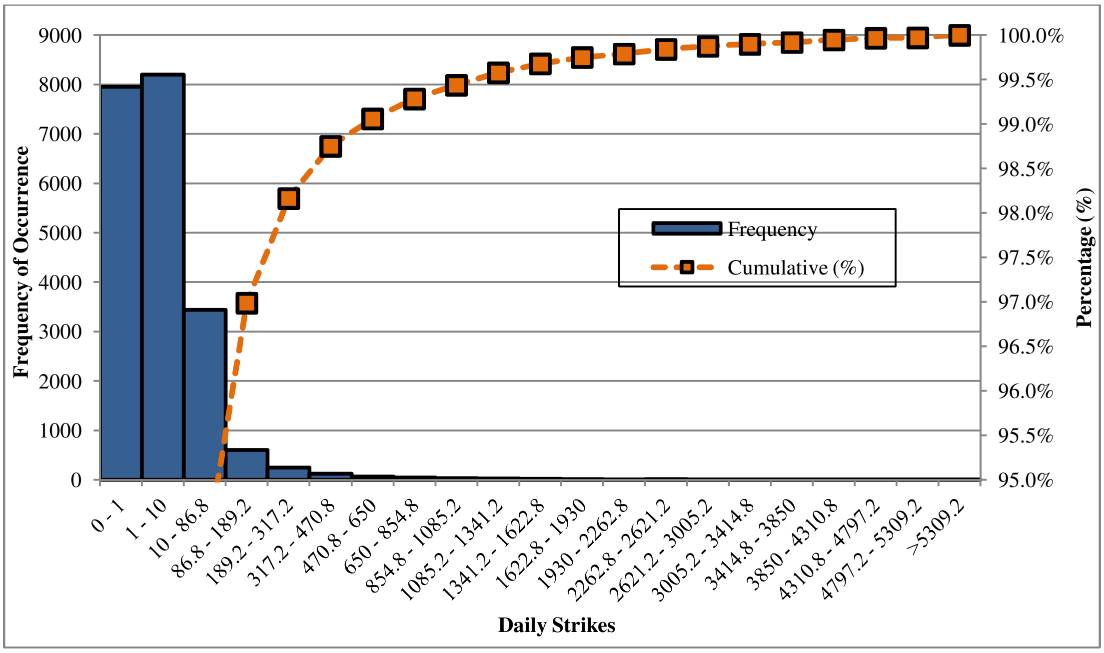


Figure 10-92 - Frequency Distribution and Cumulative Frequency Distribution for Daily Lightning Strikes, North England and North Wales

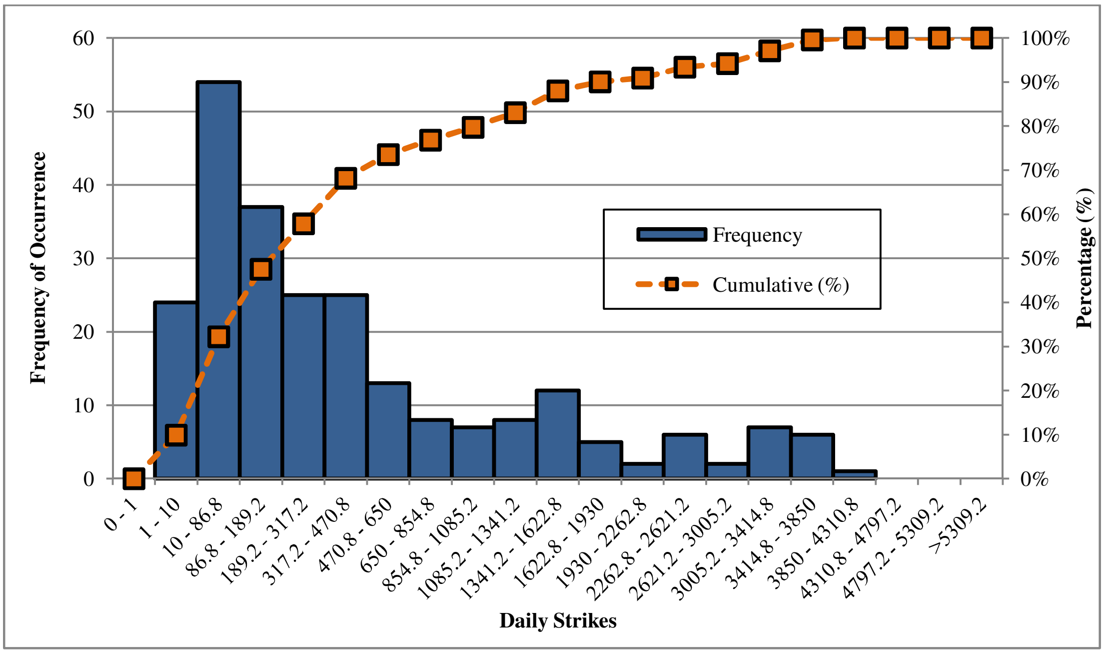


Figure 10-93 - Daily Lightning Strikes Frequency Distribution and Cumulative Frequency Distribution for Lightning-Related Outages, North England and North Wales

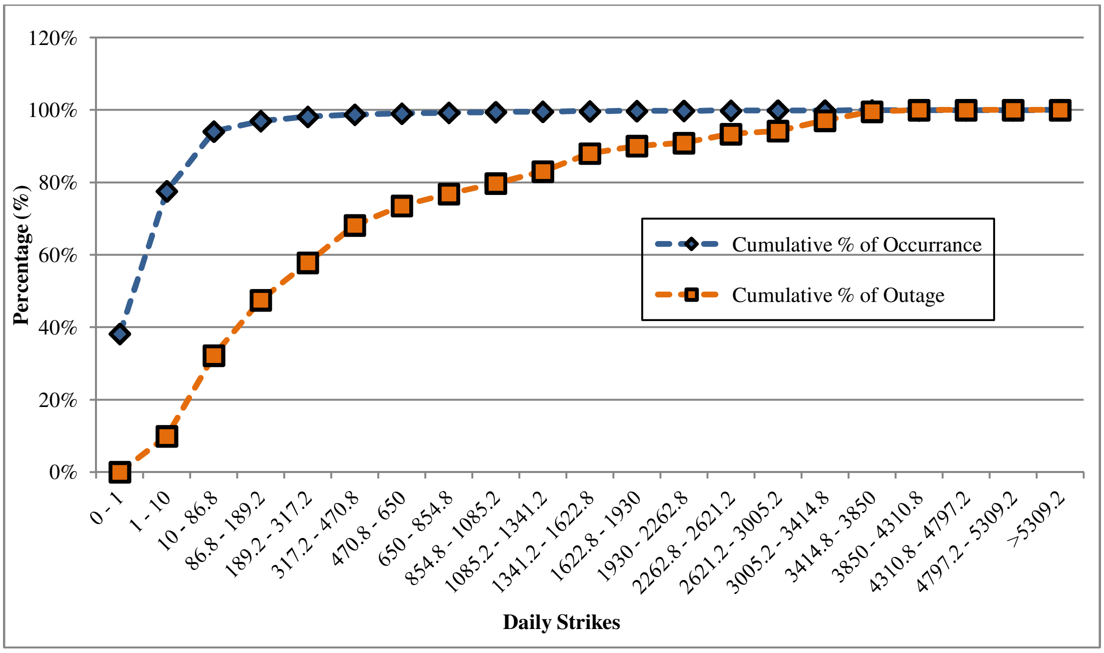


Figure 10-94 - Cumulative Distribution Function for Lightning-Related Outages and Daily Lightning Strikes, North England and North Wales

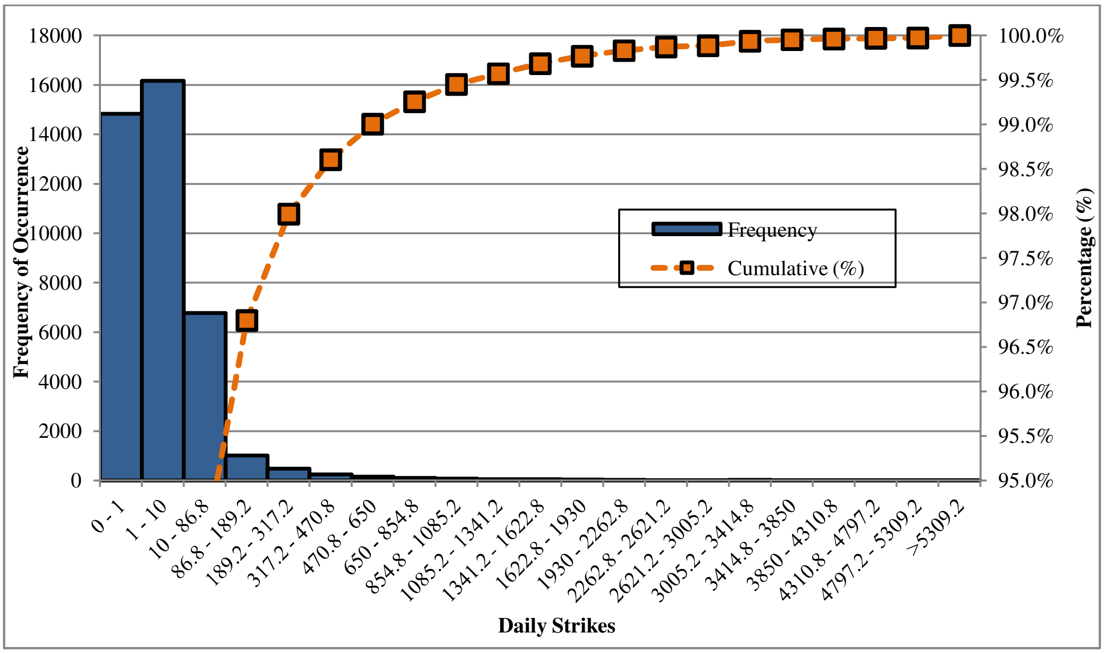


Figure 10-95 - Frequency Distribution and Cumulative Frequency Distribution for Daily Lightning Strikes, South England and South Wales

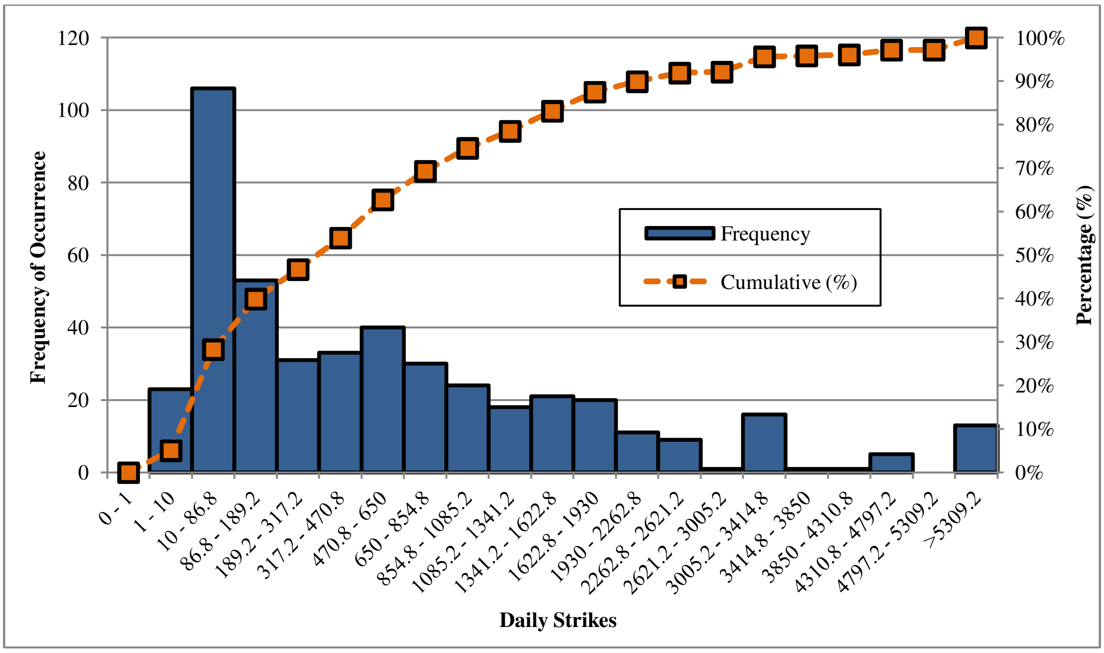


Figure 10-96 - Daily Lightning Strikes Frequency Distribution and Cumulative Frequency Distribution for Lightning-Related Outages, South England and South Wales

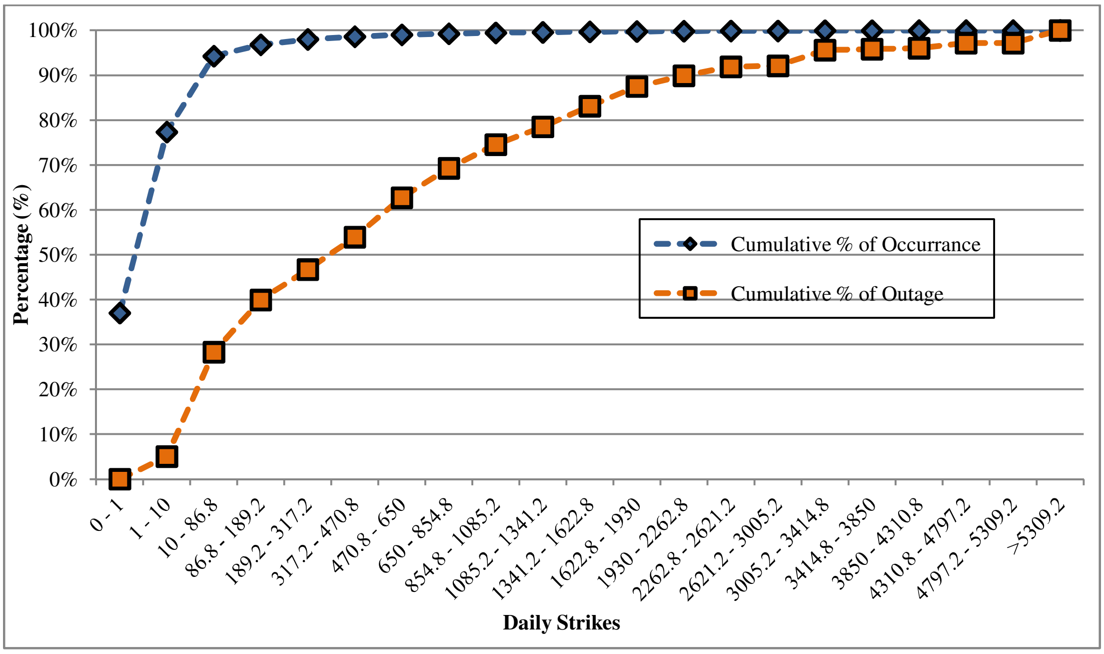


Figure 10-97 - Cumulative Distribution Function for Lightning-Related Outages and Daily Lightning Strikes, South England and South Wales

D-8 CAPE

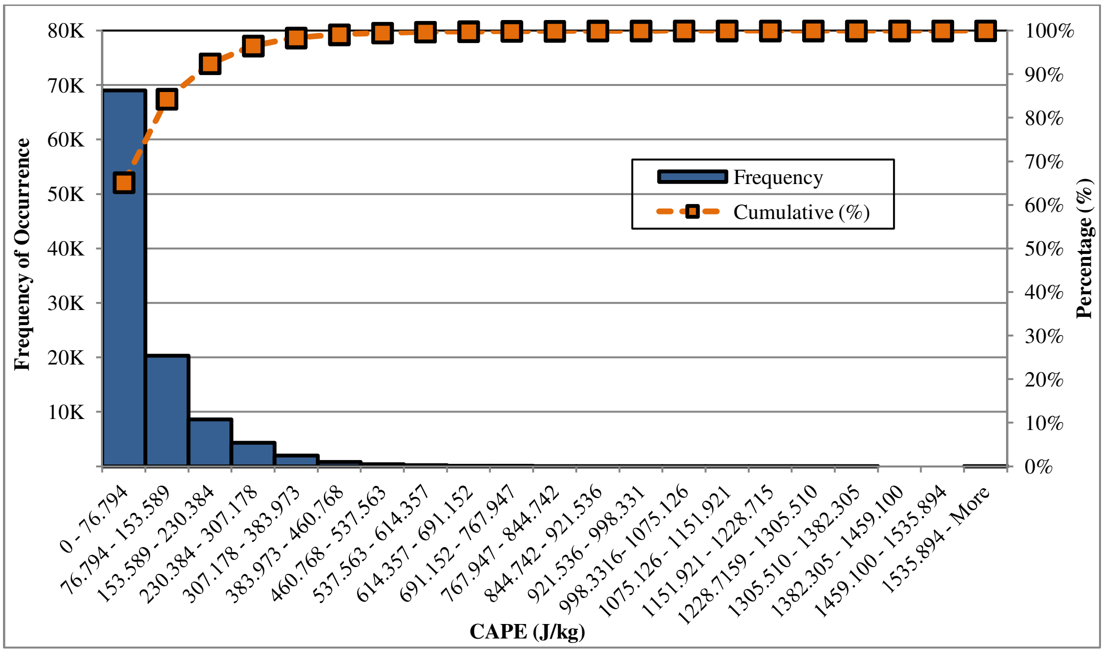


Figure 10-98 - Frequency Distribution and Cumulative Frequency Distribution for CAPE Occurrences, South Scotland

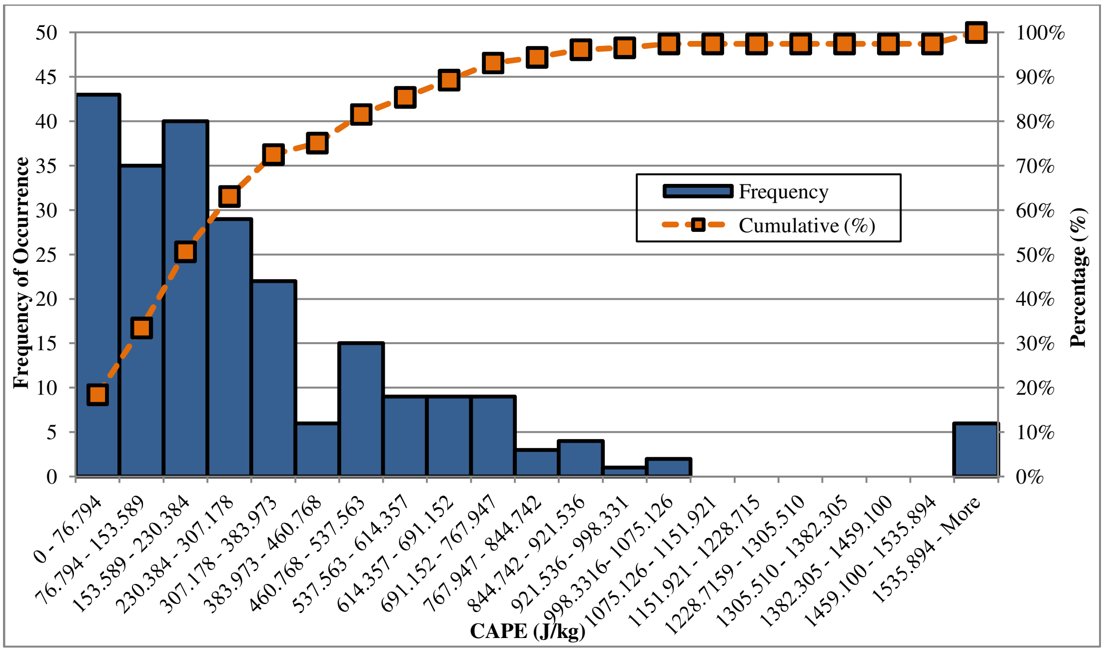


Figure 10-99 - CAPE Frequency Distribution and Cumulative Frequency Distribution for Lightning-Related Outages, South Scotland

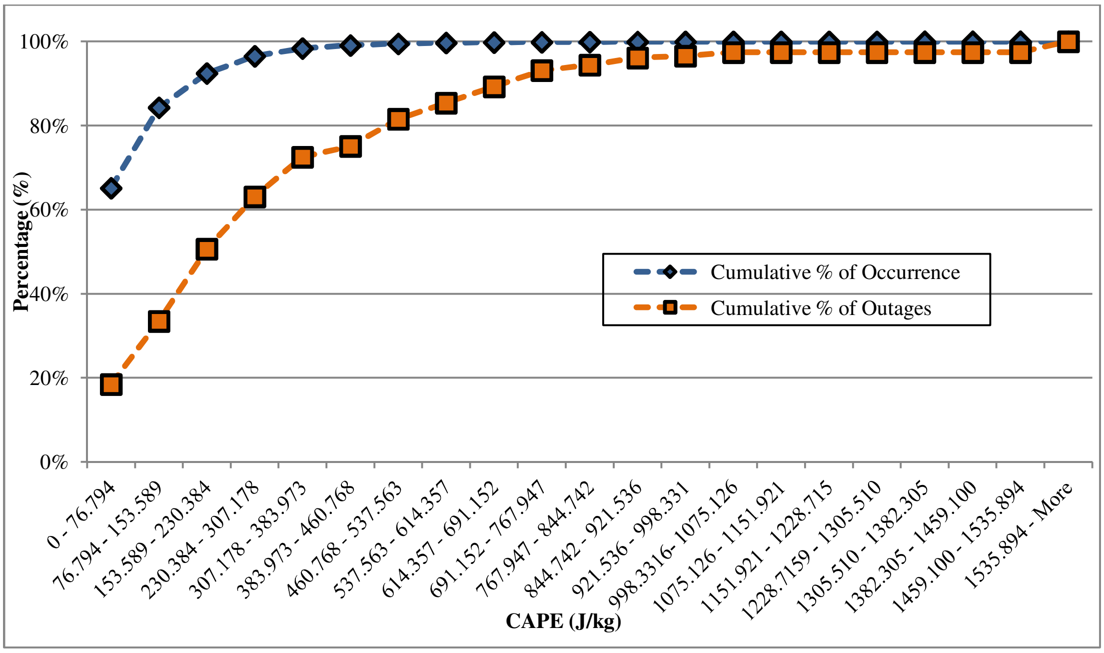


Figure 10-100 - Cumulative Distribution Function for Lightning-Related Outages and CAPE (J/kg) Occurrences, South Scotland

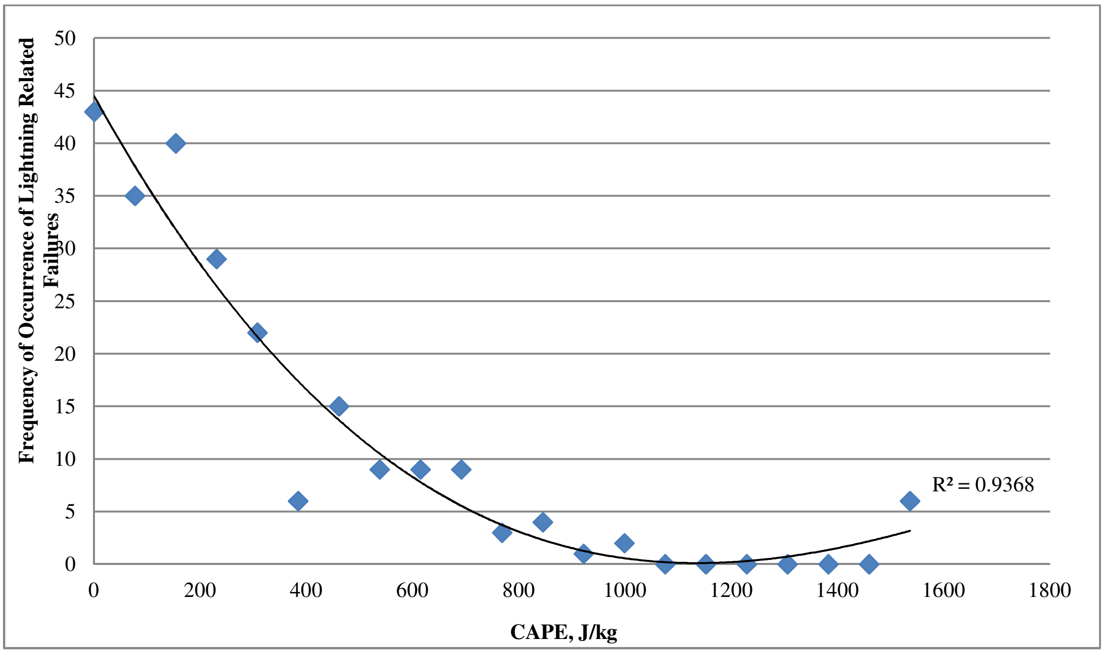


Figure 10-101 - Relationship between Lightning-Related Outages and CAPE (J/kg), South Scotland

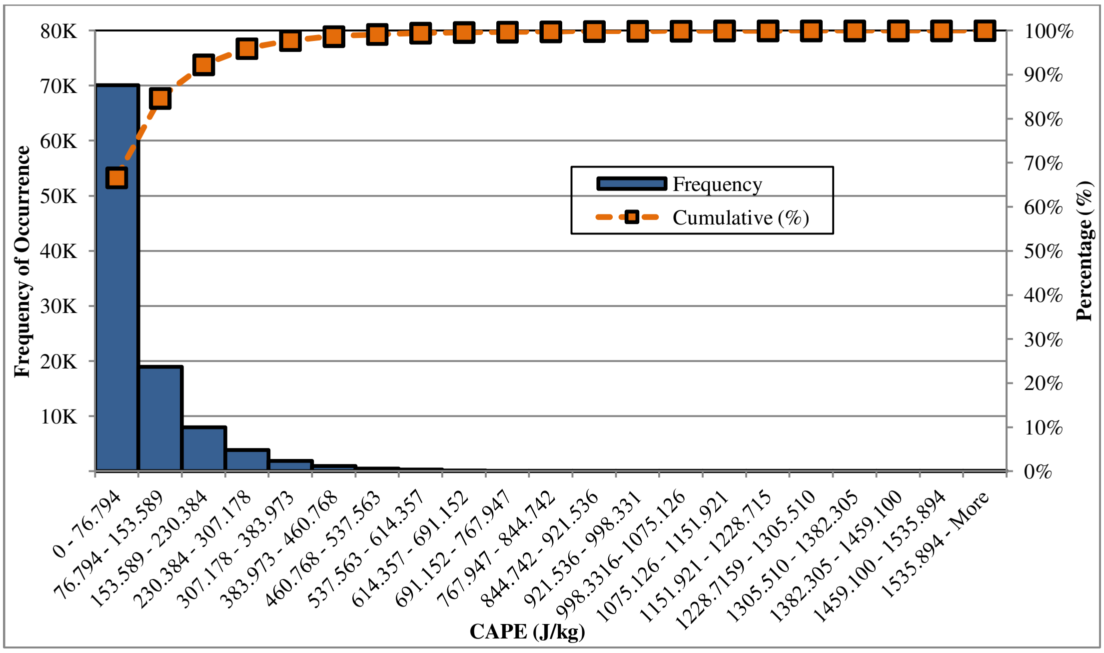


Figure 10-102 - Frequency Distribution and Cumulative Frequency Distribution for CAPE Occurrences, North England and North Wales

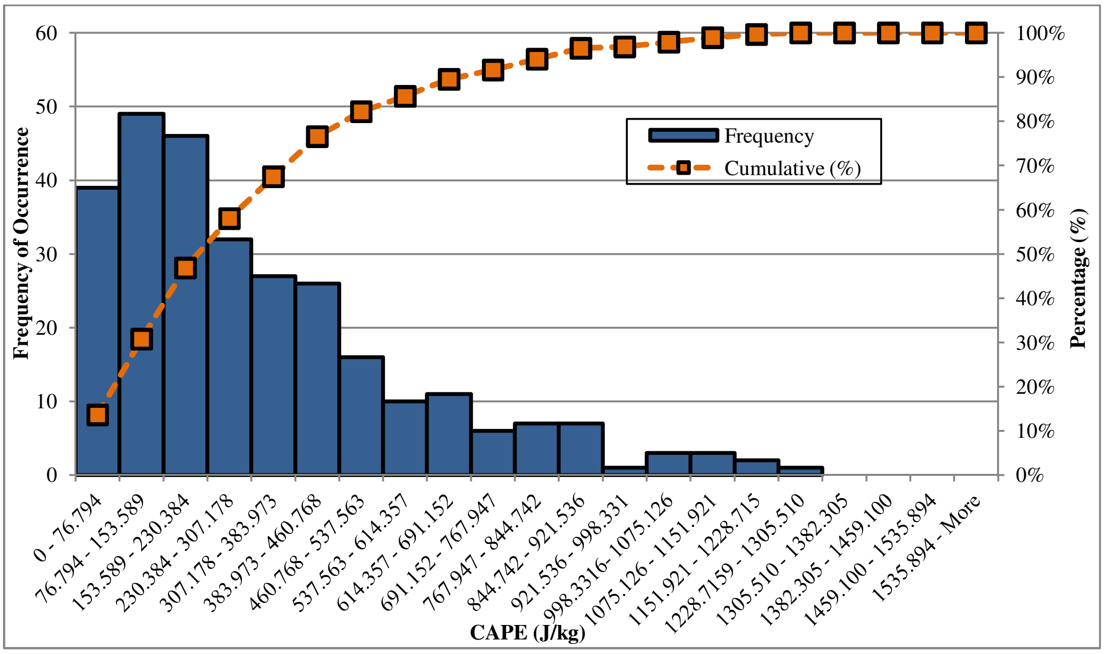


Figure 10-103 - CAPE Frequency Distribution and Cumulative Frequency Distribution for Lightning-Related Outages, North England and North Wales

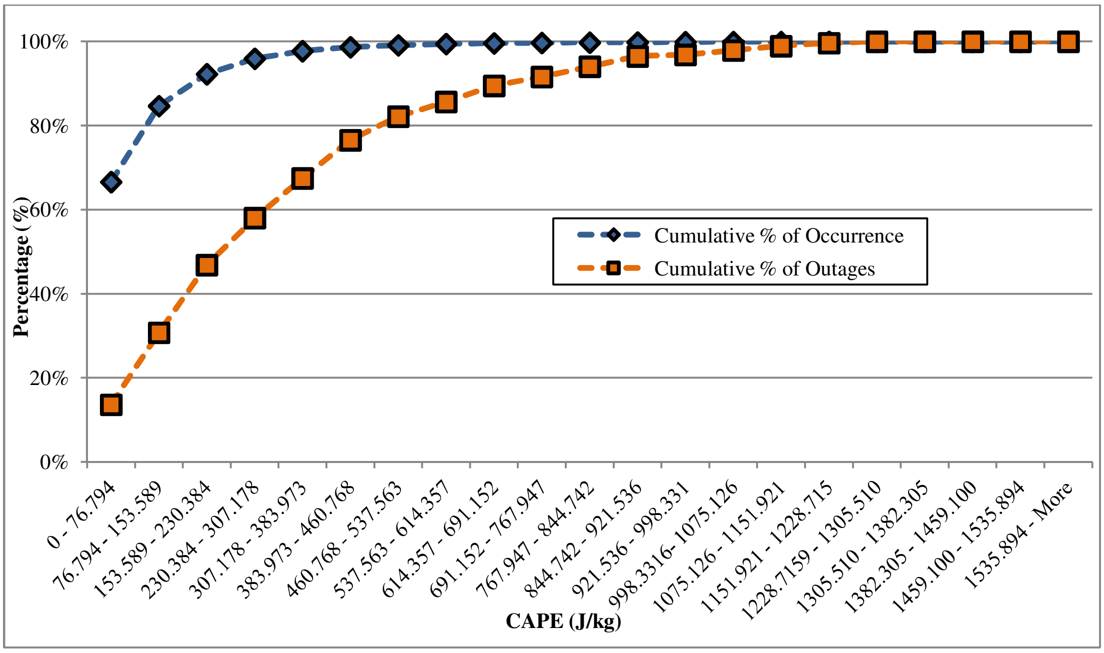


Figure 10-104 - Cumulative Distribution Function for Lightning-Related Outages and CAPE (J/kg) Occurrences, North England and North Wales

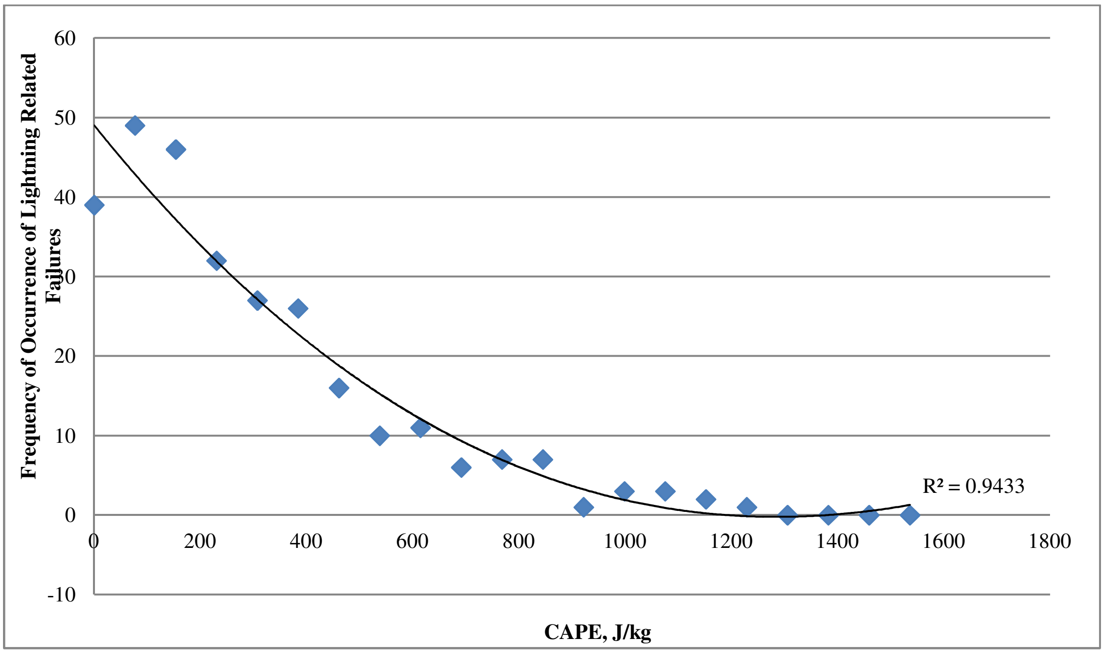


Figure 10-105 - Relationship between Lightning-Related Outages and CAPE (J/kg), North England and North Wales

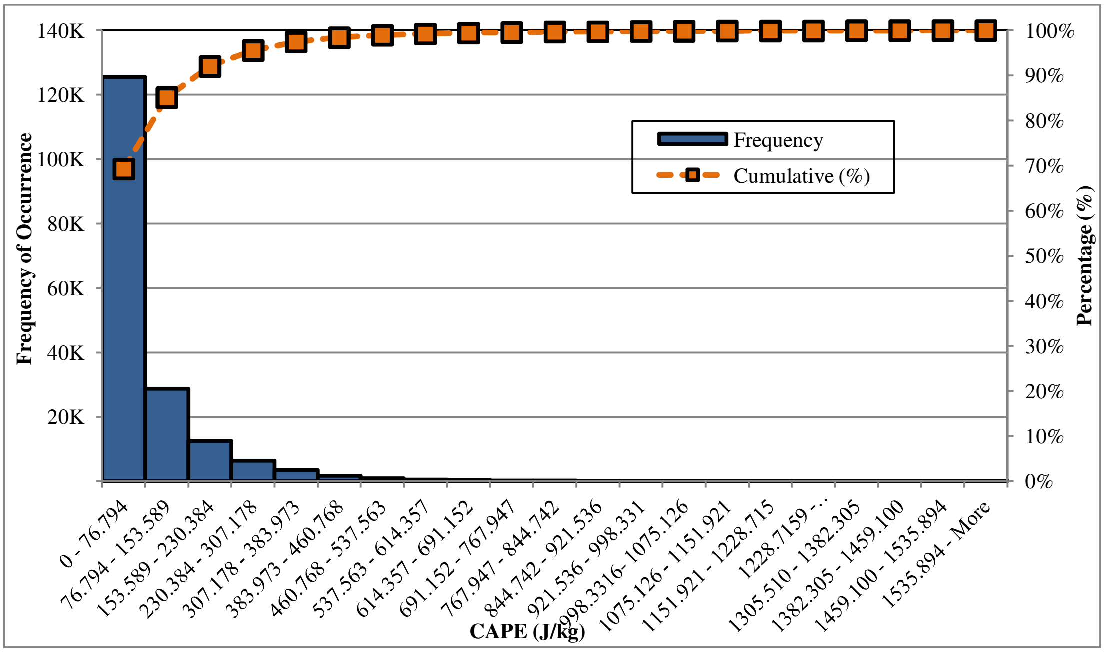


Figure 10-106 - Frequency Distribution and Cumulative Frequency Distribution for CAPE Occurrences, South England and South Wales

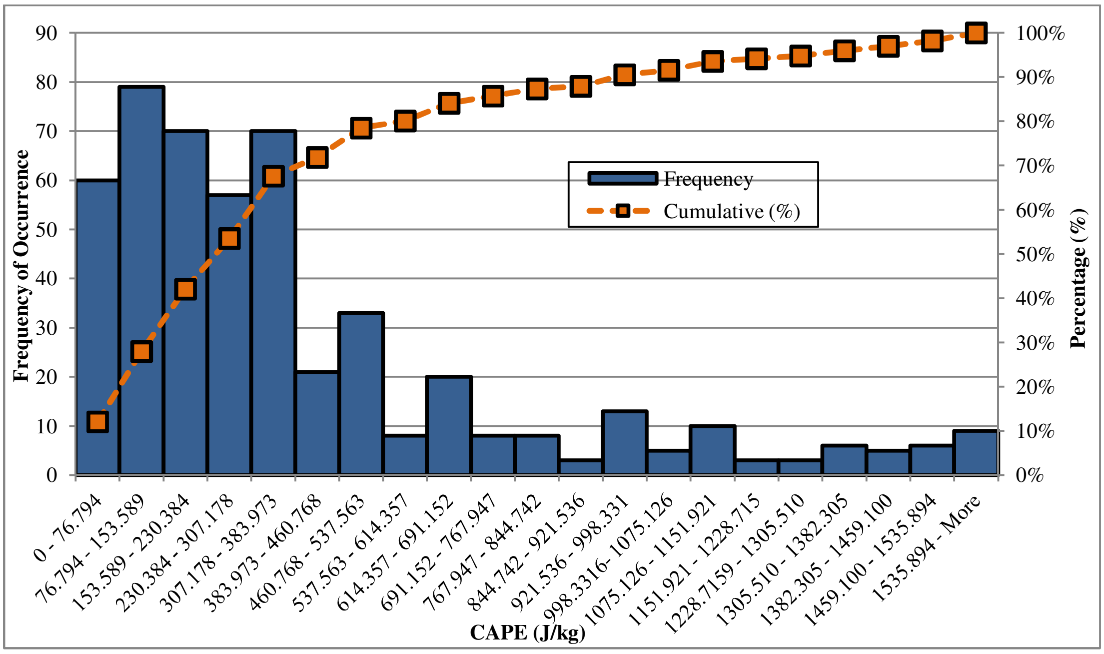


Figure 10-107 - CAPE Frequency Distribution and Cumulative Frequency Distribution for Lightning-Related Outages, South England and South Wales

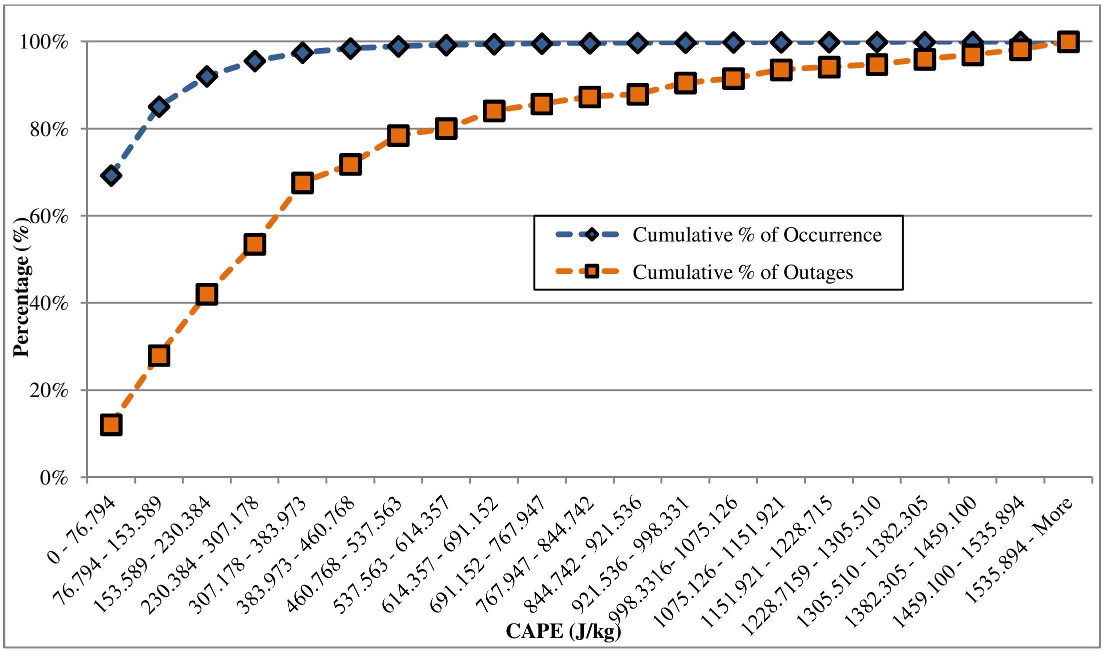


Figure 10-108 - Cumulative Distribution Function for Lightning-Related Outages and CAPE (J/kg) Occurrences, South England and South Wales

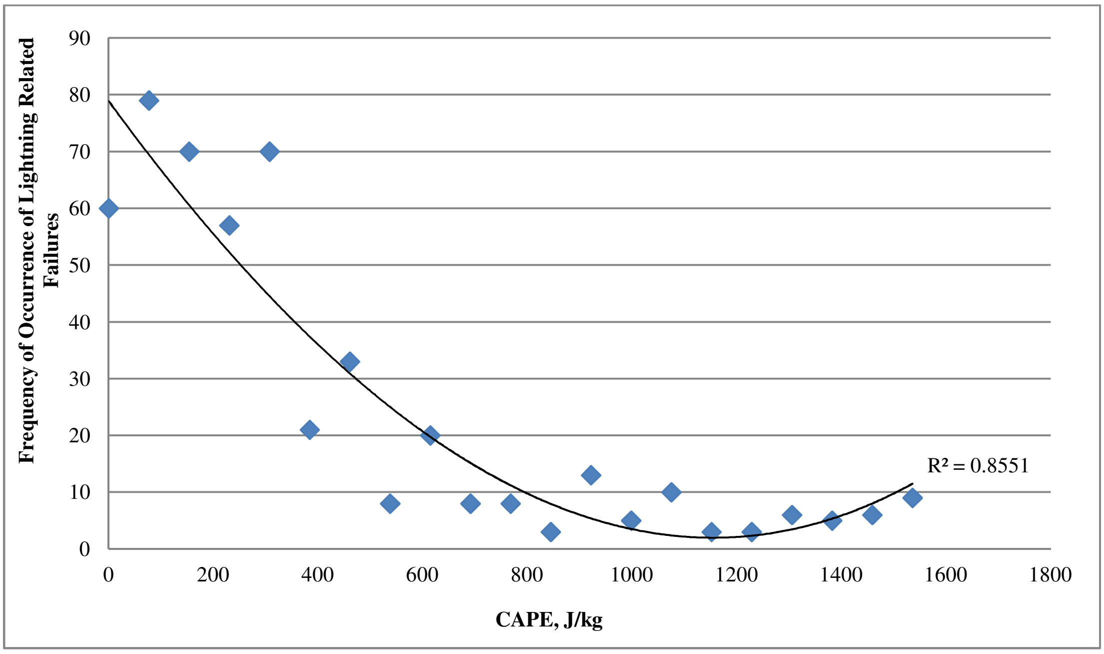


Figure 10-109 - Relationship between Lightning-Related Outages and CAPE (J/kg), South England and South Wales

Appendix E: Duration Statistical Analysis for South Scotland, North England and North Wales and South England and South Wales

This appendix contains the results for South Scotland, North England and North Wales, and South England and South Wales for the investigation into the trend between weather values and transient and permanent outages, the investigation between the mean and median and weather values and the correlation analysis between weather values and outage durations. These results are for Wind, Gales and Windborne Objects', 'Lightning', and 'SSB & Ice' related outages. As displayed in Section 7.2 for North Scotland.

E-1 Transient and Permanent Relationship to Weather Value

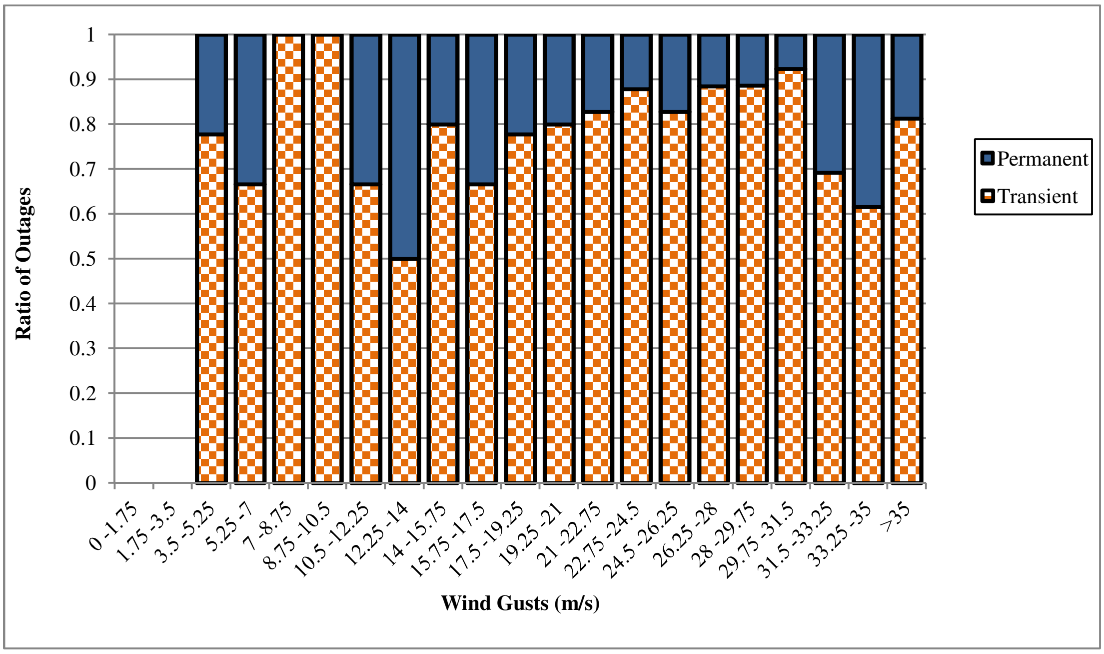


Figure 10-110 – Wind-Related Outage Ratios between Transient and Permanent – South Scotland

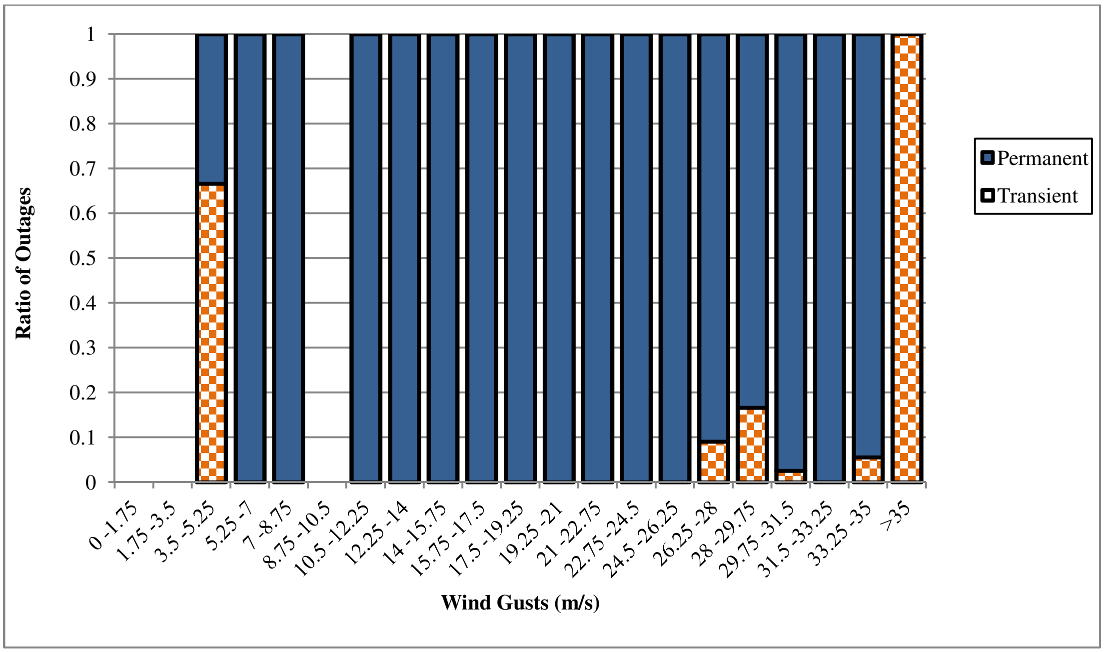


Figure 10-111 – Wind-Related Outage Ratios between Transient and Permanent – North England and North Wales

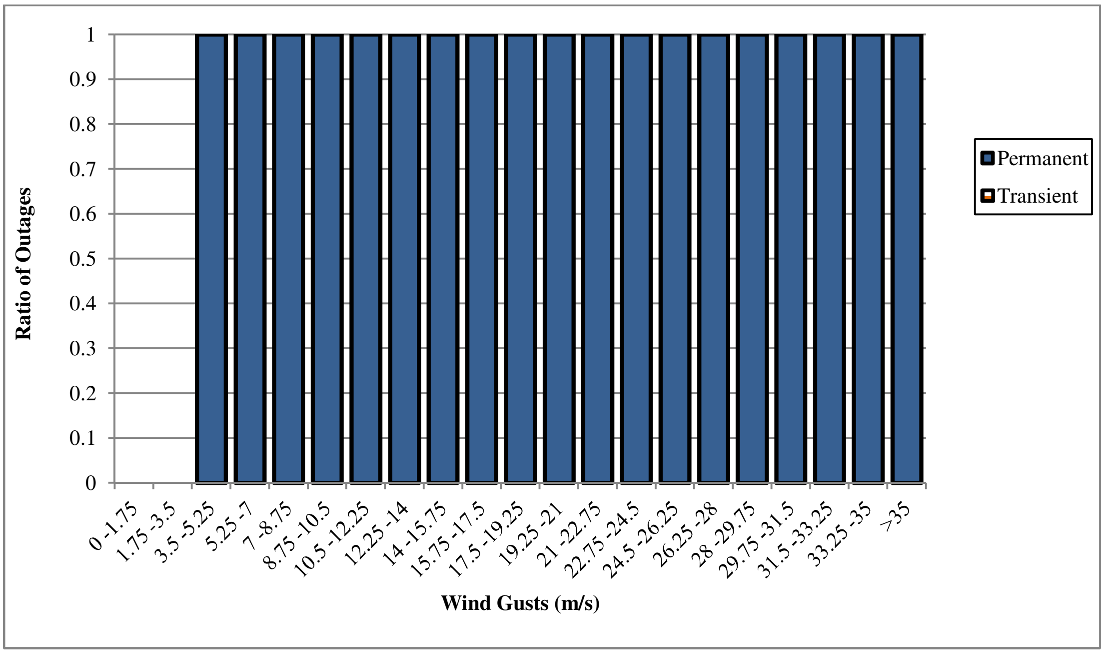


Figure 10-112 – Wind-Related Outage Ratios between Transient and Permanent – South England and South Wales

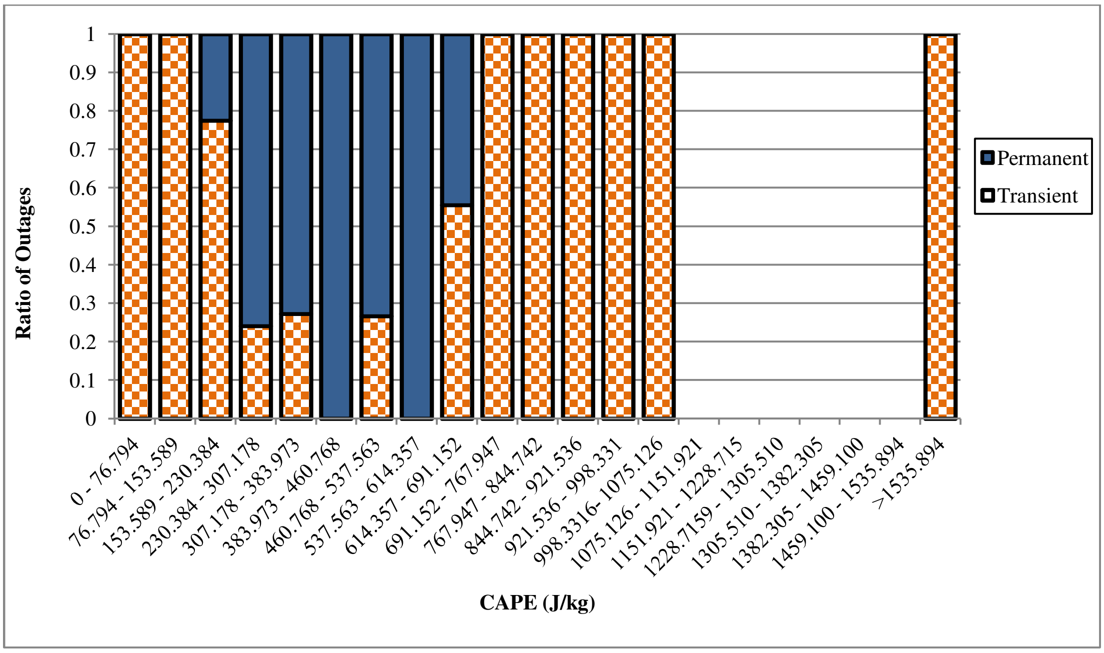


Figure 10-113 – Lightning-Related Outage Ratios between Transient and Permanent – South Scotland

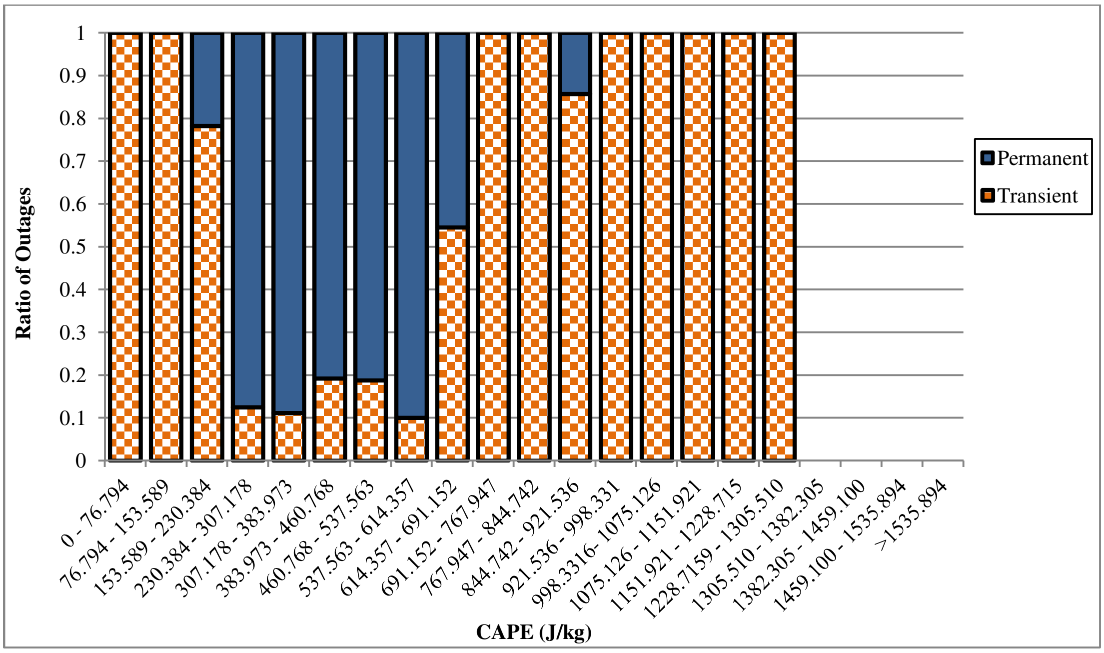


Figure 10-114 – Lightning-Related Outage Ratios between Transient and Permanent – North England and North Wales

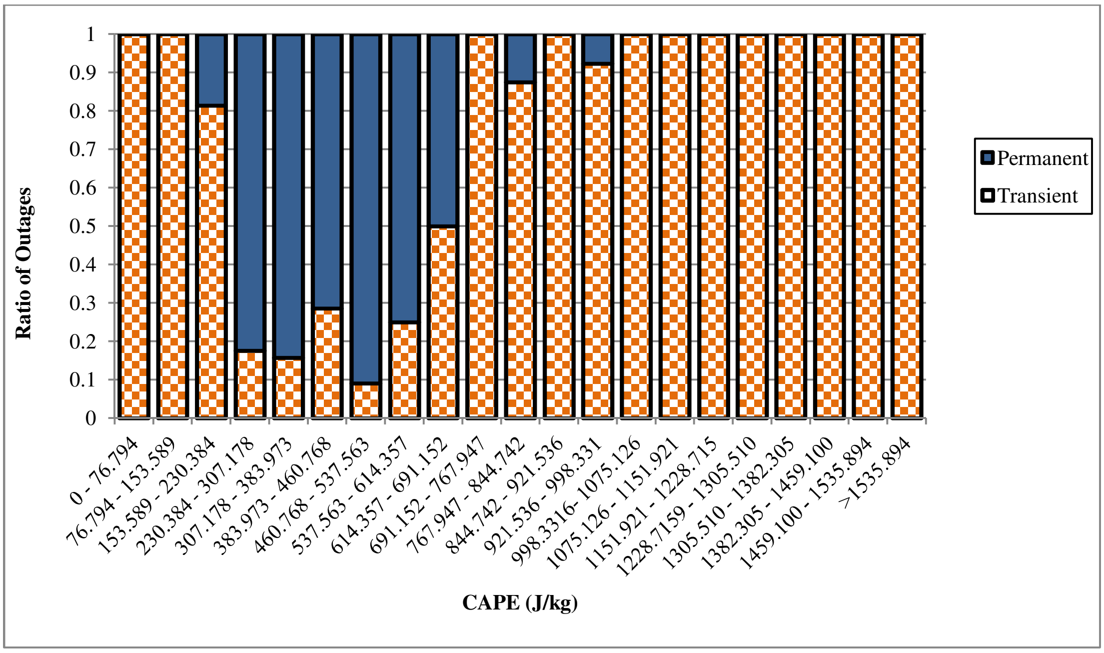


Figure 10-115 – Lightning-Related Outage Ratios between Transient and Permanent – South England and South Wales

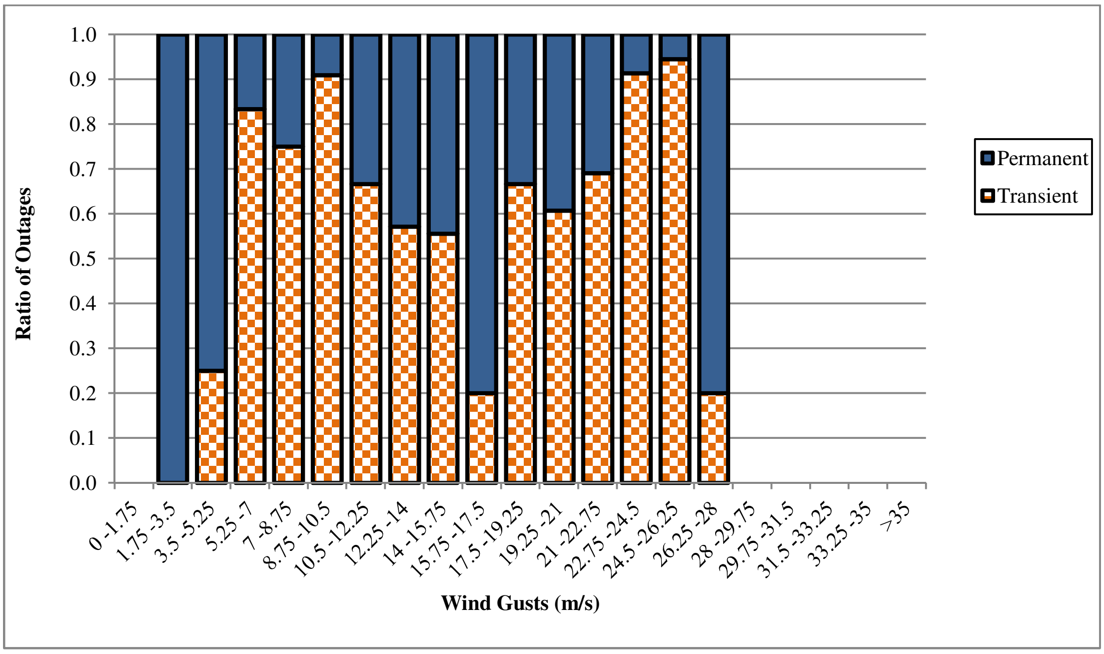


Figure 10-116 – Snow-Related Outage Ratios between Transient and Permanent – South Scotland

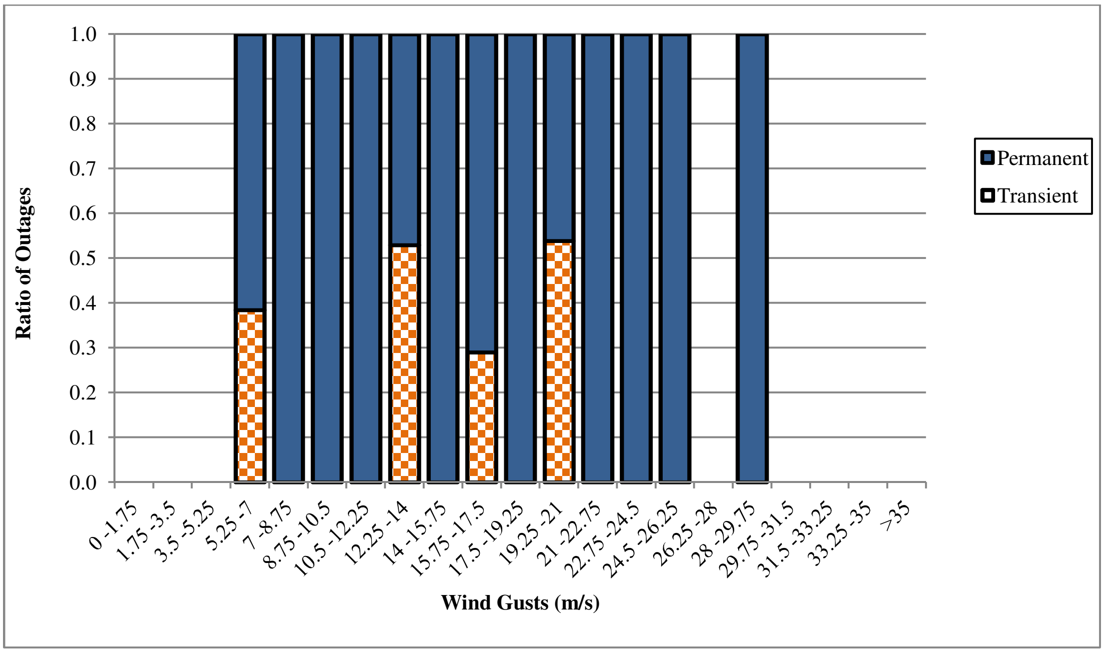


Figure 10-117 – Snow-Related Outage Ratios between Transient and Permanent – North England and North Wales

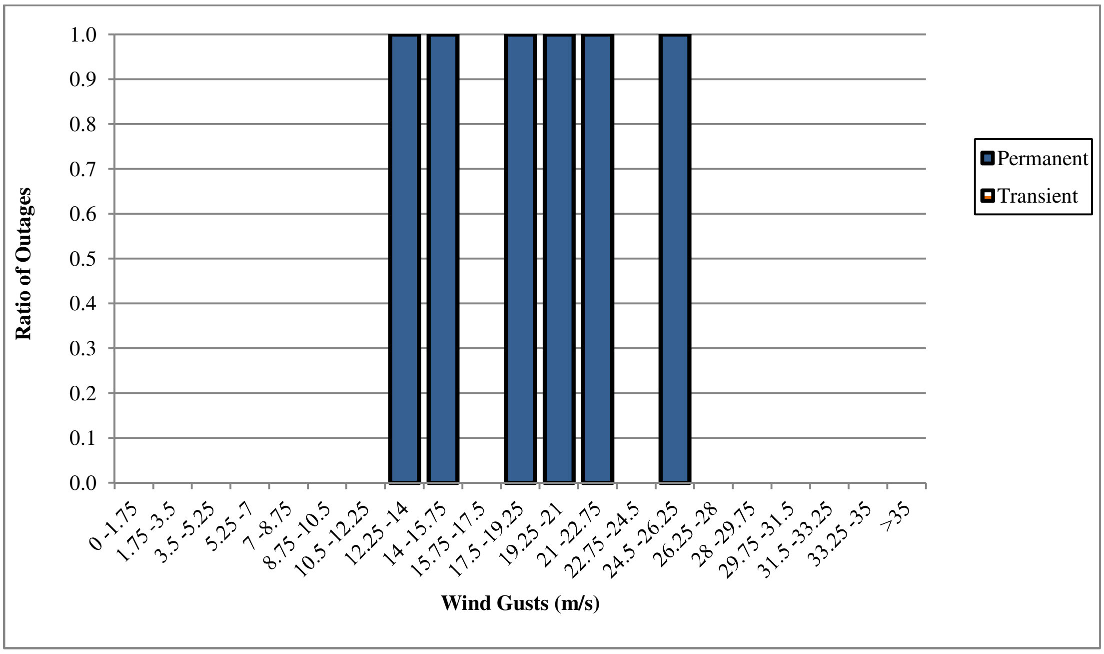


Figure 10-118 – Snow-Related Outage Ratios between Transient and Permanent – South England and South Wales

E-2 Mean and Median and Weather Values

Table E-1 – Wind-Related Outage Mean and Median Durations – South Scotland (hrs)

Wind Gusts (m/s)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 -1.75	N/A	N/A	N/A	N/A
1.75 -3.5	0.000	0.000	3.330	3.330
3.5 -5.25	0.284	0.261	12.850	12.850
5.25 -7	0.000	0.000	3.150	3.150
7 -8.75	0.000	0.000	N/A	N/A
8.75 -10.5	0.063	0.04	N/A	N/A
10.5 -12.25	0.285	0.115	30.994	18.920
12.25 -14	0.110	0.100	6.527	7.670
14 -15.75	0.105	0.060	1.480	1.480
15.75 -17.5	0.000	0.000	125.480	125.480
17.5 -19.25	0.241	0.080	40.835	40.835
19.25 -21	0.098	0.020	14.735	13.820
21 -22.75	0.112	0.000	8.009	4.255
22.75 -24.5	0.095	0.000	16.462	3.280
24.5 -26.25	0.085	0.020	6.453	2.470
26.25 -28	0.070	0.000	118.173	173.670
28 -29.75	0.124	0.030	18.666	24.270
29.75 -31.5	0.304	0.165	110.755	110.755
31.5 -33.25	0.230	0.120	42.195	1.935
33.25 -35	0.144	0.020	55.709	13.770
>35	0.287	0.221	5.102	3.370

Table E-2 – Wind-Related Outage Mean and Median Durations – North England and North Wales (hrs)

Wind Gusts (m/s)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 -1.75	N/A	N/A	N/A	N/A
1.75 -3.5	N/A	N/A	12.750	12.750
3.5 -5.25	0.000	0.000	2.930	2.930
5.25 -7	N/A	N/A	2.013	2.013
7 -8.75	N/A	N/A	13.436	13.436
8.75 -10.5	N/A	N/A	N/A	N/A
10.5 -12.25	N/A	N/A	6.179	4.283
12.25 -14	N/A	N/A	5.887	5.340
14 -15.75	N/A	N/A	3.622	2.625
15.75 -17.5	N/A	N/A	2.904	1.870
17.5 -19.25	N/A	N/A	2.895	2.975
19.25 -21	N/A	N/A	3.350	3.535
21 -22.75	N/A	N/A	15.074	4.155
22.75 -24.5	N/A	N/A	2.303	2.354
24.5 -26.25	N/A	N/A	12.473	2.750
26.25 -28	0.000	0.000	8.886	4.335
28 -29.75	0.220	0.220	2.386	2.835
29.75 -31.5	0.020	0.020	18.452	2.498
31.5 -33.25	N/A	N/A	24.379	2.865
33.25 -35	0.000	0.000	4.530	2.229
>35	0.015	0.000	N/A	N/A

Table E-3 – Wind-Related Outage Mean and Median Durations – South England and South Wales (hrs)

Wind Gusts (m/s)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 -1.75	N/A	N/A	N/A	N/A
1.75 -3.5	N/A	N/A	0.000	0.000
3.5 -5.25	N/A	N/A	5.930	5.930
5.25 -7	N/A	N/A	2.053	2.053
7 -8.75	N/A	N/A	3.437	3.437
8.75 -10.5	N/A	N/A	4.224	4.224
10.5 -12.25	N/A	N/A	4.367	2.401
12.25 -14	N/A	N/A	0.000	0.000
14 -15.75	N/A	N/A	2.436	2.063
15.75 -17.5	N/A	N/A	5.171	4.978
17.5 -19.25	N/A	N/A	1.588	1.558
19.25 -21	N/A	N/A	2.158	1.865
21 -22.75	N/A	N/A	2.770	1.909
22.75 -24.5	N/A	N/A	3.977	2.155
24.5 -26.25	N/A	N/A	5.162	3.861
26.25 -28	N/A	N/A	2.503	2.122
28 -29.75	N/A	N/A	2.557	2.606
29.75 -31.5	N/A	N/A	2.247	1.886
31.5 -33.25	N/A	N/A	8.430	8.430
33.25 -35	N/A	N/A	3.382	2.779
>35	N/A	N/A	1.278	1.278

Table E-4 – Lightning-Related Mean and Median Durations – South Scotland (hrs)

CAPE (J/kg)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 - 76.794	0.187	0.000	N/A	N/A
76.794 - 153.589	0.166	0.02	N/A	N/A
153.589 - 230.384	0.351	0.3	85.315	1.902
230.384 - 307.178	0.346	0.38	11.316	2.500
307.178 - 383.973	0.140	0.099	22.646	1.969
383.973 - 460.768	N/A	N/A	636.723	2.300
460.768 - 537.563	0.423	0.405	6.051	1.768
537.563 - 614.357	N/A	N/A	26.062	3.100
614.357 - 691.152	0.000	0.000	2.362	1.901
691.152 - 767.947	0.021	0.000	N/A	N/A
767.947 - 844.742	0.057	0.000	N/A	N/A
844.742 - 921.536	0.005	0.000	N/A	N/A
921.536 - 998.331	0.000	0.000	N/A	N/A
998.3316- 1075.126	0.000	0.000	N/A	N/A
1075.126 - 1151.921	N/A	N/A	N/A	N/A
1151.921 - 1228.715	N/A	N/A	N/A	N/A
1228.7159 - 1305.510	N/A	N/A	N/A	N/A
1305.510 - 1382.305	N/A	N/A	N/A	N/A
1382.305 - 1459.100	N/A	N/A	N/A	N/A
1459.100 - 1535.894	N/A	N/A	N/A	N/A
>1535.894	0.000	0.000	N/A	N/A

Table E-5 – Lightning-Related Mean and Median Durations – North England and North Wales (hrs)

CAPE (J/kg)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 - 76.794	0.160	0.000	N/A	N/A
76.794 - 153.589	0.265	0.103	N/A	N/A
153.589 - 230.384	0.279	0.070	2.754	1.840
230.384 - 307.178	0.208	0.085	28.639	2.622
307.178 - 383.973	0.243	0.220	3.275	2.270
383.973 - 460.768	0.386	0.400	2.452	2.104
460.768 - 537.563	0.143	0.130	5.636	4.019
537.563 - 614.357	0.330	0.330	5.068	3.100
614.357 - 691.152	0.050	0.000	2.350	1.471
691.152 - 767.947	0.005	0.000	N/A	N/A
767.947 - 844.742	0.000	0.000	N/A	N/A
844.742 - 921.536	0.067	0.010	2.450	2.450
921.536 - 998.331	0.020	0.020	N/A	N/A
998.3316- 1075.126	0.033	0.000	N/A	N/A
1075.126 - 1151.921	0.007	0.000	N/A	N/A
1151.921 - 1228.715	0.000	0.000	N/A	N/A
1228.7159 - 1305.510	0.000	0.000	N/A	N/A
1305.510 - 1382.305	N/A	N/A	N/A	N/A
1382.305 - 1459.100	N/A	N/A	N/A	N/A
1459.100 - 1535.894	N/A	N/A	N/A	N/A
>1535.894	N/A	N/A	N/A	N/A

Table E-6 – Lightning-Related Mean and Median Durations – South England and South Wales (hrs)

CAPE (J/kg)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 - 76.794	0.273	0.225	N/A	N/A
76.794 - 153.589	0.239	0.098	N/A	N/A
153.589 - 230.384	0.373	0.383s	154.237	3.808
230.384 - 307.178	0.296	0.150	11.438	3.577
307.178 - 383.973	0.357	0.220	19.686	2.485
383.973 - 460.768	0.209	0.180	2.330	2.127
460.768 - 537.563	0.378	0.200	3.038	2.823
537.563 - 614.357	0.455	0.455	3.509	3.071
614.357 - 691.152	0.015	0.000	4.959	2.007
691.152 - 767.947	0.003	0.000	N/A	N/A
767.947 - 844.742	0.000	0.000	2.220	2.220
844.742 - 921.536	0.020	0.020	N/A	N/A
921.536 - 998.331	0.018	0.000	1.330	1.330
998.3316- 1075.126	0.000	0.000	N/A	N/A
1075.126 - 1151.921	0.029	0.000	N/A	N/A
1151.921 - 1228.715	0.007	0.000	N/A	N/A
1228.7159 - 1305.510	0.010	0.000	N/A	N/A
1305.510 - 1382.305	0.000	0.000	N/A	N/A
1382.305 - 1459.100	0.000	0.000	N/A	N/A
1459.100 - 1535.894	0.042	0.000	N/A	N/A
>1535.894	0.052	0.000	N/A	N/A

Table E-7 – Snow-Related Outage Mean and Median Durations – South Scotland (hrs)

Wind Gusts (m/s)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 -1.75	N/A	N/A	N/A	N/A
1.75 -3.5	N/A	N/A	5.950	5.950
3.5 -5.25	0.000	0.000	25.943	8.080
5.25 -7	0.018	0.000	5.000	5.000
7 -8.75	0.035	0.010	5.365	5.365
8.75 -10.5	0.017	0.000	28.880	28.880
10.5 -12.25	0.160	0.195	7.840	7.840
12.25 -14	0.015	0.020	1.767	1.500
14 -15.75	0.078	0.050	19.123	14.750
15.75 -17.5	0.238	0.075	12.414	6.710
17.5 -19.25	0.141	0.020	15.245	2.715
19.25 -21	0.189	0.020	12.355	2.870
21 -22.75	0.038	0.000	4.790	4.782
22.75 -24.5	0.055	0.020	23.205	2.061
24.5 -26.25	0.115	0.050	2.450	2.450
26.25 -28	0.000	0.000	38.203	16.950
28 -29.75	N/A	N/A	N/A	N/A
29.75 -31.5	N/A	N/A	N/A	N/A
31.5 -33.25	N/A	N/A	N/A	N/A
33.25 -35	N/A	N/A	N/A	N/A
>35	N/A	N/A	N/A	N/A

Table E-8 – Snow-Related Outage Mean and Median Durations – North England and North Wales (hrs)

Wind Gusts (m/s)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 -1.75	N/A	N/A	N/A	N/A
1.75 -3.5	N/A	N/A	N/A	N/A
3.5 -5.25	N/A	N/A	N/A	N/A
5.25 -7	0.020	0.020	7.967	3.653
7 -8.75	N/A	N/A	8.067	3.113
8.75 -10.5	N/A	N/A	9.573	5.536
10.5 -12.25	N/A	N/A	5.728	3.389
12.25 -14	0.020	0.020	3.725	2.692
14 -15.75	N/A	N/A	37.153	36.670
15.75 -17.5	0.199	0.020	3.740	2.509
17.5 -19.25	N/A	N/A	3.662	4.171
19.25 -21	0.167	0.020	35.731	6.995
21 -22.75	N/A	N/A	6.203	4.975
22.75 -24.5	N/A	N/A	3.514	3.514
24.5 -26.25	N/A	N/A	3.740	3.294
26.25 -28	N/A	N/A	N/A	N/A
28 -29.75	N/A	N/A	5.388	2.039
29.75 -31.5	N/A	N/A	N/A	N/A
31.5 -33.25	N/A	N/A	N/A	N/A
33.25 -35	N/A	N/A	N/A	N/A
>35	N/A	N/A	N/A	N/A

Table E-9 – Snow-Related Outage Mean and Median Durations – South England and South Wales (hrs)

Wind Gusts (m/s)	Transient Mean Duration (hrs)	Transient Median Duration (hrs)	Permanent Mean Duration (hrs)	Permanent Median Duration (hrs)
0 -1.75	N/A	N/A	N/A	N/A
1.75 -3.5	N/A	N/A	N/A	N/A
3.5 -5.25	N/A	N/A	N/A	N/A
5.25 -7	N/A	N/A	N/A	N/A
7 -8.75	N/A	N/A	N/A	N/A
8.75 -10.5	N/A	N/A	N/A	N/A
10.5 -12.25	N/A	N/A	N/A	N/A
12.25 -14	N/A	N/A	74.921	6.195
14 -15.75	N/A	N/A	77.341	14.680
15.75 -17.5	N/A	N/A	N/A	N/A
17.5 -19.25	N/A	N/A	7.987	3.359
19.25 -21	N/A	N/A	4.224	2.335
21 -22.75	N/A	N/A	4.624	4.493
22.75 -24.5	N/A	N/A	N/A	N/A
24.5 -26.25	N/A	N/A	1.456	1.456
26.25 -28	N/A	N/A	N/A	N/A
28 -29.75	N/A	N/A	N/A	N/A
29.75 -31.5	N/A	N/A	N/A	N/A
31.5 -33.25	N/A	N/A	N/A	N/A
33.25 -35	N/A	N/A	N/A	N/A
>35	N/A	N/A	N/A	N/A

E-3 Correlation Analysis

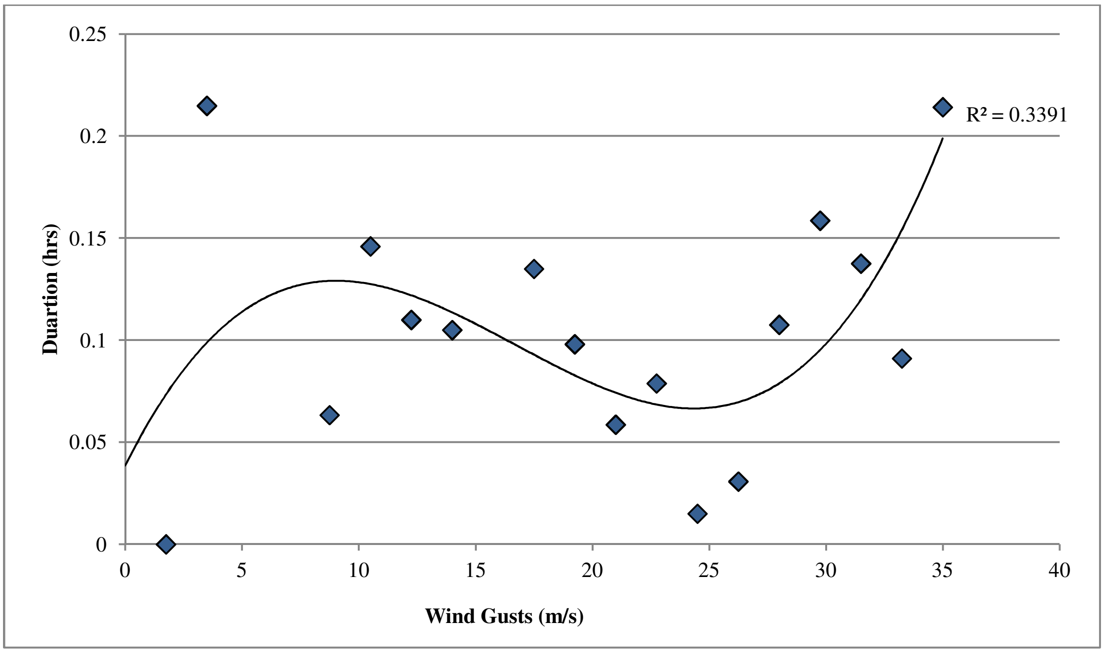


Figure 10-119 – Extremes Removed Mean Duration of Wind-Related Outage at Specific Wind Gust Values – Transient Outages South Scotland

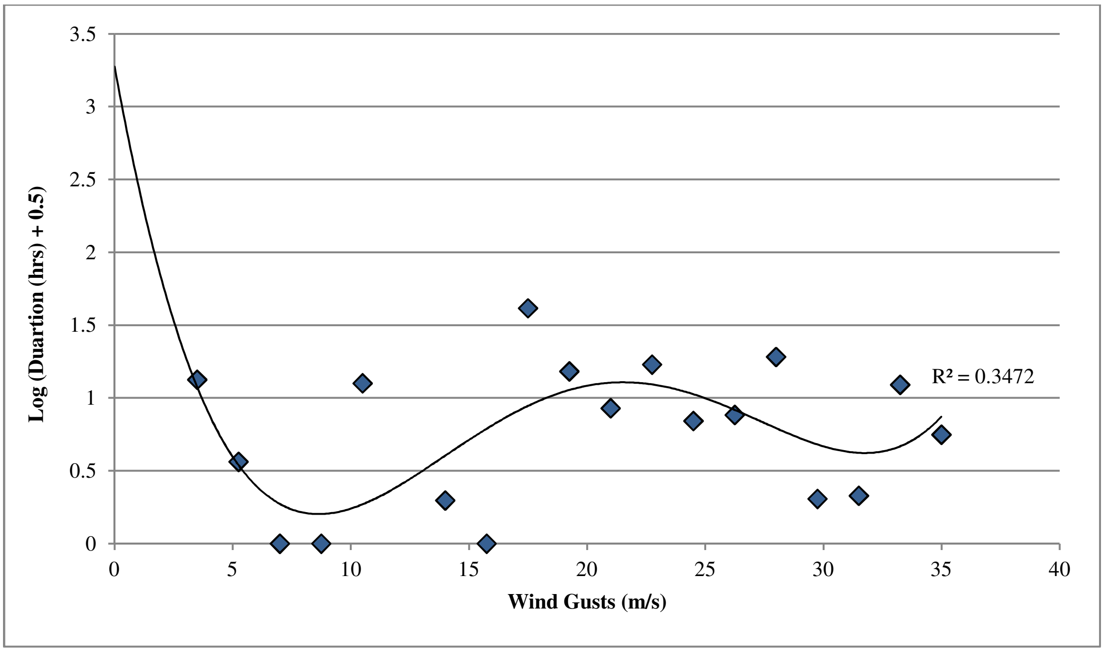


Figure 10-120 – Log Transformed Extremes Removed Mean Duration of Wind-Related Outage at Specific Wind Gust Values – Permanent Outages South Scotland

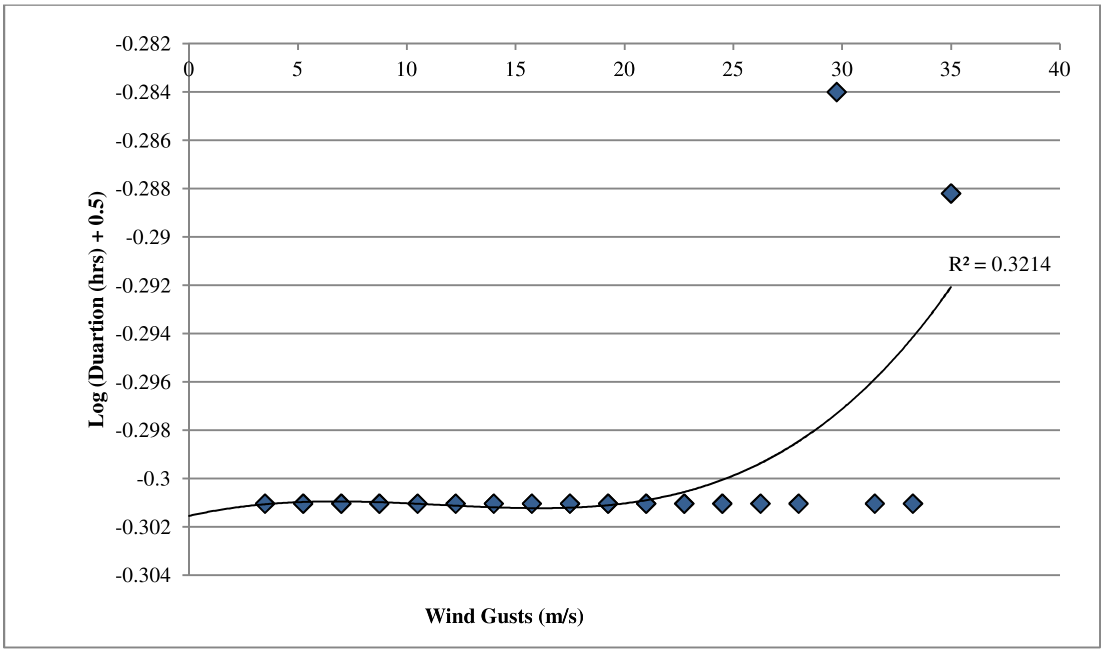


Figure 10-121 – Log Transformed Extremes Removed Mean Duration of Wind-Related Outage at Specific Wind Gust Values – Transient Outages North England and North Wales

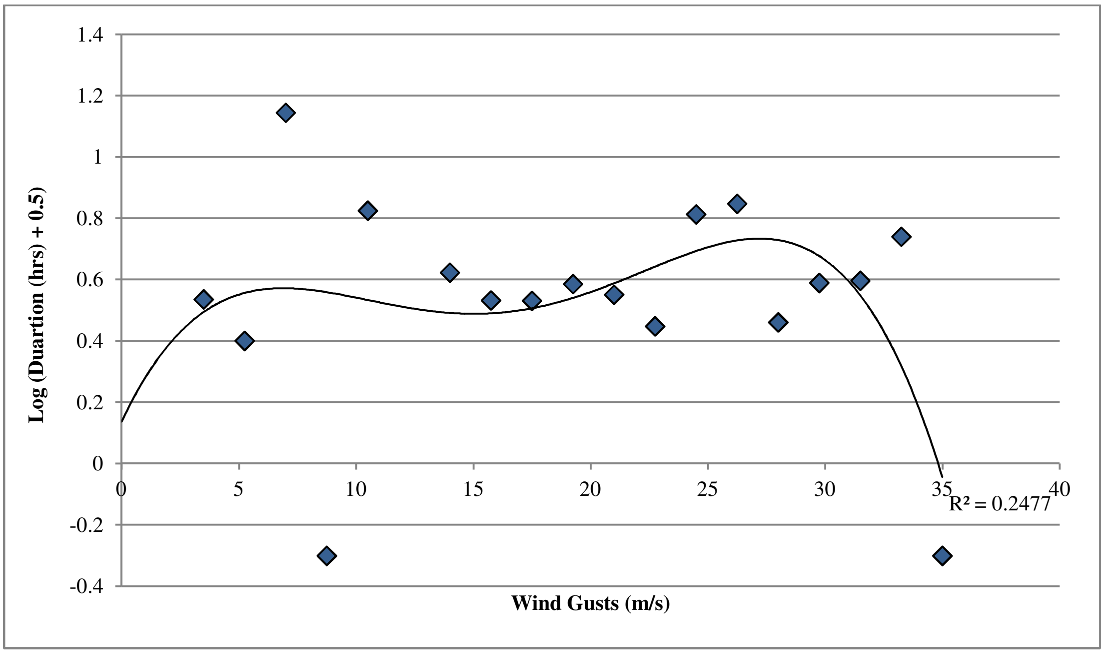


Figure 10-122 – Log Transformed Extremes Removed Mean Duration of Wind-Related Outage at Specific Wind Gust Values – Permanent Outages North England and North Wales

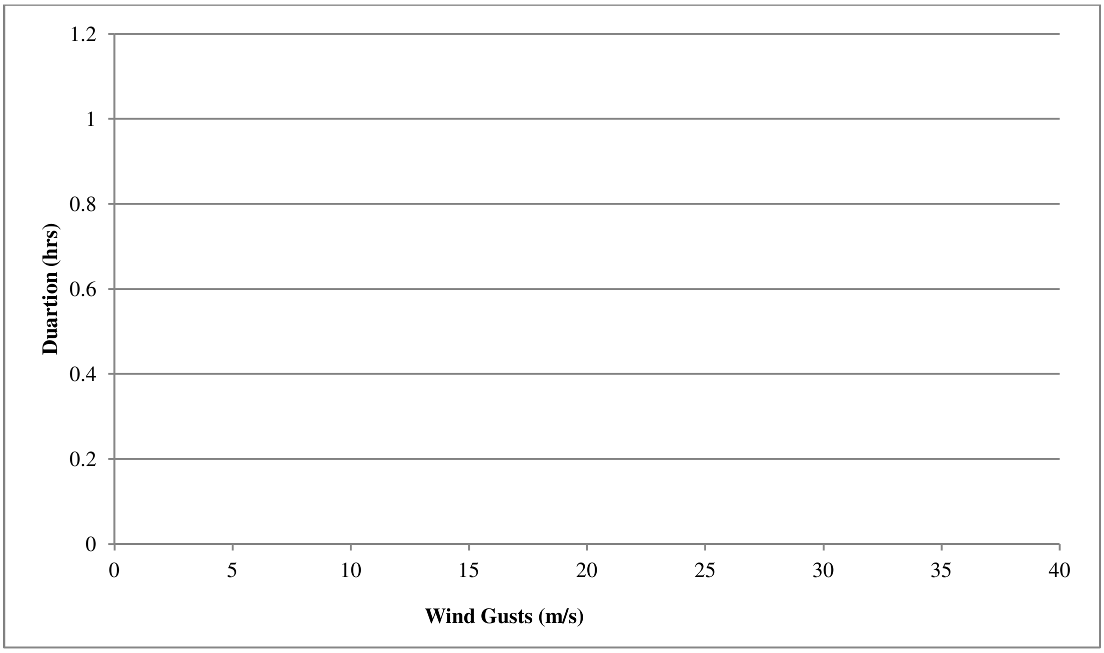


Figure 10-123 –Extremes Removed Mean Duration of Wind-Related Outage at Specific Wind Gust Values – Transient Outages South England and South Wales

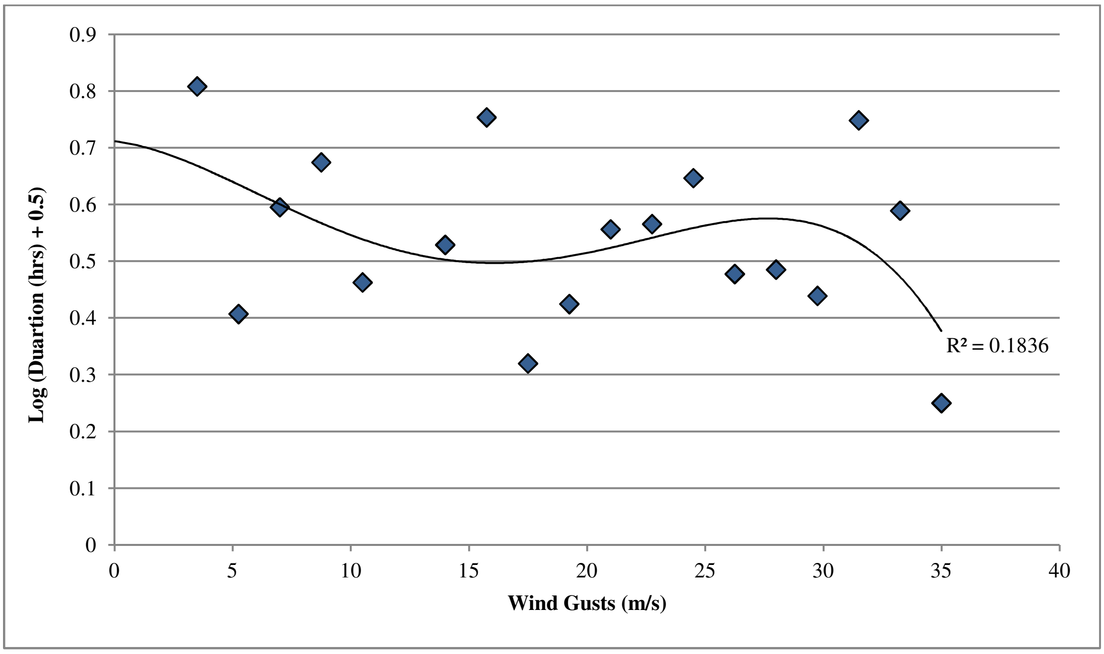


Figure 10-124 – Log Transformed Extremes Removed Mean Duration of Wind-Related Outage at Specific Wind Gust Values – Permanent Outages South England and South Wales

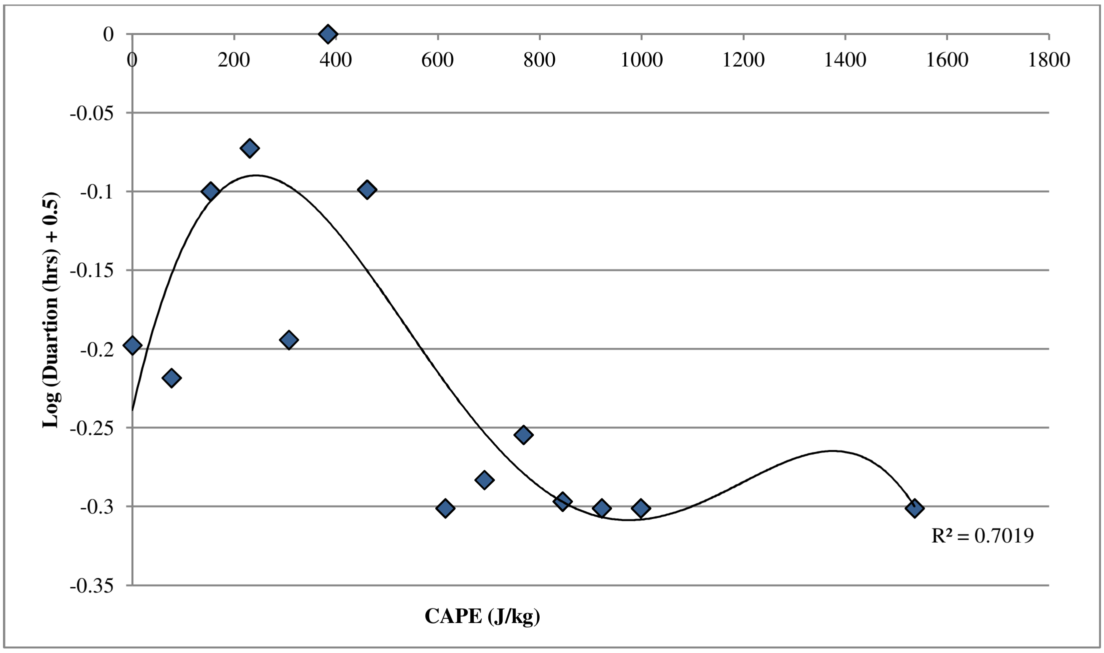


Figure 10-125 – Log Transformed Extremes Removed Mean Duration of Lightning-Related Outage at Specific CAPE Values – Transient Outages South Scotland

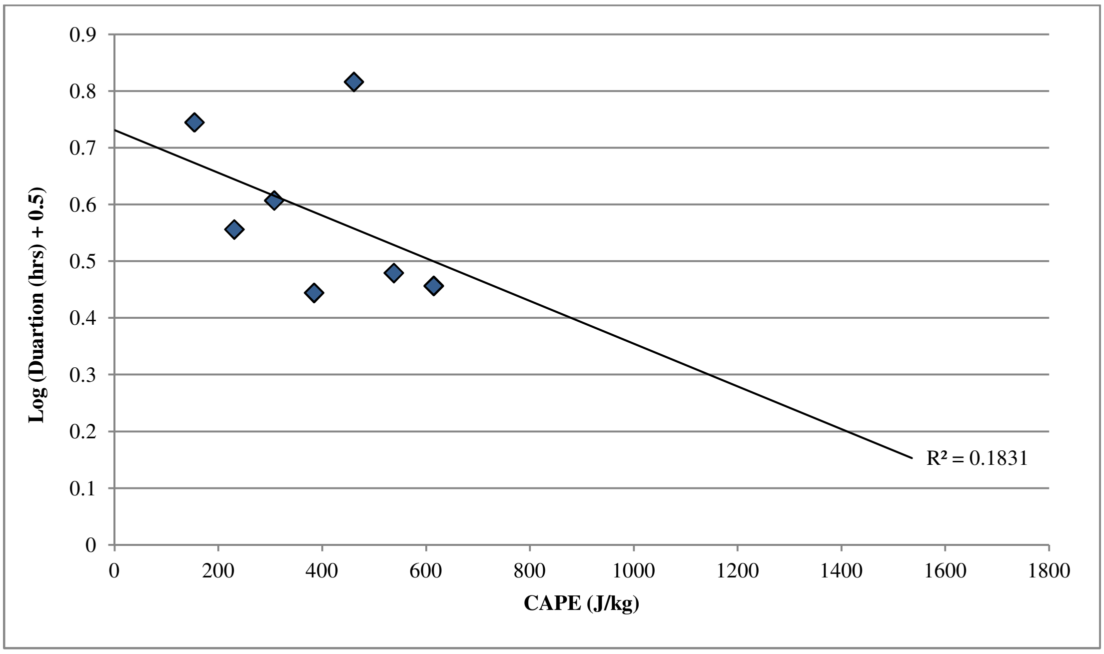


Figure 10-126 - Log Transformed Extremes Removed Mean Duration of Lightning-Related Outage at Specific CAPE Values – Permanent Outages South Scotland

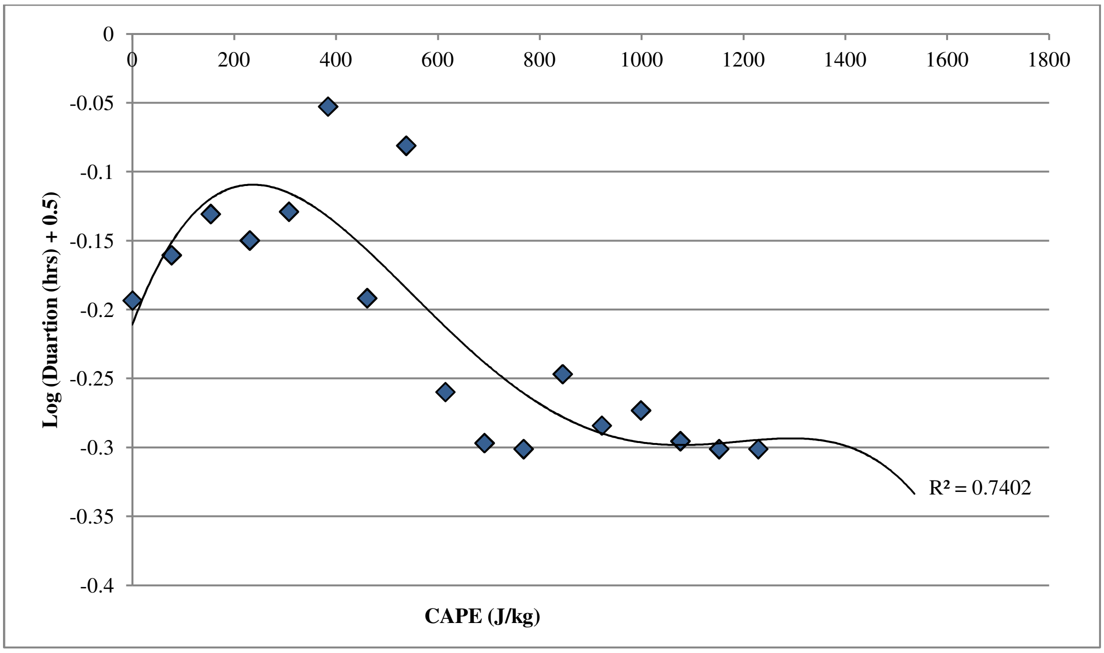


Figure 10-127 – Log Transformed Extremes Removed Mean Duration of Lightning-Related Outage at Specific CAPE Values – Transient Outages North England and North Wales

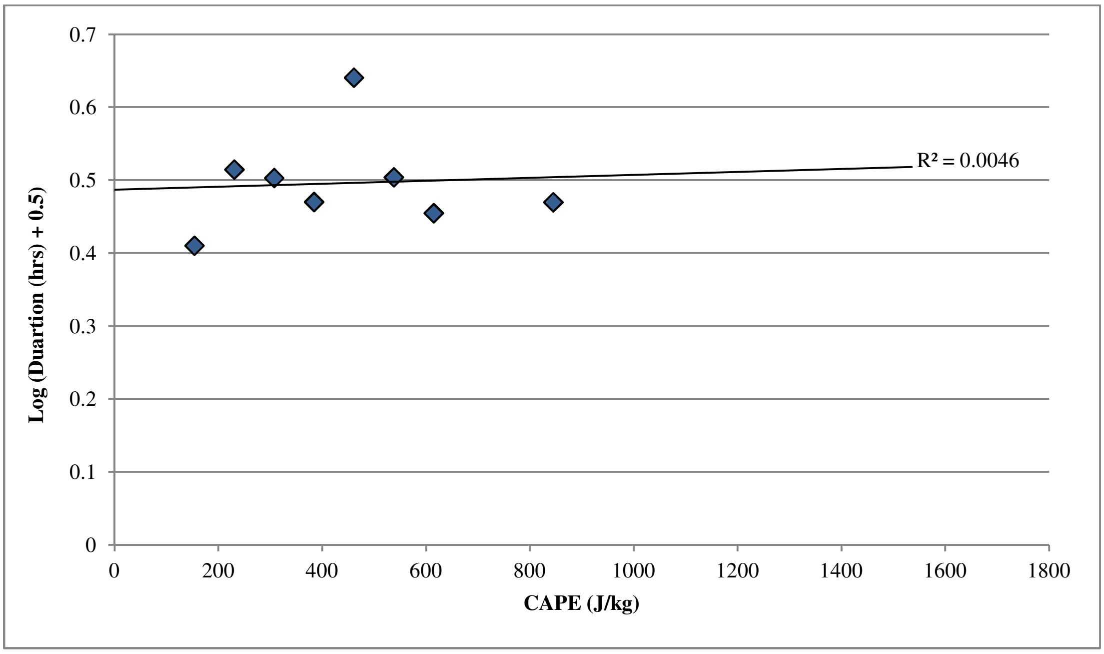


Figure 10-128 - Log Transformed Extremes Removed Mean Duration of Lightning-Related Outage at Specific CAPE Values – Permanent Outages North England and North Wales

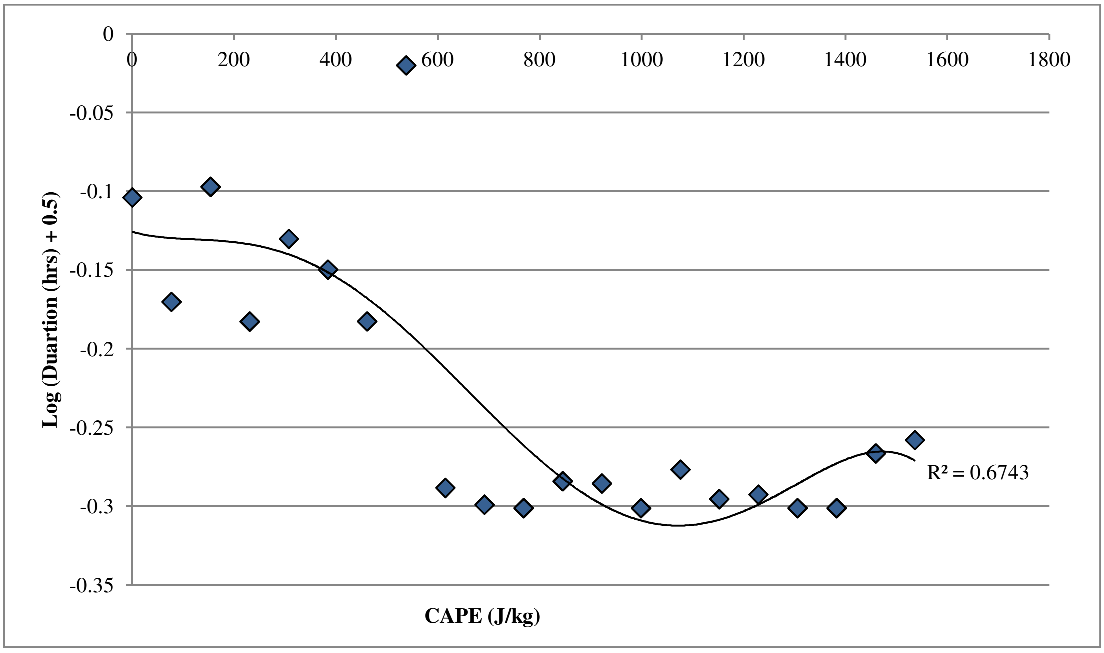


Figure 10-129 – Log Transformed Extremes Removed Mean Duration of Lightning-Related Outage at Specific CAPE Values – Transient Outages South England and South Wales

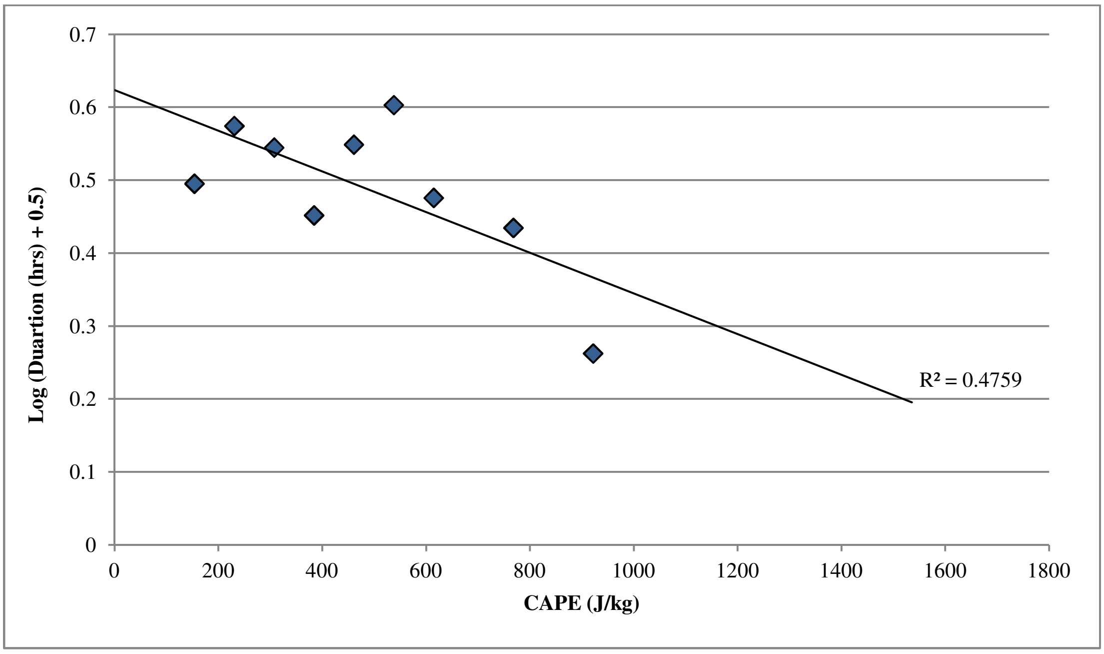


Figure 10-130 - Log Transformed Extremes Removed Mean Duration of Lightning-Related Outage at Specific CAPE Values – Permanent Outages South England and South Wales

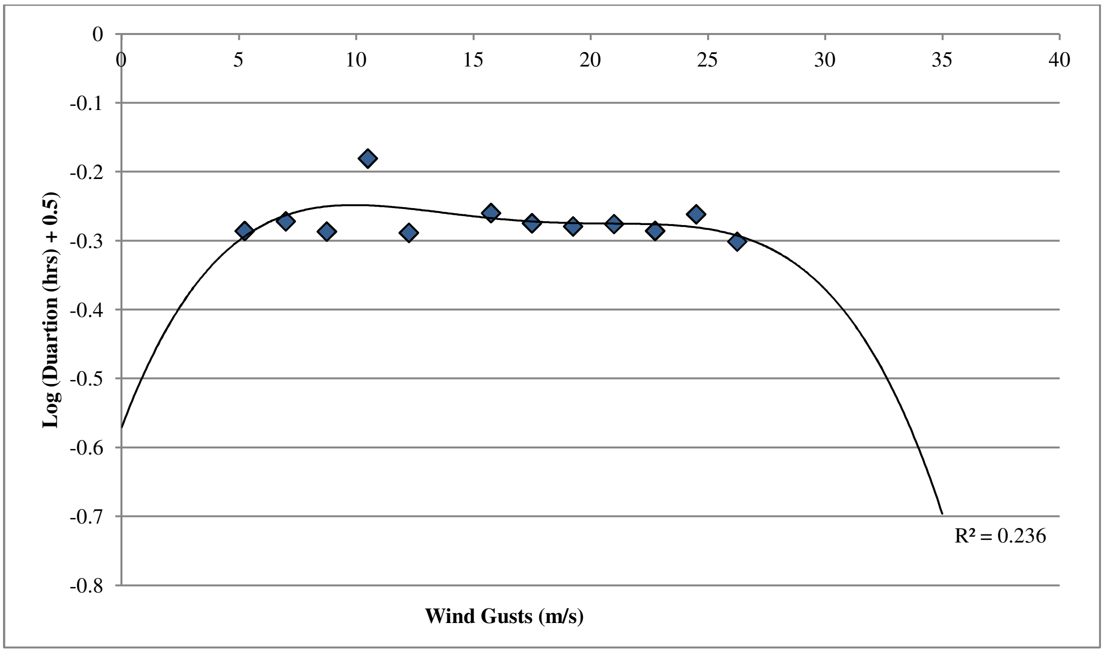


Figure 10-131 – Log Transformed Extremes Removed Mean Duration of Snow-Related Outage at Specific Wind Gust Values – Transient Outages South Scotland

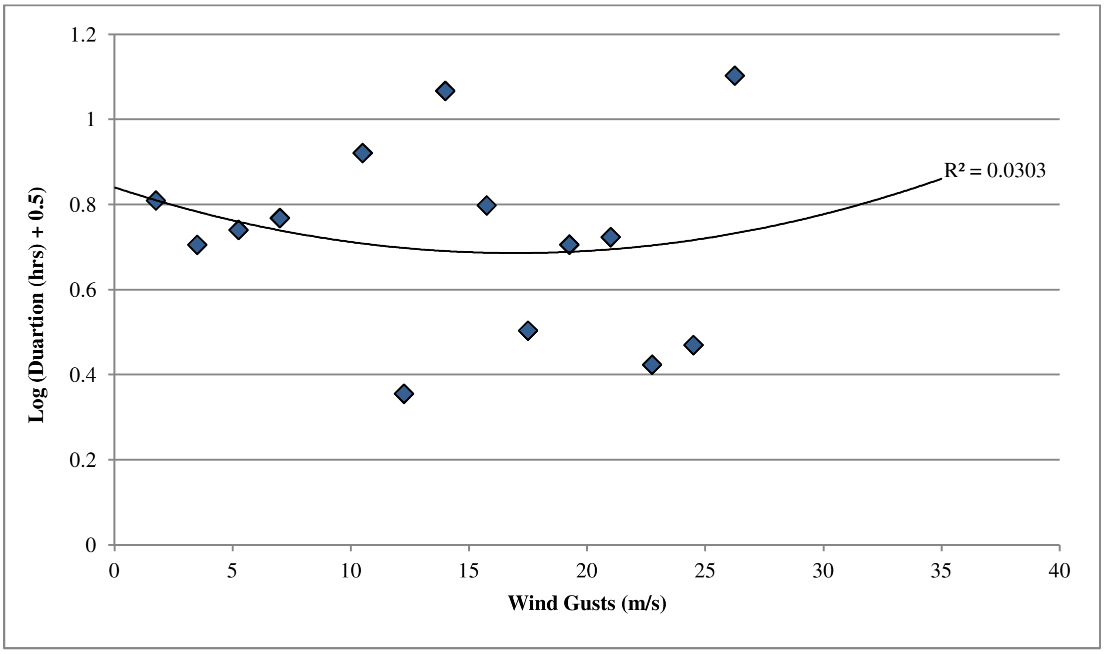


Figure 10-132 – Log Transformed Extremes Removed Mean Duration of Snow-Related Outage at Specific Wind Gust Values – Permanent Outages South Scotland

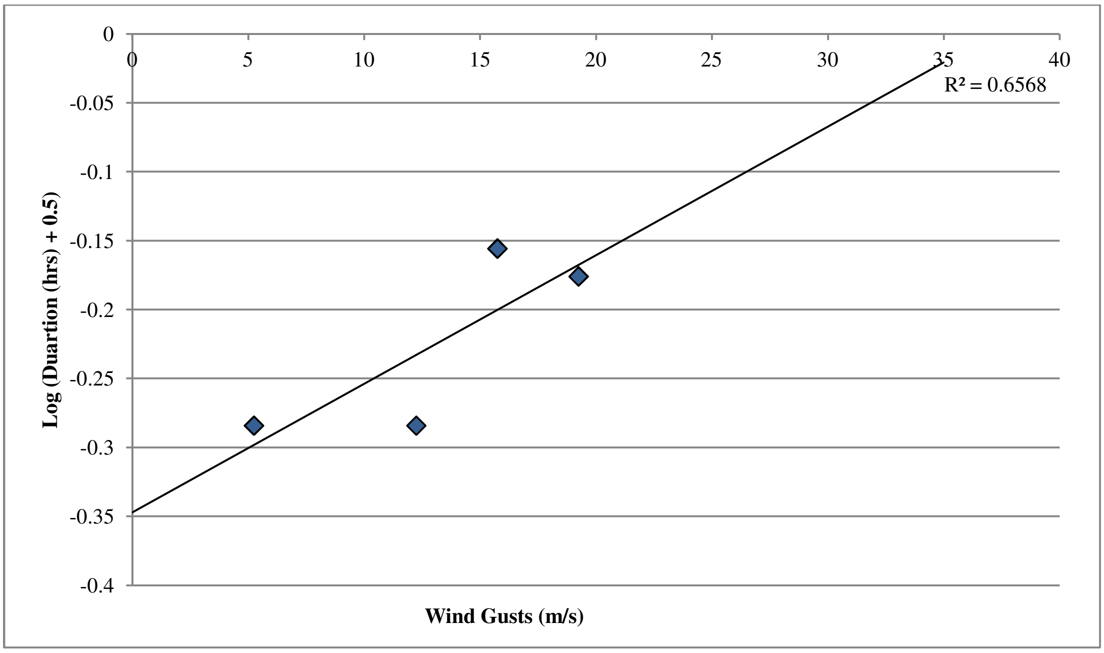


Figure 10-133 – Log Transformed Extremes Removed Mean Duration of Snow-Related Outage at Specific Wind Gust Values – Transient Outages North England and North Wales

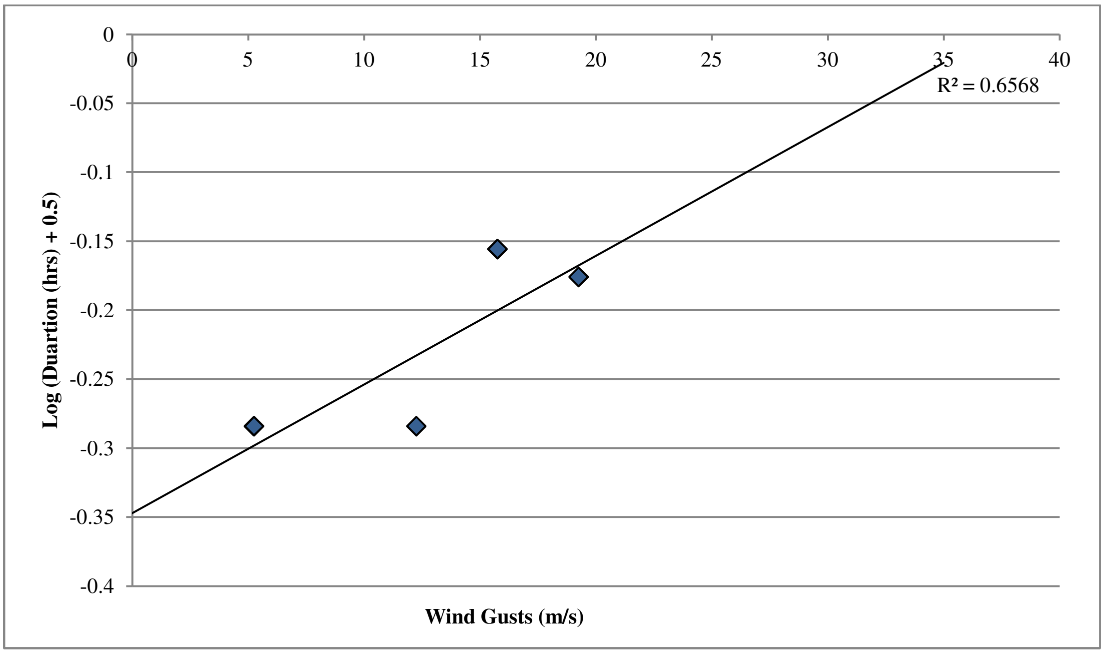


Figure 10-134 – Log Transformed Extremes Removed Mean Duration of Snow-Related Outage at Specific Wind Gust Values – Permanent Outages North England and North Wales

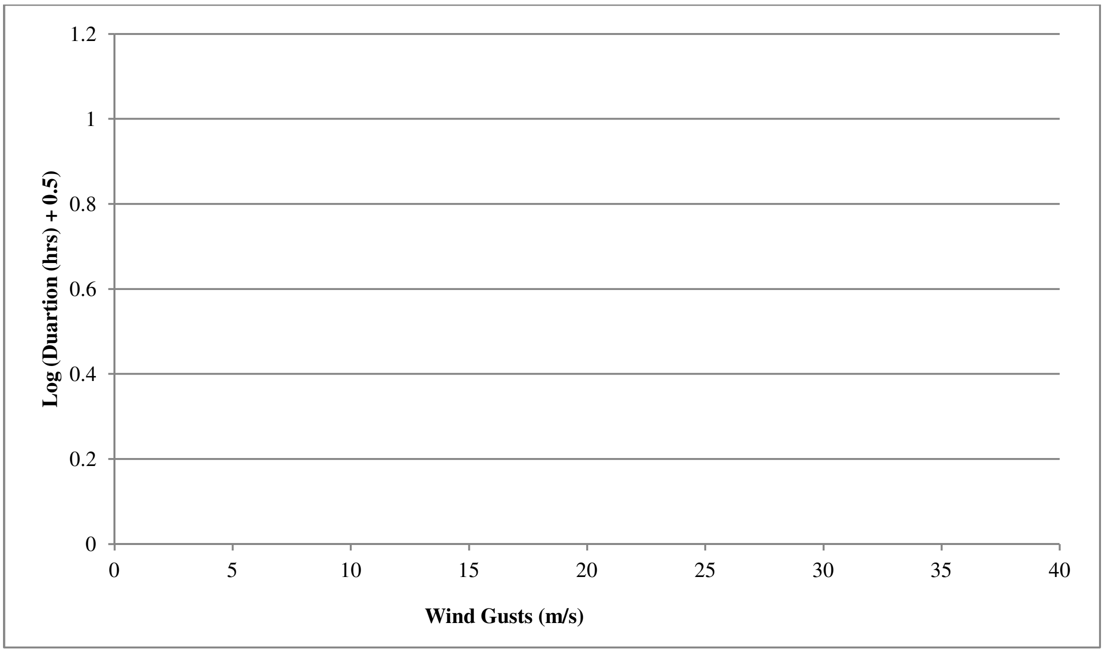


Figure 10-135 – Log Transformed Extremes Removed Mean Duration of Snow-Related Outage at Specific Wind Gust Values – Transient Outages South England and South Wales

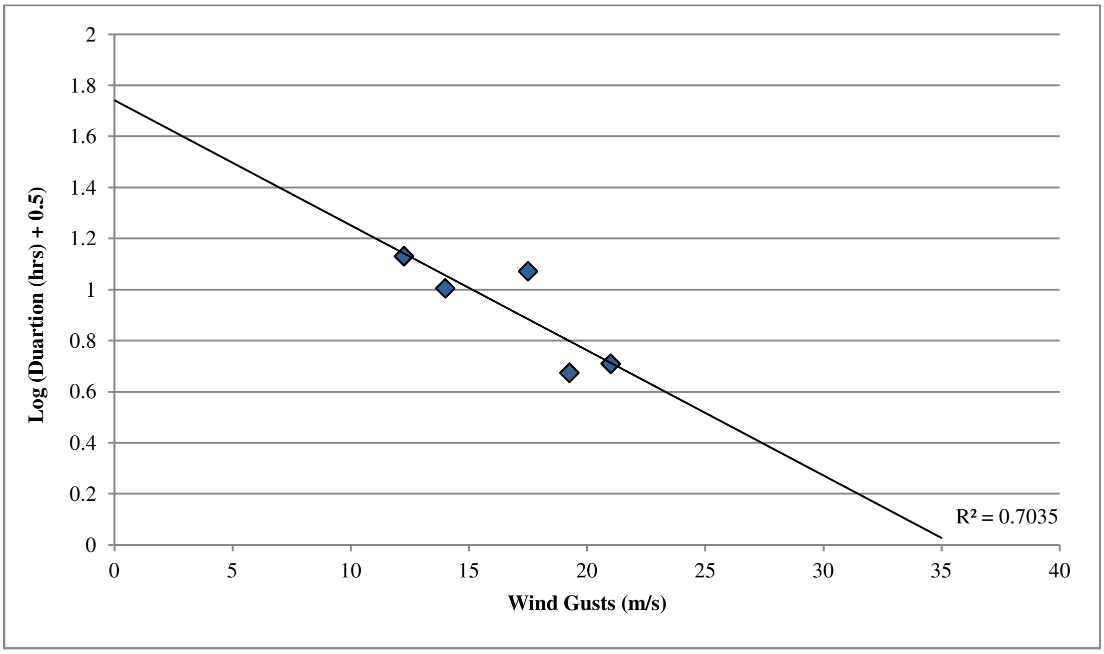


Figure 10-136 – Log Transformed Extremes Removed Mean Duration of Snow-Related Outage at Specific Wind Gust Values – Permanent Outages South England and South Wales

Appendix F: Weather Test Case Histograms for South Scotland, North England and North Wales and South England and South Wales

This appendix contains the histograms for South Scotland, North England and North Wales, and South England and South Wales for the weather test cases for the three main weather types that affect the GB network.

F-1 Wind

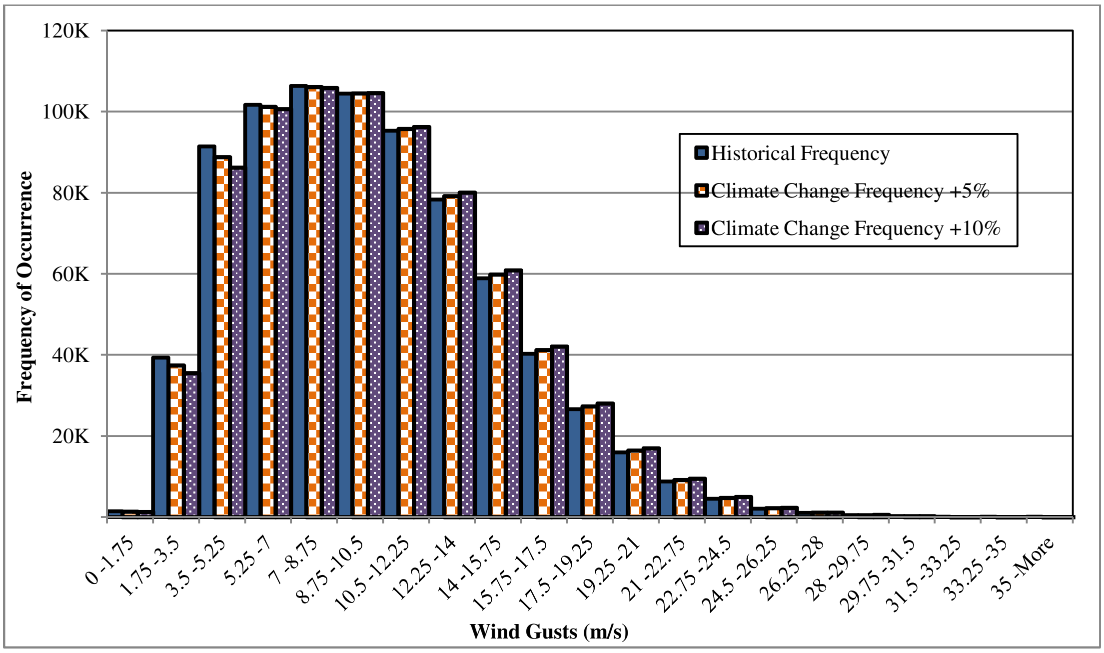


Figure 10-137 - Frequency Distribution for 10m Wind Gust Occurrences, Historical, 5% increase and 10% Increase, South Scotland

Table F-1 - Wind Gusts Extreme to Normal Ratio with 5% Increase – South Scotland

	Before	**After**
Occurrences Above Extreme	0.043	0.044
Occurrences Below Extreme	0.957	0.956

Table F-2 - Wind Gusts Extreme to Normal Ratio with 10% Increase – South Scotland

	Before	After
Occurrences Above Extreme	0.043	0.046
Occurrences Below Extreme	0.957	0.954

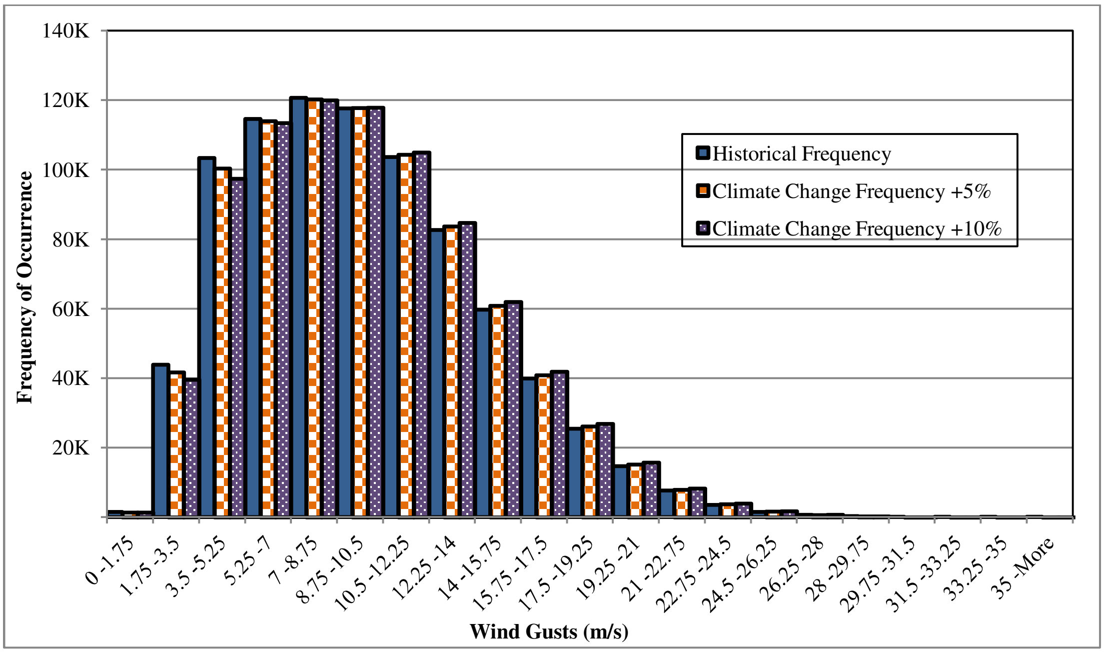


Figure 10-138 - Frequency Distribution for 10m Wind Gust Occurrences, Historical, 5% increase and 10% Increase, North England and North Wales

Table F-3 - Wind Gusts Extreme to Normal Ratio with 5% Increase – North England and North Wales

	Before	After
Occurrences Above Extreme	0.064	0.066
Occurrences Below Extreme	0.936	0.934

Table F-4 - Wind Gusts Extreme to Normal Ratio with 10% Increase – North England and North Wales

	Before	After
Occurrences Above Extreme	0.064	0.069
Occurrences Below Extreme	0.936	0.931

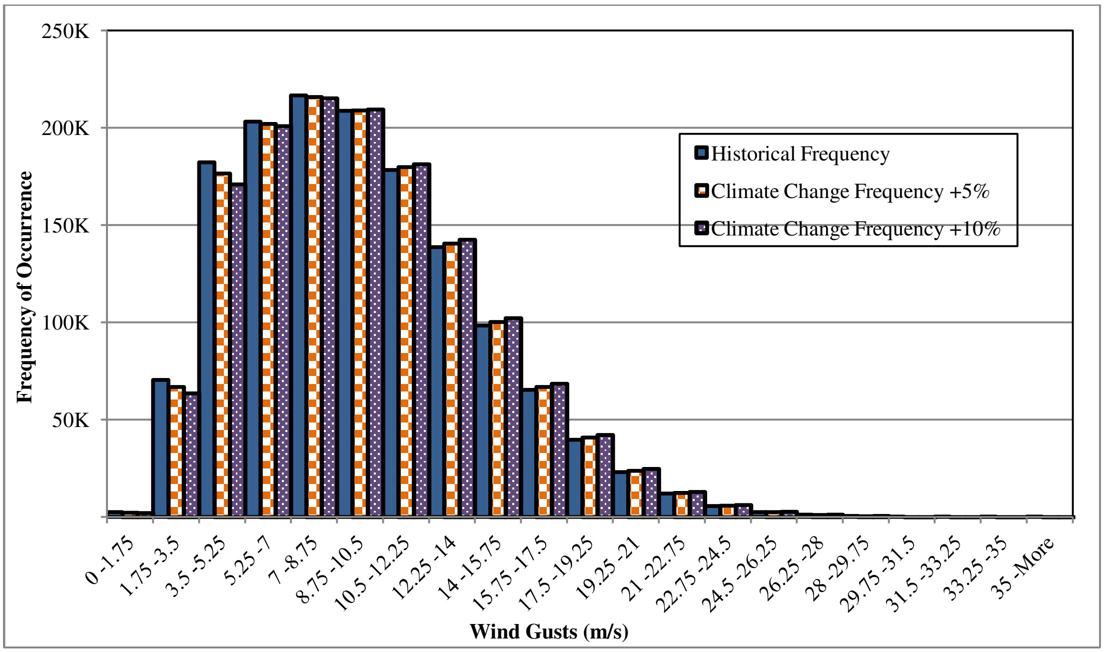


Figure 10-139 - Frequency Distribution for 10m Wind Gust Occurrences, Historical, 5% increase and 10% Increase, South England and South Wales

Table F-5 - Wind Gusts Extreme to Normal Ratio with 5% Increase – South England and South Wales

	Before	**After**
Occurrences Above Extreme	0.059	0.061
Occurrences Below Extreme	0.941	0.939

Table F-6 - Wind Gusts Extreme to Normal Ratio with 10% Increase – South England and South Wales

	Before	**After**
Occurrences Above Extreme	0.059	0.063
Occurrences Below Extreme	0.941	0.937

F-2 Lightning

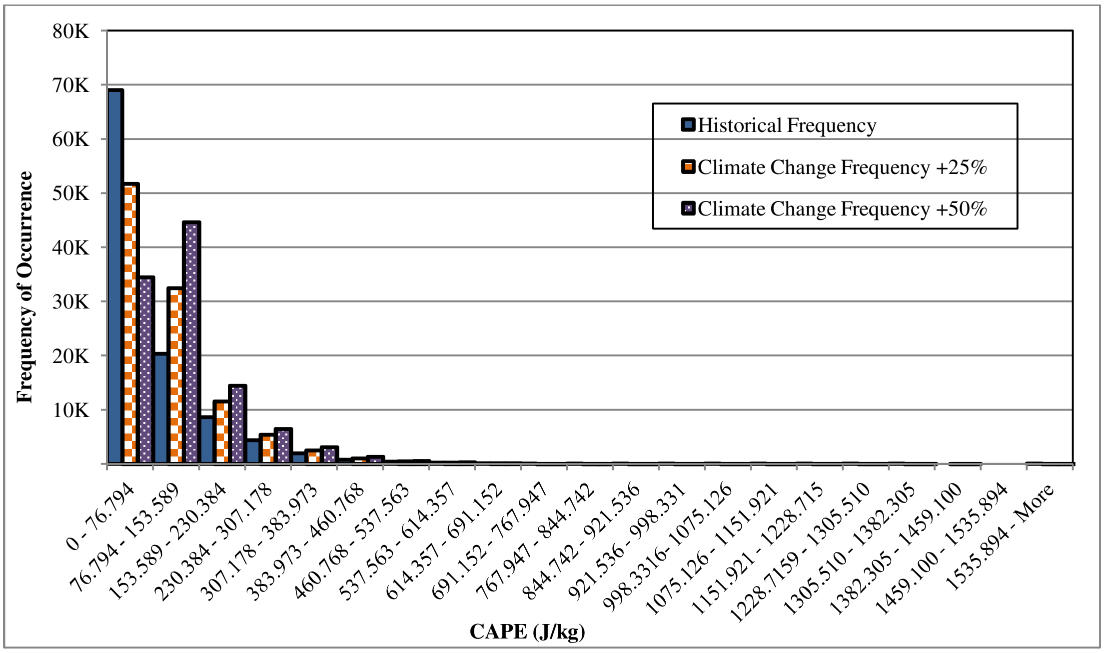


Figure 10-140 - Frequency Distribution for CAPE Occurrences, Historical, 25% increase and 50% Increase, South Scotland

Table F-7 - CAPE Extreme to Normal Ratio with 25% Increase – South Scotland

	Before	After
Occurrences Above Extreme	0.076	0.096
Occurrences Below Extreme	0.924	0.904

Table F-8 - CAPE Extreme to Normal Ratio with 50% Increase – South Scotland

	Before	After
Occurrences Above Extreme	0.076	0.116
Occurrences Below Extreme	0.924	0.884

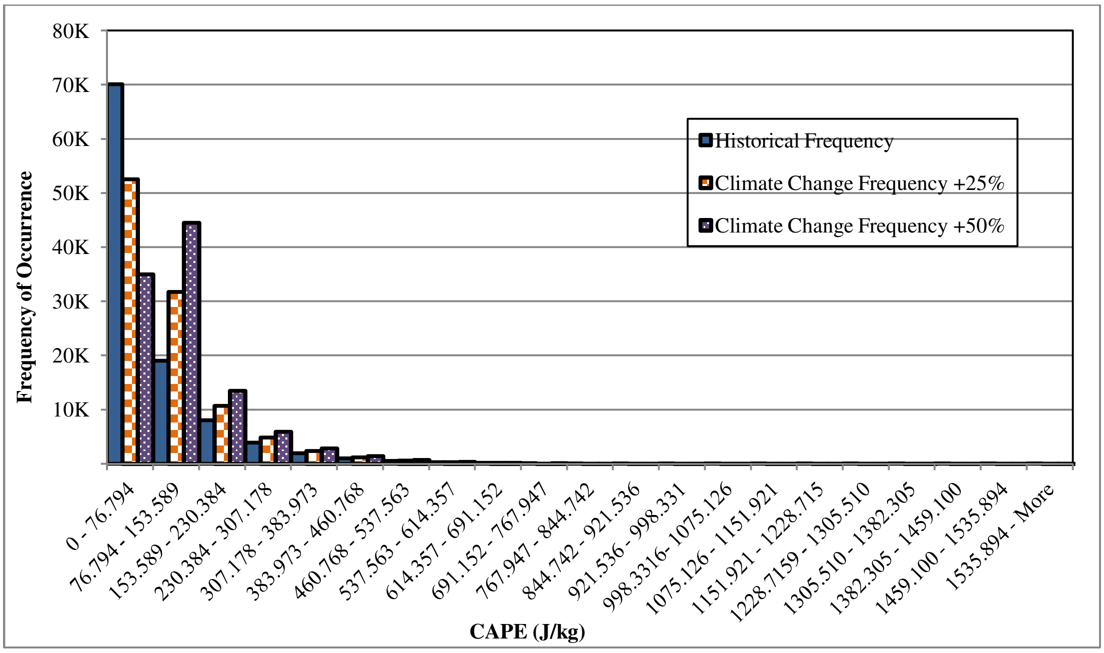


Figure 10-141 - Frequency Distribution for CAPE Occurrences, Historical, 25% increase and 50% Increase, North England and North Wales

Table F-9 - CAPE Extreme to Normal Ratio with 25% Increase – North England and North Wales

	Before	After
Occurrences Above Extreme	0.077	0.096
Occurrences Below Extreme	0.923	0.904

Table F-10 - CAPE Extreme to Normal Ratio with 50% Increase – North England and North Wales

	Before	After
Occurrences Above Extreme	0.077	0.115
Occurrences Below Extreme	0.923	0.885

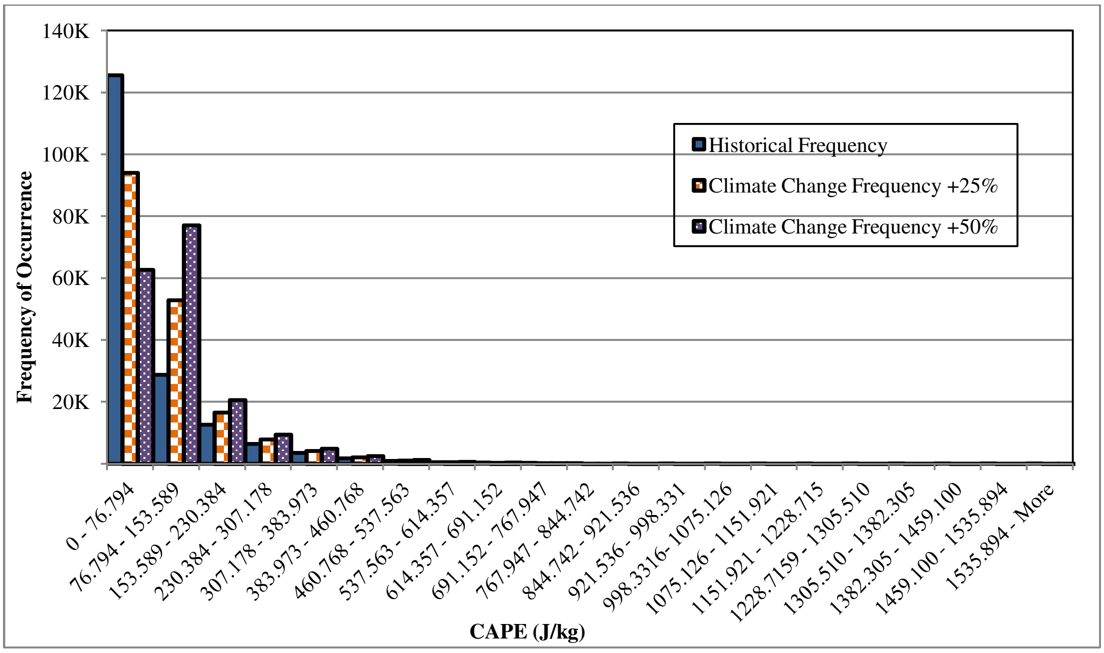


Figure 10-142 - Frequency Distribution for CAPE Occurrences, Historical, 25% increase and 50% Increase, South England and South Wales

Table F-11 - CAPE Extreme to Normal Ratio with 25% Increase – South England and South Wales

	Before	After
Occurrences Above Extreme	0.080	0.097
Occurrences Below Extreme	0.920	0.903

Table F-12 - CAPE Extreme to Normal Ratio with 50% Increase – South England and South Wales

	Before	After
Occurrences Above Extreme	0.080	0.114
Occurrences Below Extreme	0.920	0.886

F-3 Snow

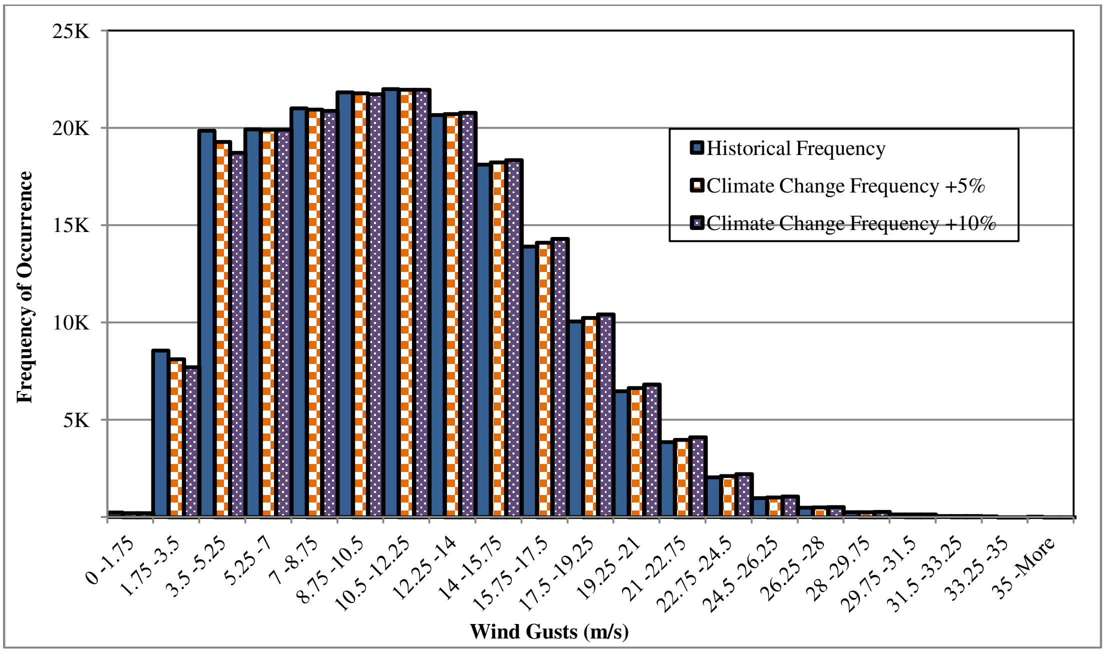


Figure 10-143 - Frequency Distribution for 10m Wind Gust on Snow Days Occurrences, Historical, 5% increase and 10% Increase, South Scotland

Table F-13 – Wind Gusts on Snow Days Extreme to Normal Ratio with 5% Increase – South Scotland

	Before	**After**
Occurrences Above Extreme	0.041	0.043
Occurrences Below Extreme	0.959	0.957

Table F-14 - Wind Gusts on Snow Days Extreme to Normal Ratio with 10% Increase – South Scotland

	Before	**After**
Occurrences Above Extreme	0.041	0.044
Occurrences Below Extreme	0.959	0.956

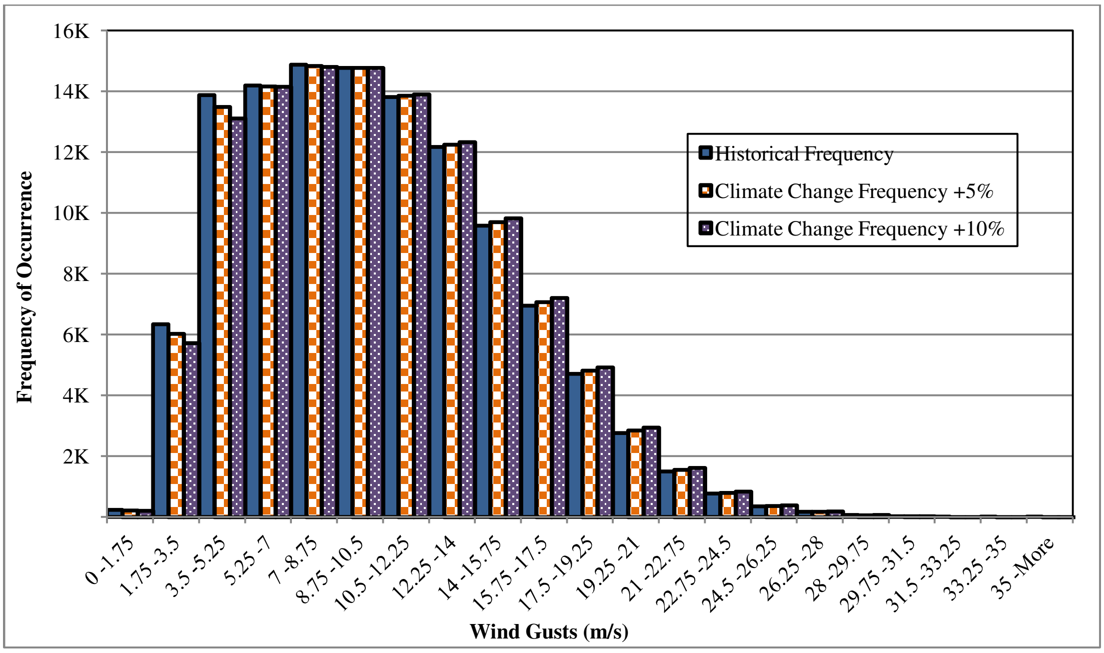


Figure 10-144 - Frequency Distribution for 10m Wind Gust on Snow Days Occurrences, Historical, 5% increase and 10% Increase, North England and North Wales

Table F-15 – Wind Gusts on Snow Days Extreme to Normal Ratio with 5% Increase – North England and North Wales

	Before	**After**
Occurrences Above Extreme	0.048	0.050
Occurrences Below Extreme	0.952	0.950

Table F-16 - Wind Gusts on Snow Days Extreme to Normal Ratio with 10% Increase – North England and North Wales

	Before	**After**
Occurrences Above Extreme	0.048	0.052
Occurrences Below Extreme	0.952	0.948

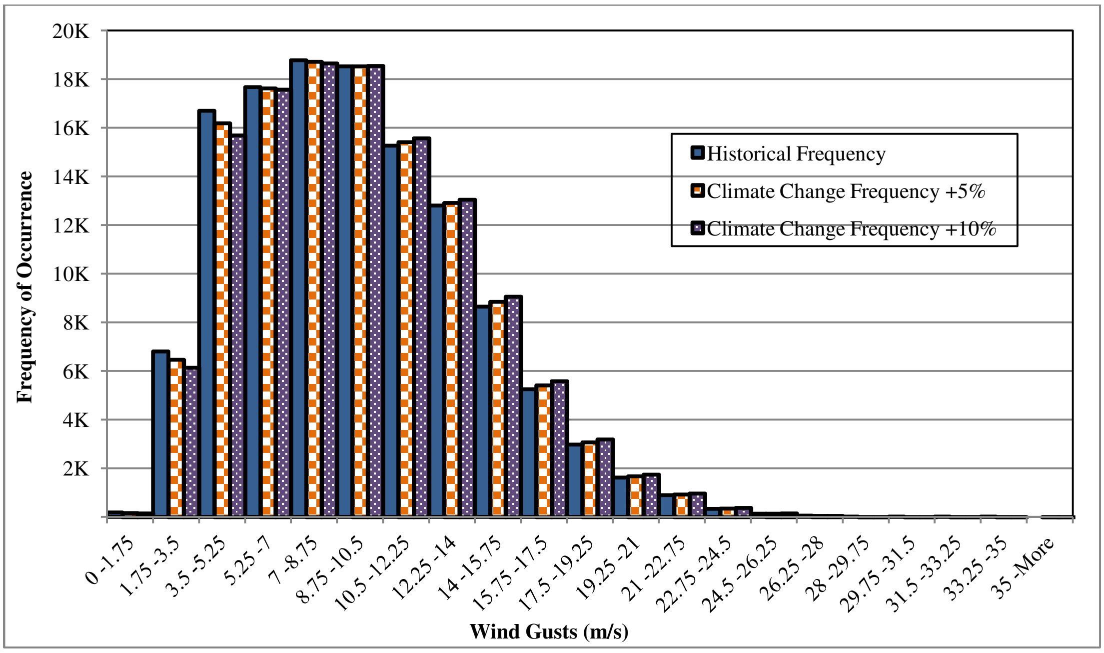


Figure 10-145 - Frequency Distribution for 10m Wind Gust on Snow Days Occurrences, Historical, 5% increase and 10% Increase, South England and South Wales

Table F-17 – Wind Gusts on Snow Days Extreme to Normal Ratio with 5% Increase – South England and South Wales

	Before	**After**
Occurrences Above Extreme	0.048	0.050
Occurrences Below Extreme	0.952	0.950

Table F-18 - Wind Gusts on Snow Days Extreme to Normal Ratio with 10% Increase – South England and South Wales

	Before	**After**
Occurrences Above Extreme	0.048	0.052
Occurrences Below Extreme	0.952	0.948

Appendix G: GB Network Model Details

This appendix contains the information relating to the bus, branch and generation data for the GB network model used within the presented thesis.

Table G-1 - Bus Data for GB Network Model

bus_id	type	Pd (MW)	Qd(Mvar)	Bs (Mvar)	Vm (pu)	Va (deg)	baseKV (kV)	Vmax (pu)	Vmin (pu)
9	2	135.62	95.73	397.08	0.99	-3.36	400	1.1	0.9
10	1	2616.26	697.90	765.00	1.02	-3.80	400	1.1	0.9
11	1	3459.34	1196.01	1306.00	1.01	-10.84	400	1.1	0.9
12	1	1224.84	575.22	676.00	1.01	-11.01	400	1.1	0.9
13	1	2586.67	990.41	861.00	1.01	-13.75	400	1.1	0.9
14	1	1874.75	719.43	243.00	1.01	-11.11	400	1.1	0.9
15	1	2707.19	1064.74	876.53	1.01	-9.61	400	1.1	0.9
16	1	1691.39	1493.24	346.40	1.01	-9.51	400	1.1	0.9
17	1	1111.28	546.01	561.56	1.01	-16.50	400	1.1	0.9
18	1	5514.45	2465.59	4282.33	0.99	-17.01	400	1.1	0.9
19	1	2088.08	982.96	564.00	0.99	-18.54	400	1.1	0.9
20	1	1056.28	453.81	370.70	1.00	-18.63	400	1.1	0.9
21	1	726.41	400.21	384.01	1.01	-19.65	400	1.1	0.9
22	1	1881.86	920.27	2022.40	1.01	-20.40	400	1.1	0.9
23	1	4856.55	1903.52	1737.30	1.01	-22.24	400	1.1	0.9
24	1	1449.52	640.31	510.67	1.00	-23.05	400	1.1	0.9
25	1	9969.24	3719.25	4205.88	1.00	-23.11	400	1.1	0.9
26	1	704.67	748.28	1314.00	0.99	-18.71	400	1.1	0.9
27	1	-1350.40	205.94	778.40	0.97	-18.18	400	1.1	0.9
28	1	2811.87	963.98	965.42	1.00	-22.65	400	1.1	0.9
29	1	2643.21	529.97	1493.54	1.00	-23.33	400	1.1	0.9
32	1	0.00	0.00	0.00	1.01	-11.90	400	1.1	0.9
33	1	0.00	0.00	0.00	1.01	-11.90	400	1.1	0.9
34	1	0.00	0.00	0.00	1.01	-11.57	400	1.1	0.9

35	1	0.00	0.00	0.00	1.01	-11.57	400	1.1	0.9
36	1	0.00	0.00	0.00	1.01	-12.85	400	1.1	0.9
37	1	0.00	0.00	0.00	1.01	-12.87	400	1.1	0.9
38	1	0.00	0.00	0.00	1.00	-11.93	400	1.1	0.9
39	1	0.00	0.00	0.00	1.01	-26.09	400	1.1	0.9
40	1	0.00	0.00	0.00	1.00	-26.09	400	1.1	0.9
43	1	0.00	0.00	0.00	1.01	0.25	400	1.1	0.9
44	1	0.00	0.00	0.00	1.01	0.25	400	1.1	0.9
49	1	0.00	0.00	1140.00	1.01	-11.01	400	1.1	0.9
50	1	0.00	0.00	0.00	1.00	-11.01	400	1.1	0.9
902	2	0.00	0.00	0.00	1.01	4.24	0.69	1.1	0.9
1002	2	0.00	0.00	0.00	1.01	3.89	0.69	1.1	0.9
1006	2	0.00	0.00	0.00	0.99	9.35	17	1.1	0.9
1007	2	0.00	0.00	0.00	1.02	9.35	17	1.1	0.9
1102	2	0.00	0.00	0.00	1.01	-3.16	0.69	1.1	0.9
1106	2	0.00	0.00	0.00	1.01	2.29	17	1.1	0.9
1107	2	0.00	0.00	0.00	1.01	2.28	17	1.1	0.9
1202	2	0.00	0.00	0.00	1.01	-3.38	0.69	1.1	0.9
1205	2	0.00	0.00	0.00	1.01	-11.01	17	1.1	0.9
1207	2	0.00	0.00	0.00	1.01	2.03	17	1.1	0.9
1505	3	0.00	0.00	0.00	1.01	0.00	17	1.1	0.9
1602	2	0.00	0.00	0.00	0.99	-1.75	0.69	1.1	0.9
1605	2	0.00	0.00	0.00	0.99	0.03	17	1.1	0.9
1607	2	0.00	0.00	0.00	1.00	5.25	17	1.1	0.9
1705	2	0.00	0.00	0.00	1.01	-7.16	17	1.1	0.9
1707	2	0.00	0.00	0.00	1.01	-9.33	17	1.1	0.9
1802	2	0.00	0.00	0.00	1.01	-9.45	0.69	1.1	0.9
1805	2	0.00	0.00	0.00	1.00	-7.72	17	1.1	0.9
1807	2	0.00	0.00	0.00	1.00	-9.87	17	1.1	0.9
1902	2	0.00	0.00	0.00	0.99	-10.84	0.69	1.1	0.9
2002	2	0.00	0.00	0.00	0.97	-11.04	0.69	1.1	0.9
2006	2	0.00	0.00	0.00	1.00	-11.47	17	1.1	0.9
2207	2	0.00	0.00	0.00	1.00	-13.24	17	1.1	0.9

2305	2	0.00	0.00	0.00	1.01	-15.08	17	1.1	0.9
2307	2	0.00	0.00	0.00	1.01	-15.08	17	1.1	0.9
2509	2	0.00	0.00	0.00	1.01	-15.93	17	1.1	0.9
2602	2	0.00	0.00	0.00	1.01	-11.15	0.69	1.1	0.9
2607	2	0.00	0.00	0.00	1.01	-11.57	17	1.1	0.9
2702	2	0.00	0.00	0.00	1.01	-10.68	0.69	1.1	0.9
2706	2	0.00	0.00	0.00	1.00	-11.10	17	1.1	0.9
2802	2	0.00	0.00	0.00	1.01	-22.65	0.69	1.1	0.9
2807	2	0.00	0.00	0.00	1.00	-15.52	17	1.1	0.9
2809	2	0.00	0.00	0.00	1.01	-15.53	17	1.1	0.9
2906	2	0.00	0.00	0.00	1.01	-16.29	17	1.1	0.9
2907	2	0.00	0.00	0.00	1.01	-16.29	17	1.1	0.9
80400	1	112.09	44.82	0.00	1.00	1.49	400	1.1	0.9
80401	1	0.00	0.00	0.00	1.01	6.10	400	1.1	0.9
80402	1	0.00	0.00	0.00	1.01	6.11	400	1.1	0.9
80801	2	0.00	0.00	0.00	0.99	6.60	0.69	1.1	0.9
81200	1	457.02	107.56	150.00	1.02	18.14	275	1.1	0.9
81400	1	0.00	0.00	0.00	1.01	10.98	400	1.1	0.9
81801	2	0.00	0.00	0.00	1.01	18.14	0.69	1.1	0.9
81803	2	0.00	0.00	0.00	1.01	27.88	17	1.1	0.9
81804	2	0.00	0.00	0.00	1.01	25.43	17	1.1	0.9
82200	1	350.16	92.28	349.75	1.01	26.99	275	1.1	0.9
82400	1	0.00	0.00	0.00	1.01	32.25	400	1.1	0.9
82801	2	0.00	0.00	0.00	1.01	32.21	0.69	1.1	0.9
83200	1	534.44	159.03	450.00	0.99	24.41	275	1.1	0.9
83801	2	0.00	0.00	0.00	0.99	24.41	0.69	1.1	0.9
83805	2	0.00	0.00	0.00	1.00	31.65	17	1.1	0.9
83809	2	0.00	0.00	0.00	1.01	31.65	17	1.1	0.9
84400	1	82.70	18.56	0.00	1.01	7.49	400	1.1	0.9
85400	1	295.88	160.53	0.00	1.01	5.45	400	1.1	0.9
85401	1	0.00	0.00	0.00	1.00	5.45	400	1.1	0.9
85402	2	0.00	0.00	960.00	1.00	5.45	400	1.1	0.9
85801	2	0.00	0.00	0.00	0.99	10.18	0.7	1.1	0.9

85806	2	0.00	0.00	0.00	0.97	12.69	17	1.1	0.9
86200	1	373.19	80.65	228.50	1.00	11.19	275	1.1	0.9
86400	1	0.00	0.00	0.00	1.00	6.99	400	1.1	0.9
86801	2	0.00	0.00	0.00	1.01	14.58	0.69	1.1	0.9
87200	1	701.16	167.53	0.00	1.01	12.45	275	1.1	0.9
87400	1	0.00	0.00	648.27	1.01	7.06	400	1.1	0.9
87801	2	0.00	0.00	0.00	1.01	14.07	0.69	1.1	0.9
87803	2	0.00	0.00	0.00	1.01	16.56	17	1.1	0.9
87812	2	0.00	0.00	0.00	1.01	14.17	17	1.1	0.9
88400	1	416.01	99.87	161.26	1.00	5.51	400	1.1	0.9
88801	2	0.00	0.00	0.00	1.01	11.49	0.69	1.1	0.9
88802	2	0.00	0.00	0.00	1.00	5.51	0.69	1.1	0.9
88806	2	0.00	0.00	0.00	1.01	12.66	17	1.1	0.9
89200	1	0.00	0.00	0.00	1.01	6.99	275	1.1	0.9
89201	1	0.00	0.00	0.00	1.01	7.02	275	1.1	0.9
89400	1	304.10	77.37	14.57	1.00	2.98	400	1.1	0.9
89401	1	0.00	0.00	0.00	1.01	6.26	400	1.1	0.9
89402	1	0.00	0.00	0.00	1.01	6.26	400	1.1	0.9
89801	2	0.00	0.00	0.00	0.99	4.39	0.7	1.1	0.9
91200	2	244.47	51.11	222.00	1.02	48.29	275	1.1	0.9
91400	1	0.00	0.00	0.00	1.01	45.58	400	1.1	0.9
91801	2	0.00	0.00	0.00	1.01	55.16	0.69	1.1	0.9
91803	2	0.00	0.00	0.00	1.01	58.34	17	1.1	0.9
91804	2	0.00	0.00	0.00	1.01	48.29	17	1.1	0.9
92200	1	119.06	27.21	0.00	1.01	43.62	275	1.1	0.9
92801	2	0.00	0.00	0.00	1.01	45.91	0.7	1.1	0.9
93200	1	184.95	42.85	0.00	1.01	47.90	275	1.1	0.9
93801	2	0.00	0.00	0.00	0.99	52.30	0.69	1.1	0.9
93802	2	0.00	0.00	0.00	0.99	47.90	0.69	1.1	0.9
93807	2	0.00	0.00	0.00	1.00	55.10	17	1.1	0.9
93809	2	0.00	0.00	0.00	1.01	55.10	17	1.1	0.9
94200	1	308.10	67.64	238.22	1.01	41.60	275	1.1	0.9
94801	2	0.00	0.00	0.00	1.01	43.95	0.7	1.1	0.9

95200	2	352.16	66.70	90.00	1.00	31.27	275	1.1	0.9
95801	2	0.00	0.00	0.00	1.00	36.10	0.7	1.1	0.9
96100	1	179.47	41.60	10.65	0.99	35.26	132	1.1	0.9
96200	1	0.00	0.00	92.24	0.97	36.52	275	1.1	0.9
96400	1	0.00	0.00	0.00	1.00	37.90	400	1.1	0.9
96801	2	0.00	0.00	0.00	1.00	41.28	0.69	1.1	0.9
96803	2	0.00	0.00	0.00	1.01	42.47	17	1.1	0.9

Table G-2 - Branch Data for GB Network Model

Branch No	fbus	tbus	r (p.u.)	x (p.u.)	b (p.u.)	rateA (MVA)	rateB (MVA)	rateC (MVA)	Length (km)
1	9	10	0.00492	0.0343	0.2502	775	775	775	83.799
2	9	10	0.00352	0.02453	0.1898	855	855	855	83.799
3	9	43	0	-0.00512	0	0	0	0	0
4	9	43	0	0.0001	0	0	0	0	0
5	9	44	0	-0.00512	0	0	0	0	0
6	9	44	0	0.0001	0	0	0	0	0
7	9	80401	0.00135	0.01479	0.45806	2010	1859.25	1604.98	83.799
8	9	80402	0.00135	0.01478	0.45809	2010	1859.25	1604.98	83.799
9	10	15	0.00052	0.0063	1.0636	4020	4020	4020	184.26
10	10	15	0.00053	0.00835	5.373	4840	4840	4840	184.26
11	10	89401	0.0009	0.0175	0.68865	2770	2720	2390	102.24
12	10	89402	0.0009	0.0175	0.68865	2770	2720	2390	102.24
13	11	12	0.0001	0.0085	0.0798	3320	3320	3320	84.62
14	11	12	0.0001	0.0085	0.0798	3320	3320	3320	84.62
15	11	13	0.0004	0.0052	0.2664	2210	2210	2210	368.53
16	11	13	0.0004	0.0052	0.2498	2170	2170	2170	368.53
17	11	15	0.00099	0.042	0.5738	2520	2520	2520	147.65
18	11	15	0.0007	0.042	0.3907	2520	2520	2520	147.65
19	11	43	0.0013	0.0156	0.4882	3100	3100	3100	147.95
20	11	44	0.0013	0.0156	0.4882	3100	3100	3100	147.95
21	12	13	0.00096	0.01078	0.385	596.6	596.6	596.6	60.294
22	12	13	0.00096	0.01078	0.385	596.6	596.6	596.6	60.294

23	12	50	0	0.0001	0	0	0	0	0
24	13	14	0.00082	0.01201	1.2125	1040	1040	1040	100.8
25	13	15	0.00164	0.023	0.1104	955	955	955	160.71
26	13	15	0.00137	0.023	0.6643	2140	2140	2140	160.71
27	13	18	0.00084	0.007	0.7759	2400	2400	2400	174.03
28	13	18	0.00049	0.007	0.1943	2400	2400	2400	174.03
29	13	38	0.00107	0.00793	1.1745	1040	1040	1040	100.8
30	14	15	0.00018	0.00222	0.5573	5000	5000	5000	59.912
31	14	15	0.00019	0.00222	0.7592	5000	5000	5000	59.912
32	14	16	0.005	0.018	0.1466	625	625	625	115.87
33	14	16	0.0005	0.016	0.2795	2580	2580	2580	115.87
34	15	16	0.00016	0.00172	0.3992	5540	5540	5540	55.96
35	15	16	0.00033	0.0052	0.3534	2770	2770	2770	55.96
36	16	19	0.00056	0.0141	0.4496	3820	3820	3820	131.75
37	16	19	0.00056	0.0141	0.4496	2780	2780	2780	131.75
38	16	22	0.00178	0.0172	0.627	2010	2010	2010	233.5
39	16	22	0.00178	0.0172	0.8403	2010	2010	2010	233.5
40	17	18	0.00042	0.0018	0.2349	3460	3460	3460	119.85
41	17	18	0.00042	0.0018	0.2349	3100	3100	3100	119.85
42	17	22	0.00069	0.0097	0.4574	2100	2100	2100	122.96
43	17	22	0.00068	0.0097	0.4566	2100	2100	2100	122.96
44	17	32	0.001	0.00702	0.2651	2150	2150	2150	106.57
45	17	33	0.001	0.00702	0.4573	1890	1890	1890	106.57
46	18	23	0.00117	0.0096	0.4122	1970	1970	1970	106.75
47	18	23	0.00138	0.0096	0.4829	1970	1970	1970	106.75
48	18	36	0.00097	0.0053	0.3835	2400	2400	2400	128.2
49	18	37	0.00074	0.0053	0.2911	2400	2400	2400	128.2
50	19	20	0.00132	0.0143	0.3656	1590	1590	1590	140.81
51	19	20	0.00178	0.0213	0.6682	1590	1590	1590	140.81
52	19	21	0.00037	0.0059	0.2955	2780	2780	2780	94.123
53	19	21	0.00037	0.0059	0.294	3030	3030	3030	94.123
54	20	21	0.0012	0.0048	0.7	2780	2780	2780	69.301
55	20	21	0.0012	0.0048	0.4446	2780	2780	2780	69.301

56	20	26	0.00035	0.0023	0.2249	2780	2780	2780	119.93
57	20	26	0.00035	0.0023	0.2249	2780	2780	2780	119.93
58	21	22	0.00048	0.0061	0.3041	2780	2780	2780	74.452
59	21	22	0.00019	0.00111	0.1232	2780	2780	2780	74.452
60	21	25	0.00025	0.01	0.1586	2780	2780	2780	42.736
61	21	25	0.00025	0.01	0.1586	2780	2780	2780	42.736
62	21	34	0.00145	0.01454	0.9169	2780	2780	2780	225.87
63	21	35	0.00145	0.01454	0.9169	2780	2780	2780	225.87
64	22	23	0.00039	0.003	0.2466	2770	2770	2770	166.6
65	22	23	0.00055	0.003	0.3468	2780	2780	2780	166.6
66	22	25	0.00034	0.0041	0.429	3275	3275	3275	100.78
67	22	25	0.00037	0.0041	0.4098	3275	3275	3275	100.78
68	23	24	0.00023	0.0007	2.8447	4400	4400	4400	81.569
69	23	24	0.00086	0.0008	0.9622	2780	2780	2780	81.569
70	23	29	0.00151	0.0182	0.53	2010	2010	2010	227.17
71	23	29	0.00151	0.0182	0.53	2010	2010	2010	227.17
72	24	28	0.00068	0.007	0.2388	2210	2210	2210	58.65
73	24	28	0.00068	0.007	0.2388	2210	2210	2210	58.65
74	24	39	0.00104	0.0054	0.2918	1390	1390	1390	107.69
75	24	40	0.00104	0.0054	0.2918	1390	1390	1390	107.69
76	25	26	0.0002	0.0057	0.532	5540	5540	5540	92.094
77	25	26	0.0002	0.0057	0.532	6960	6960	6960	92.094
78	26	27	0.0002	0.00503	0.1797	3100	3100	3100	55.168
79	26	27	0.0002	0.00503	0.1797	3100	3100	3100	55.168
80	27	28	0.00038	0.00711	0.2998	3070	3070	3070	186.08
81	27	28	0.00038	0.00711	0.2998	3070	3070	3070	186.08
82	28	29	0.00051	0.00796	0.34	2780	2780	2780	130.37
83	28	29	0.00051	0.00796	0.34	2780	2780	2780	130.37
84	49	50	0	0.0001	0	0	0	0	0
85	80400	80401	0	-0.007288	0	0	0	0	0
86	80400	80401	0	0.0001	0	0	0	0	0
87	80400	80402	0	-0.007288	0	0	0	0	0
88	80400	80402	0	0.0001	0	0	0	0	0

89	80400	87400	0.00084	0.0092	0.28982	2210	2130	1980	48.41
90	80400	87400	0.00084	0.0092	0.28981	2210	2130	1980	48.41
91	81200	82200	0.00271	0.02233	0.18009	950	885	760	54.12
92	81200	83200	0.00305	0.02811	0.2336	1050	965	880	71.37
93	81200	86200	0.0013	0.02583	0.07118	1000	1000	990	25.35
94	81400	84400	0.00074	0.00793	0.2868	1000	1000	990	44.57
95	82200	83200	0.00215	0.02073	0.18358	820	650	650	53.49
96	82200	96200	0.00277	0.0356	0.3198	1910	1830	1710	93.38
97	82400	96400	0.00130905	0.0168087	0.57852	2780	2670	2480	93.38
98	83200	87200	0.00137	0.01917	0.2035	1500	1500	1500	54.69
99	83200	87200	0.00142	0.01958	0.20616	1500	1500	1500	54.69
100	83200	89200	0.00577	0.06699	0.65895	1050	965	880	150.67
101	83200	89201	0.00571	0.06646	0.63893	1090	1030	925	149.21
102	83200	94200	0.009	0.0774	0.5172	955	885	760	180.97
103	83200	95200	0.00224	0.019	0.12766	1520	1240	1240	96.19
104	83200	95200	0.0048	0.0414	0.2578	955	880	760	96.19
105	84400	85400	0.0005	0.00561	0.89334	1320	1070	1070	61.79
106	84400	87400	0.00151	0.01613	0.59296	1390	1280	1110	91.26
107	85400	85401	0	0.0001	0	0	0	0	0
108	85400	86400	0.00055	0.0059	0.19434	1350	1350	1350	31.87
109	85400	87400	0.00168	0.01729	0.58777	1390	1280	1110	94.06
110	85401	85402	0	0.0001	0	0	0	0	0
111	86200	87200	0.00177	0.01452	0.09848	955	885	760	35.66
112	86200	87200	0.00178	0.01462	0.09911	750	690	630	35.66
113	87400	88400	0.00247	0.02447	1.22105	1250	1180	1105	132.05
114	87400	88400	0.00253	0.02444	1.22105	1390	1280	1110	132.05
115	88400	89400	0.00049	0.00635	1.07481	2470	2350	2150	36.48
116	88400	89400	0.00049	0.00635	1.07481	2470	2350	2150	36.48
117	89400	89401	0	-0.00575	0	0	0	0	0
118	89400	89401	0	0.0001	0	0	0	0	0
119	89400	89402	0	-0.00575	0	0	0	0	0
120	89400	89402	0	0.0001	0	0	0	0	0
121	91200	92200	0.00625	0.04352	0.2959	935	880	790	106.4

122	91200	92200	0.00625	0.04352	0.2959	935	880	790	106.4
123	91200	96200	0.0039	0.0484	0.371	1910	1830	1710	125.87
124	91400	96400	0.00176095	0.0226113	0.77823	2780	2670	2480	125.87
125	92200	93200	0.0042	0.03576	0.21598	1090	1030	920	82.72
126	92200	94200	0.00302	0.02106	0.14322	935	880	790	51.5
127	92200	94200	0.00302	0.02106	0.14322	935	880	790	51.5
126	92200	94200	0.00302	0.02106	0.14322	935	880	790	51.5
129	93200	94200	0.0038	0.0331	0.1994	1090	1030	920	70.5
130	93200	94200	0.0036	0.0307	0.1848	1090	1030	920	70.5
129	93200	94200	0.0026	0.0219	0.1322	1090	1030	920	70.5
132	94200	95200	0.0061	0.0536	0.22142	955	880	760	116.7
133	94200	95200	0.0061	0.0536	0.22142	955	880	760	116.7
132	94200	95200	0.0059	0.051	0.3072	955	880	760	116.7
135	9	902	0.00028	0.02836	0	528.97	528.97	528.97	0
136	10	1002	0.0028	0.28002	0	53.57	53.57	53.57	0
137	10	1006	0.00018	0.01815	0	1487.93	1487.93	1487.93	0
138	10	1007	0.00011	0.0112	0	2411.76	2411.76	2411.76	0
139	11	1102	0.00038	0.0376	0	398.92	398.92	398.92	0
140	11	1106	0.0001	0.00957	0	2822.36	2822.36	2822.36	0
141	11	1107	0.00148	0.14847	0	181.86	181.86	181.86	0
142	12	36	0	0.0037	0	2400	2400	2400	26.442
143	12	37	0	0.0037	0	2400	2400	2400	26.442
144	12	1202	0.00032	0.03197	0	469.13	469.13	469.13	0
145	12	1205	0.00027	0.02703	0	999	999	999	0
146	12	1207	0.0001	0.01039	0	2598.5	2598.5	2598.5	0
147	38	14	0	0.0037	0	1040	1040	1040	0
148	15	1505	6.00E-05	0.00588	0	5357.05	5357.05	5357.05	0
149	16	32	0	0.0037	0	2150	2150	2150	0
150	16	33	0	0.0037	0	1890	1890	1890	0
151	34	16	0	0.0037	0	2780	2780	2780	0
152	35	16	0	0.0037	0	2780	2780	2780	0
153	16	1602	0.00052	0.05239	0	286.34	286.34	286.34	0
154	16	1605	6.00E-05	0.00564	0	3458.88	3458.88	3458.88	0

155	16	1607	3.00E-05	0.00342	0	8764.61	8764.61	8764.61	0
156	17	1705	0.00017	0.01672	0	1166.26	1166.26	1166.26	0
157	17	1707	0.00056	0.05607	0	267.51	267.51	267.51	0
158	18	1802	0.00063	0.06288	0	238.55	238.55	238.55	0
159	18	1805	0.00013	0.01261	0	1546.41	1546.41	1546.41	0
160	18	1807	0.00017	0.01692	0	886.71	886.71	886.71	0
161	19	1902	0.00025	0.02507	0	598.38	598.38	598.38	0
162	20	2002	0.00019	0.01921	0	781.01	781.01	781.01	0
163	20	2006	0.00011	0.01065	0	1407.95	1407.95	1407.95	0
164	22	2207	8.00E-05	0.00844	0	1777.54	1777.54	1777.54	0
165	23	2305	0.00015	0.01504	0	997.3	997.3	997.3	0
166	23	2307	4.00E-05	0.0038	0	3946.98	3946.98	3946.98	0
167	39	25	0	0.0037	0	1390	1390	1390	13.194
168	40	25	0	0.0037	0	1390	1390	1390	13.194
169	25	2509	7.00E-05	0.00748	0	2006.33	2006.33	2006.33	0
170	26	2602	0.00019	0.0188	0	797.84	797.84	797.84	0
171	26	2607	6.00E-05	0.00555	0	2704.46	2704.46	2704.46	0
172	27	2702	0.00063	0.06267	0	239.35	239.35	239.35	0
173	27	2706	0.00011	0.01139	0	1316.56	1316.56	1316.56	0
174	28	2802	0.00015	0.01502	0	999	999	999	0
175	28	2807	0.00014	0.01421	0	1055.97	1055.97	1055.97	0
176	28	2809	0.00081	0.08091	0	185.38	185.38	185.38	0
177	29	2906	0.0001	0.01014	0	1479.53	1479.53	1479.53	0
178	29	2907	0.00014	0.01413	0	1061.83	1061.83	1061.83	0
179	80400	80801	0.00044	0.04358	0	344.18	344.18	344.18	0
180	81400	81200	0.00018	0.01617	0	1000	1000	1000	0
181	81200	81801	0.00068	0.0675	0	222.22	222.22	222.22	0
182	81200	81803	0.00079	0.07896	0	253.29	253.29	253.29	0
183	81200	81804	0.00038	0.0375	0	400	400	400	0
184	96100	81200	0.0574947	0.184667	0	132	123	106	126.18
185	82200	82400	0.00013	0.016	0	1000	1000	1000	0
186	82200	82801	0.00042	0.04192	0	357.84	357.84	357.84	0
187	83200	83801	0.00068	0.0675	0	222.22	222.22	222.22	0

188	83200	83805	6.00E-05	0.00558	0	2687.06	2687.06	2687.06	0
189	83200	83809	0.00075	0.07544	0	198.82	198.82	198.82	0
190	85400	85801	0.00052	0.05168	0	290.24	290.24	290.24	0
191	85400	85806	0.00012	0.01187	0	1263.53	1263.53	1263.53	0
192	86400	86200	0.00018	0.01617	0	1000	1000	1000	0
193	86200	86801	0.00075	0.07533	0	199.11	199.11	199.11	0
194	87400	87200	0.00018	0.01706	0	1000	1000	1000	0
195	87400	87200	0.00018	0.01706	0	1000	1000	1000	0
196	87400	87801	9.00E-05	0.00938	0	1599.31	1599.31	1599.31	0
197	87400	87803	0.00247	0.24745	0	80.82	80.82	80.82	0
198	87400	87812	0.00283	0.28333	0	52.94	52.94	52.94	0
199	88400	88801	0.00028	0.02834	0	529.28	529.28	529.28	0
200	88400	88802	0.00015	0.01502	0	999	999	999	0
201	88400	88806	0.0001	0.01032	0	1452.94	1452.94	1452.94	0
202	89400	89200	0.00013	0.016	0	1000	1000	1000	0
203	89400	89201	0.00013	0.016	0	1000	1000	1000	0
204	89400	89801	0.0011	0.10993	0	136.44	136.44	136.44	0
205	91200	91400	6.50E-05	0.008	0	2400	2400	2400	0
206	91200	91801	0.00017	0.01678	0	893.71	893.71	893.71	0
207	91200	91803	0.00034	0.03436	0	582	582	582	0
208	91200	91804	0.00015	0.01502	0	999	999	999	0
209	92200	92801	0.00094	0.09431	0	159.04	159.04	159.04	0
210	93200	93801	0.00057	0.05705	0	262.91	262.91	262.91	0
211	93200	93802	0.00015	0.01502	0	999	999	999	0
212	93200	93807	9.00E-05	0.00887	0	1690.59	1690.59	1690.59	0
213	93200	93809	0.0069	0.68994	0	21.74	21.74	21.74	0
214	94200	94801	0.00093	0.09337	0	160.64	160.64	160.64	0
215	95200	95801	0.0005	0.04991	0	300.51	300.51	300.51	0
216	96100	95200	0.025618	0.0686929	0	480	480	480	117.58
217	96200	96100	0.001565	0.054125	0	480	480	480	0
218	96100	96803	0.00056	0.05563	0	269.65	269.65	269.65	0
219	96200	96801	0.0005	0.05018	0	298.91	298.91	298.91	0

Table G-3 - Generation Data for GB Network Model

bus_id	Generation Class	PG (MW)	QG (Mvar)	Qmax (Mvar)	Qmin (Mvar)	mBase (MVA)	Pmax (MW)	Pmin (MW)
9	Wind	0	105.13	300	-150	450	0	0
902	Wind	476.072	26.908	169.27	-169.27	528.969	476.072	0
1002	Nuclear	48.21	7.137	17.141	-17.141	53.567	48.21	0
1006	CCGT	1264.74	200.594	743.965	-371.982	1487.929	1264.74	0
1007	Wind	2050	325.372	1205.882	-602.941	2411.765	2050	0
1102	Nuclear	359.028	48.691	127.654	-127.654	398.92	359.028	0
1106	CCGT	2399.009	361.554	1411.182	-705.591	2822.364	2399.009	0
1107	Wind	154.581	23.37	90.93	-45.465	181.86	154.581	0
1202	Coal	422.218	36.344	150.122	-150.122	469.131	422.218	0
1205	CCGT	0	0	499.5	-249.75	999	0	0
1207	Coal	2208.723	269.128	1299.249	-649.624	2598.498	2208.723	0
1505	Wind	2847.96	535.886	2678.525	-1339.262	5357.05	3959.559	0
1602	Coal	257.703	56.069	91.628	-91.628	286.337	257.703	0
1605	CCGT	2940.045	596.195	1729.438	-864.719	3458.876	2940.045	0
1607	Coal	7449.922	1528.736	4382.307	-2191.154	8764.614	7449.922	0
1705	CCGT	991.318	64.01	583.128	-291.564	1166.256	991.318	0
1707	Wind	227.383	9.942	133.755	-66.877	267.509	227.383	0
1802	Coal	214.699	3.509	76.337	-76.337	238.554	214.699	0
1805	CCGT	1314.444	50.762	773.202	-386.601	1546.405	1314.444	0
1807	Wind	753.704	7.766	443.355	-221.678	886.711	753.704	0
1902	Wind	538.542	90.134	191.482	-191.482	598.38	538.542	0
2002	Nuclear	702.907	26.561	249.922	-249.922	781.008	702.907	0
2006	CCGT	1196.76	38.899	703.976	-351.988	1407.953	1196.76	0
2207	Coal	1510.912	58.498	888.772	-444.386	1777.544	1510.912	0
2305	CCGT	847.704	31.91	498.649	-249.325	997.299	847.704	0
2307	CCGT	3354.935	124.414	1973.491	-986.746	3946.982	3354.935	0
2509	Wind	1705.383	97.347	1003.167	-501.583	2006.333	1705.383	0
2602	CCGT	718.055	5.7	255.308	-255.308	797.839	718.055	0
2607	Wind	2298.791	1.841	1352.23	-676.115	2704.46	2298.791	0
2702	Nuclear	215.418	-10.298	76.593	-76.593	239.353	215.418	0
2706	Wind	1119.08	-64.022	658.282	-329.141	1316.565	1119.08	0
2802	CCGT	0	0	319.68	-319.68	999	0	0
2807	CCGT	897.571	-10.974	527.983	-263.991	1055.966	897.571	0
2809	Nuclear	157.574	-1.96	92.691	-46.345	185.381	157.574	0
2906	Wind	1257.597	-151.994	739.763	-369.881	1479.526	1257.597	0
2907	Wind	902.558	-109.106	530.916	-265.458	1061.833	902.558	0
80801	Wind	0	0	35.556	-35.556	111.111	100	0

80801	Wind	209.76	-6.099	74.581	-74.581	233.067	209.76	0
81801	Wind	0	0	35.556	-35.556	111.111	100	0
81801	Hydro/Pumped Storage	0	0	35.556	-35.556	111.111	100	0
81803	Hydro/Pumped Storage	215.3	38.113	126.647	-63.324	253.294	215.3	0
81804	Wind	340	64.392	200	-100	400	340	0
82801	Wind	0	0	35.556	-35.556	111.111	100	0
82801	Wind	222.06	1.36	78.955	-78.955	246.733	222.06	0
83801	Wind	0	0	35.556	-35.556	111.111	100	0
83801	Coal	0	0	35.556	-35.556	111.111	100	0
83805	CCGT	2284	309.225	1343.529	-671.765	2687.059	2284	0
83809	CCGT	169	23.019	99.412	-49.706	198.824	169	0
85402	Wind	0	-37.485	250	-250	500	0	0
85801	Wind	0	0	35.556	-35.556	111.111	100	0
85801	Nuclear	161.22	24.562	57.323	-57.323	179.133	161.22	0
85806	Wind	1074	142.101	631.765	-315.882	1263.529	1074	0
86801	Wind	0	0	35.556	-35.556	111.111	100	0
86801	Wind	79.2	19.726	28.16	-28.16	88	79.2	0
87801	Wind	0	0	35.556	-35.556	111.111	100	0
87801	Hydro/Pumped Storage	1339.38	-40.165	476.224	-476.224	1488.2	1339.38	0
87803	CCGT	68.7	0.875	40.412	-20.206	80.824	68.7	0
87812	Wind	45	-1.272	26.471	-13.235	52.941	45	0
88801	Wind	0	0	35.556	-35.556	111.111	100	0
88801	Wind	376.35	5.558	133.813	-133.813	418.167	376.35	0
88802	Nuclear	0	0	319.68	-319.68	999	0	0
88806	Wind	1235	36.687	726.471	-363.235	1452.941	1235	0
89801	Wind	0	0	35.556	-35.556	111.111	100	0
89801	CCGT	22.8	4.907	8.107	-8.107	25.333	22.8	0
91200	Wind	0	-32.72	150	-150	300	0	0
91801	Wind	0	0	35.556	-35.556	111.111	100	0
91801	Hydro/Pumped Storage	704.34	-32.72	250.432	-250.432	782.6	704.34	0
91803	Hydro/Pumped Storage	494.7	-32.72	291	-145.5	582	494.7	0
91804	Wind	0	0	499.5	-249.75	999	0	0
92801	Wind	0	0	35.556	-35.556	111.111	100	0
92801	Wind	43.14	7.3	15.339	-15.339	47.933	43.14	0
93801	Wind	0	0	35.556	-35.556	111.111	100	0
93801	Wind	136.62	11.129	48.576	-48.576	151.8	136.62	0
93802	CCGT	0	0	319.68	-319.68	999	0	0
93807	CCGT	1437	122.418	845.294	-422.647	1690.588	1437	0

93809	Wind	18.48	1.577	10.871	-5.435	21.741	18.48	0
94801	Wind	0	0	35.556	-35.556	111.111	100	0
94801	CCGT	44.58	6.866	15.851	-15.851	49.533	44.58	0
95200	Wind	0	74.215	225	-75	300	0	0
95801	Wind	0	0	35.556	-35.556	111.111	100	0
95801	Wind	170.46	25.699	60.608	-60.608	189.4	170.46	0
96801	Wind	0	0	35.556	-35.556	111.111	100	0
96801	Wind	169.02	1.035	60.096	-60.096	187.8	169.02	0
96803	Hydro/Pumped Storage	229.2	20.635	134.824	-67.412	269.647	229.2	0

Appendix H: Failure Rates and Associated Confidence Limits for State Sampling for the Weather Test Cases

This appendix contains the weather histograms for South Scotland, North England and North Wales, and South England and South Wales for the basecase state sampling model. As well at the results for the weather tests cases for the weather types not changed.

H-1 State Sampling Weather Frequency Distributions

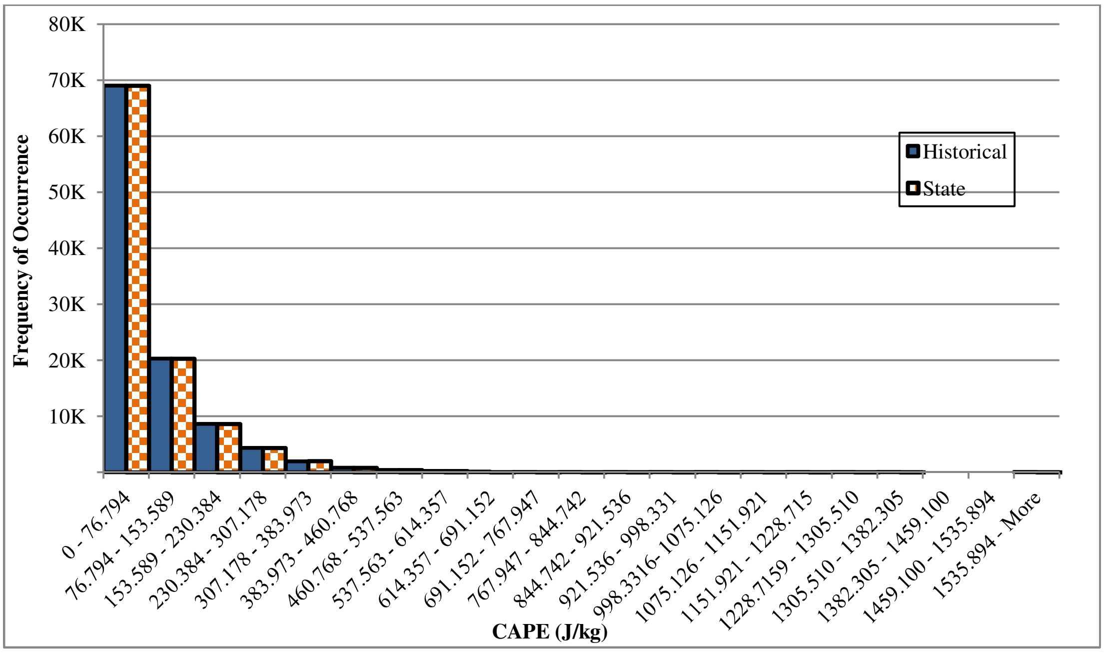


Figure 10-146 - State Basecase and Historical CAPE (J/kg) Distribution, South Scotland

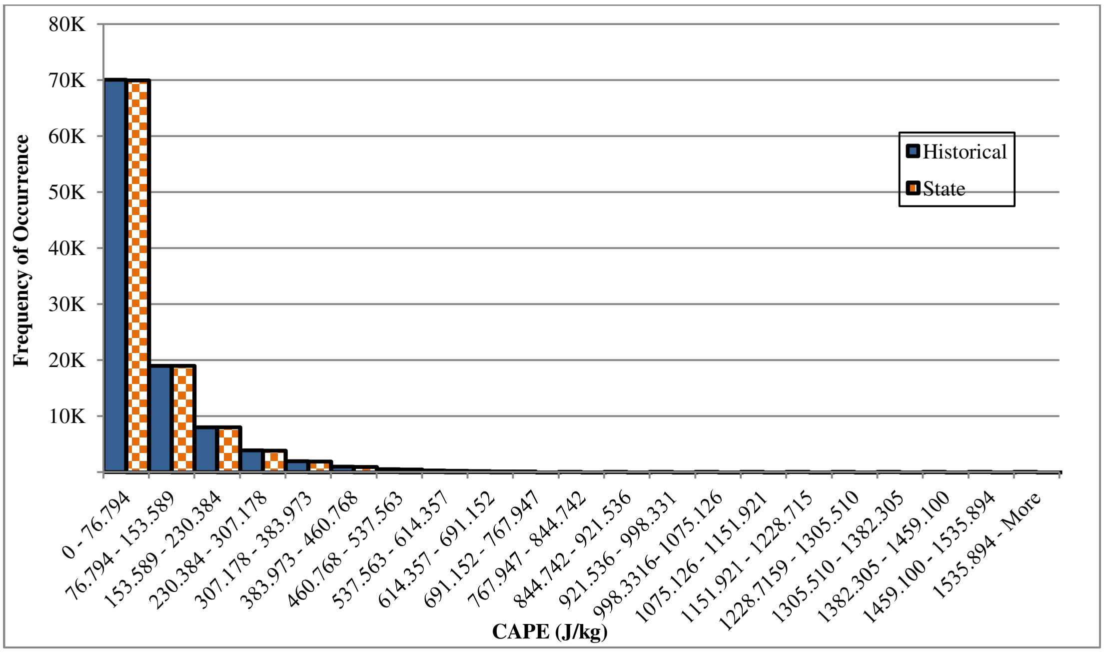


Figure 10-147 - State Basecase and Historical CAPE (J/kg) Distribution, North England and North Wales

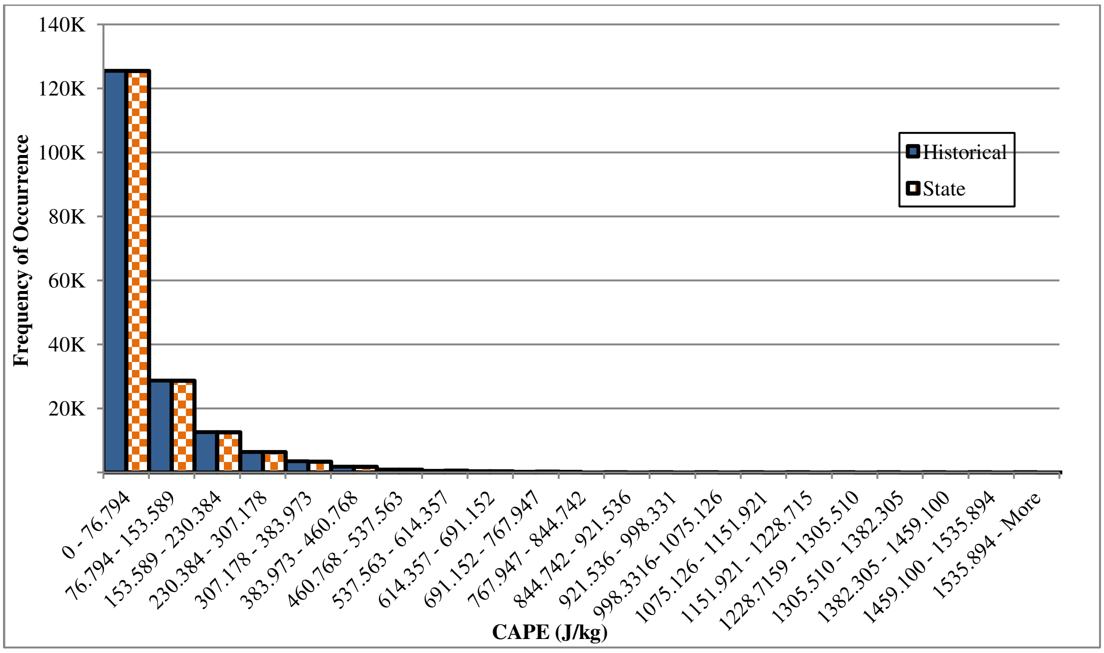


Figure 10-148 - State Basecase and Historical CAPE (J/kg) Distribution, South England and South Wales

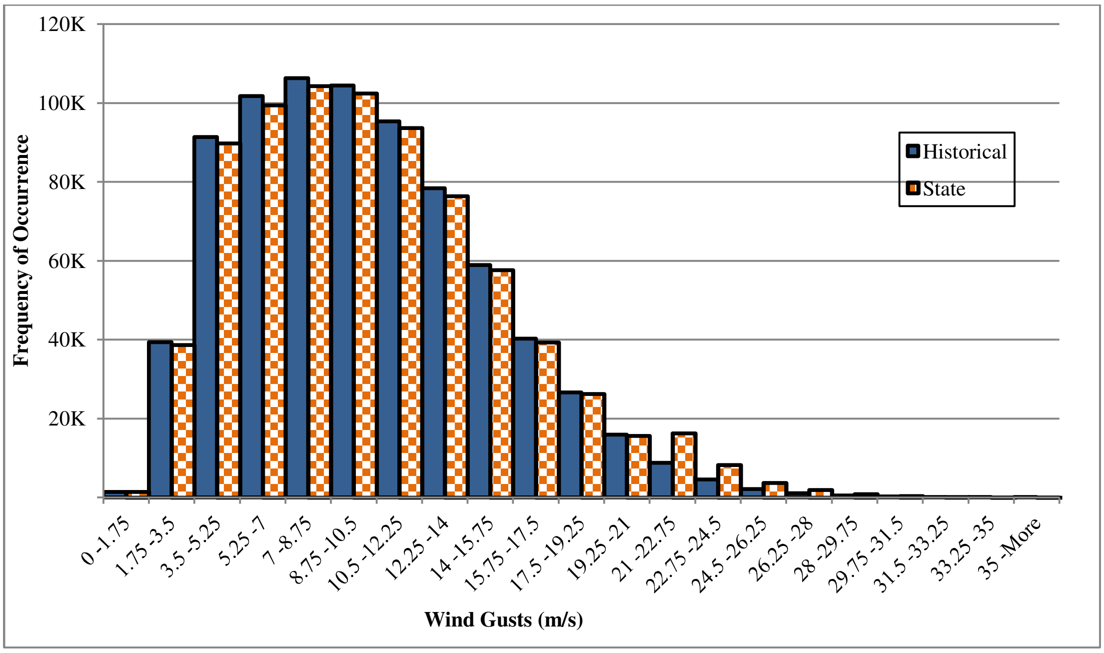


Figure 10-149 - State Basecase and Historical Wind Gusts (m/s) Distribution, South Scotland

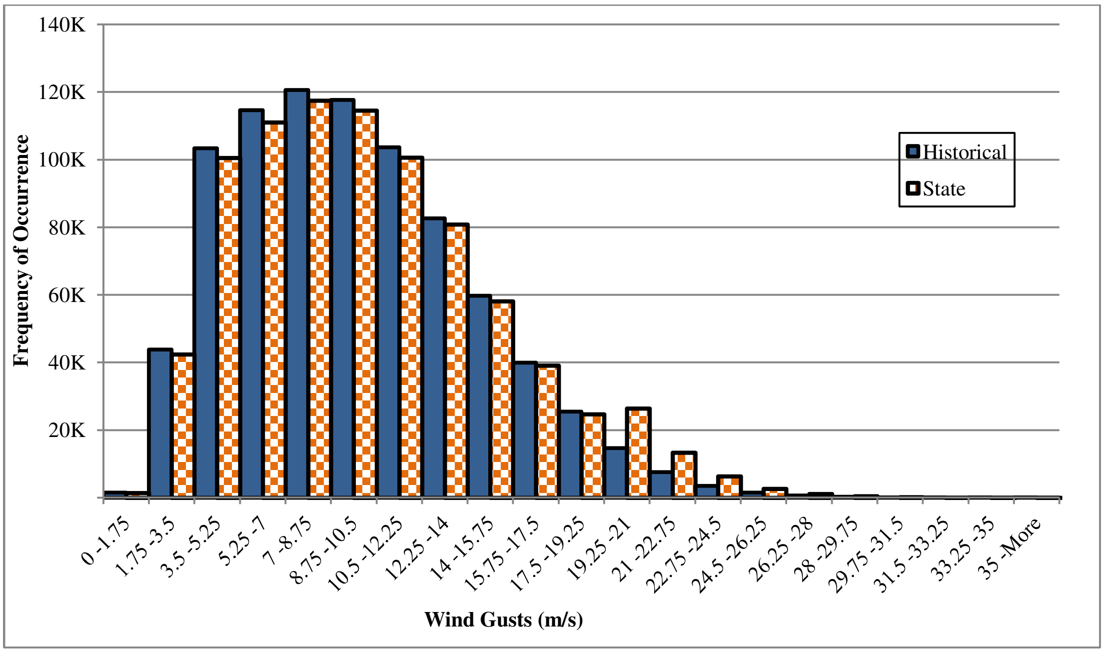


Figure 10-150 - State Basecase and Historical Wind Gusts (m/s) Distribution, North England and North Wales

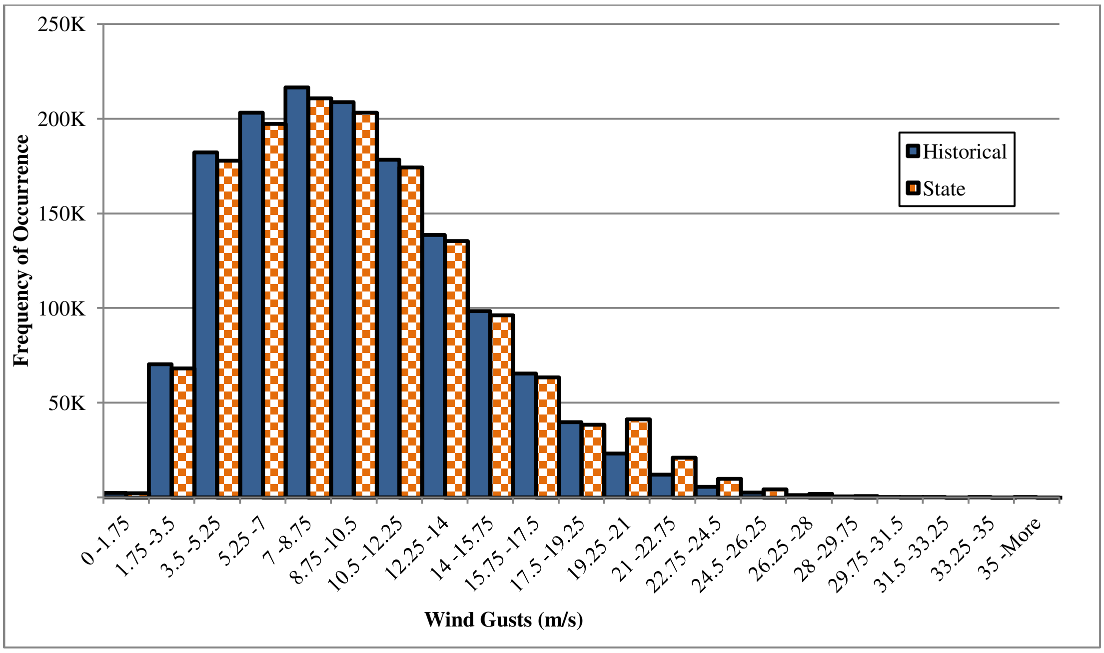


Figure 10-151 - State Basecase and Historical Wind Gusts (m/s) Distribution, South England and South Wales

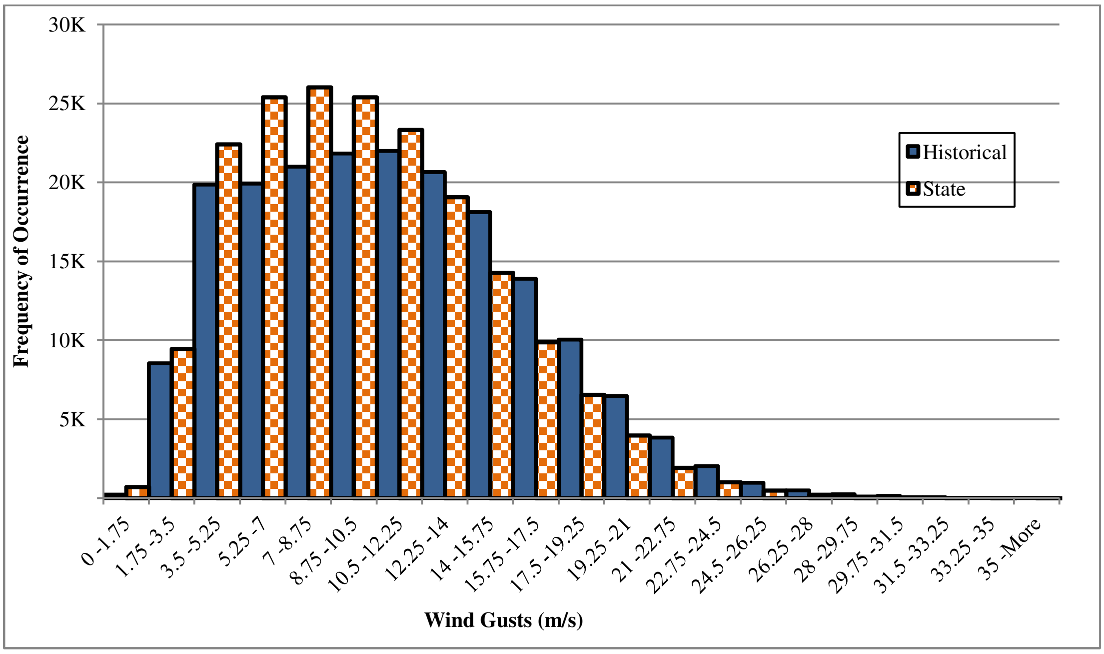


Figure 10-152 - State Basecase and Historical Wind Gusts on Snow Days (m/s) Distribution, South Scotland

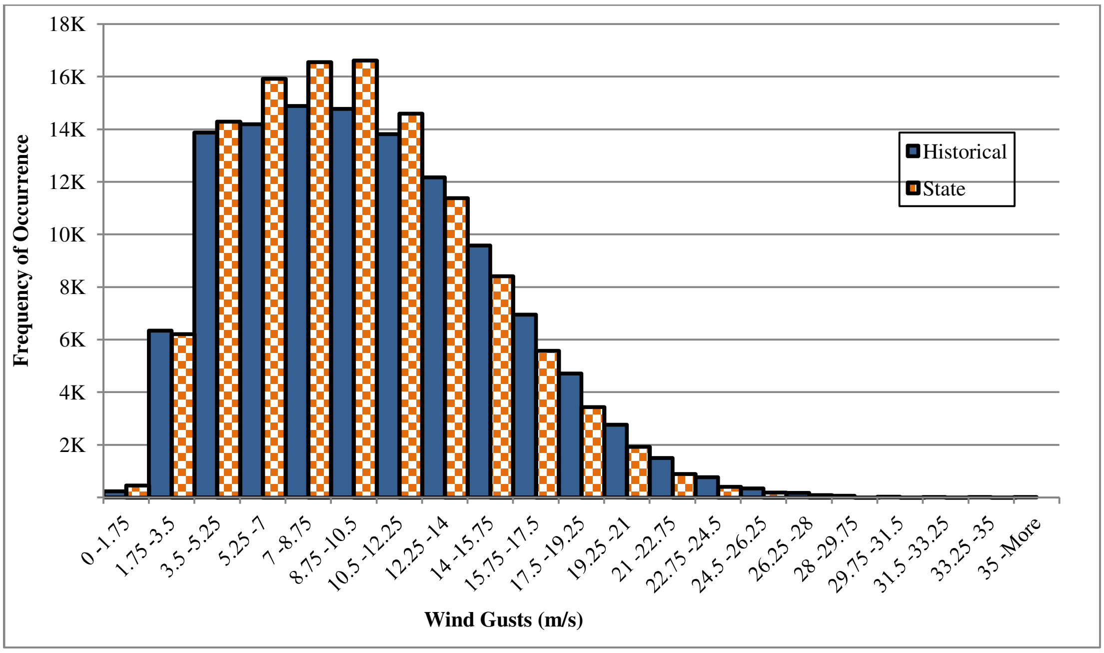


Figure 10-153 - State Basecase and Historical Wind Gusts on Snow Days (m/s) Distribution, North England and North Wales

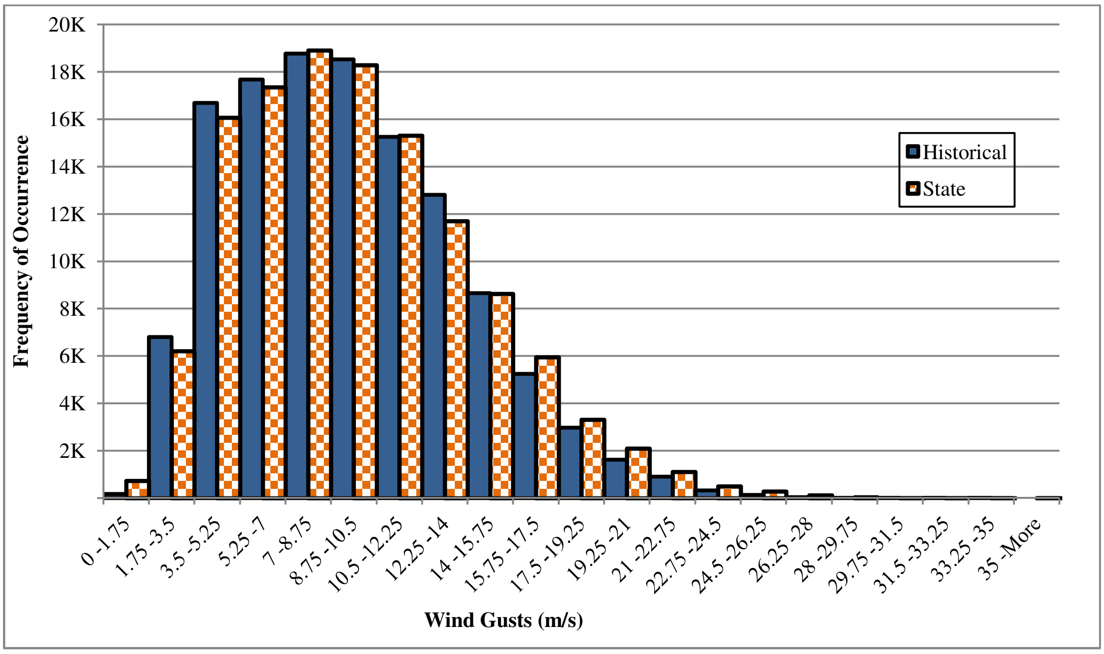


Figure 10-154 - State Basecase and Historical Wind Gusts on Snow Days (m/s) Distribution, South England and South Wales

H-2 Test Case One - 5% Wind Gust Increase

Table H-1 - Lightning Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case One)

	Lightning Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.96	0.597<0.961<1.326	1.92	0.94	0.602<0.943<1.284
S Scotland	0.96	0.00<0.958<2.435	2.54	0.93	0.00<0.934<2.434
N England and N Wales	1.03	0.494<1.033<1.572	0.57	1.03	0.52<1.027<1.534
S England and S Wales	0.90	0.00<0.902<1.988	3.06	0.88	0.00<0.875<1.967

Table H-2 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case One)

	Snow Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.03	0.00<0.034<0.299	-2.44	0.04	0.00<0.035<0.344
S Scotland	0.03	0.00<0.035<0.885	-13.16	0.04	0.00<0.04<1.018
N England and N Wales	0.03	0.00<0.034<0.376	5.08	0.03	0.00<0.032<0.423
S England and S Wales	0.01	0.00<0.007<0.634	2.86	0.01	0.00<0.007<0.729

Table H-3 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case One)

	Other Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.37	0.00<0.375<0.951	4.31	0.36	0.332<0.359<0.387
S Scotland	0.86	0.00<0.86<2.773	-3.15	0.89	0.82<0.888<0.956
N England and N Wales	0.39	0.00<0.388<1.158	-1.72	0.39	0.367<0.395<0.423
S England and S Wales	0.53	0.00<0.53<1.943	-2.39	0.54	0.503<0.543<0.583

Table H-4 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case One)

	Non-Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	4.94	4.635<4.938<5.241	0.43	4.92	4.58<4.917<5.26
S Scotland	19.28	18.05<19.279<20.51	-0.63	19.40	17.99<19.402<20.81
N England and N Wales	7.05	6.609<7.049<7.489	0.16	7.04	6.54<7.038<7.53
S England and S Wales	14.27	13.35<14.267<15.18	0.38	14.21	13.185<14.213<15.24

H-3 Test Case Two - 10% Wind Gust Increase

Table H-5 - Lightning Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Two)

	Lightning Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.95	0.673<0.954<1.235	1.14	0.94	0.602<0.943<1.284
S Scotland	0.87	0.00<0.871<2.095	-6.72	0.93	0.00<0.934<2.434
N England and N Wales	1.01	0.579<1.009<1.438	-1.78	1.03	0.52<1.027<1.534
S England and S Wales	0.87	0.00<0.867<1.765	-0.87	0.88	0.00<0.875<1.967

Table H-6 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Two)

	Snow Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.04	0.00<0.039<0.593	9.76	0.04	0.00<0.035<0.344
S Scotland	0.04	0.00<0.036<1.908	-9.21	0.04	0.00<0.04<1.018
N England and N Wales	0.04	0.00<0.036<0.775	12.69	0.03	0.00<0.032<0.423
S England and S Wales	0.01	0.00<0.011<1.376	48.57	0.01	0.00<0.007<0.729

Table H-7 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Two)

	Other Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.39	0.354<0.385<0.416	7.19	0.36	0.332<0.359<0.387
S Scotland	0.88	0.817<0.881<0.945	-0.83	0.89	0.82<0.888<0.956
N England and N Wales	0.39	0.361<0.39<0.419	-1.23	0.39	0.367<0.395<0.423
S England and S Wales	0.53	0.488<0.535<0.581	-1.48	0.54	0.503<0.543<0.583

Table H-8 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Two)

	Non-Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	4.88	4.442<4.877<5.311	-0.82	4.92	4.58<4.917<5.26
S Scotland	19.46	17.70<19.459<21.21	0.29	19.40	17.99<19.402<20.81
N England and N Wales	7.06	6.429<7.061<7.693	0.33	7.04	6.54<7.038<7.53
S England and S Wales	14.27	12.98<14.268<15.55	0.39	14.21	13.185<14.213<15.24

H-4 Test Case Three - 25% CAPE Increase

Table H-9 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Three)

	Wind Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.23	0.00<0.227<0.76	7.55	0.21	0.00<0.211<0.714
S Scotland	0.40	0.00<0.4<2.286	2.43	0.39	0.00<0.391<2.113
N England and N Wales	0.16	0.00<0.159<0.891	1.03	0.16	0.00<0.157<0.836
S England and S Wales	0.06	0.00<0.064<1.437	-3.99	0.07	0.00<0.067<1.325

Table H-10 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Three)

	Snow Failure Rates			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.03	0.00<0.035<0.605	-1.22	0.04	0.00<0.035<0.344
S Scotland	0.03	0.00<0.029<1.933	-28.95	0.04	0.00<0.04<1.018
N England and N Wales	0.04	0.00<0.036<0.818	11.17	0.03	0.00<0.032<0.423
S England and S Wales	0.00	0.00<0.005<1.438	-37.14	0.01	0.00<0.007<0.729

Table H-11 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Three)

	Other Weather Failure Rates			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.35	0.323<0.349<0.375	-2.75	0.36	0.332<0.359<0.387
S Scotland	0.84	0.782<0.842<0.901	-5.23	0.89	0.82<0.888<0.956
N England and N Wales	0.38	0.361<0.383<0.405	-3.04	0.39	0.367<0.395<0.423
S England and S Wales	0.53	0.494<0.528<0.562	-2.77	0.54	0.503<0.543<0.583

Table H-12 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Three)

	Non-Weather Failure Rates			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	4.81	4.507<4.808<5.109	-2.21	4.92	4.58<4.917<5.26
S Scotland	19.21	17.96<19.207<20.46	-1.01	19.40	17.99<19.402<20.81
N England and N Wales	7.02	6.571<7.022<7.473	-0.22	7.04	6.54<7.038<7.53
S England and S Wales	14.24	13.32<14.241<15.17	0.20	14.21	13.185<14.213<15.24

H-5 Test Case Four - 50% CAPE Increase

Table H-13 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Four)

	Wind Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.20	0.182<0.201<0.219	-4.69	0.21	0.00<0.211<0.714
S Scotland	0.46	0.433<0.464<0.494	18.78	0.39	0.00<0.391<2.113
N England and N Wales	0.14	0.128<0.139<0.15	-11.55	0.16	0.00<0.157<0.836
S England and S Wales	0.07	0.063<0.071<0.078	5.52	0.07	0.00<0.067<1.325

Table H-14 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Four)

	Snow Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.04	0.03<0.037<0.045	6.10	0.04	0.00<0.035<0.344
S Scotland	0.03	0.024<0.032<0.039	-21.05	0.04	0.00<0.04<1.018
N England and N Wales	0.04	0.031<0.036<0.041	12.69	0.03	0.00<0.032<0.423
S England and S Wales	0.01	0.005<0.007<0.009	0.00	0.01	0.00<0.007<0.729

Table H-15 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Four)

	Other Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.35	0.329<0.353<0.377	-1.68	0.36	0.332<0.359<0.387
S Scotland	0.80	0.76<0.799<0.839	-10.04	0.89	0.82<0.888<0.956
N England and N Wales	0.39	0.371<0.388<0.404	-1.85	0.39	0.367<0.395<0.423
S England and S Wales	0.53	0.511<0.532<0.553	-1.94	0.54	0.503<0.543<0.583

Table H-16 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Four)

	Non-Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	4.90	4.81<4.895<4.98	-0.45	4.92	4.58<4.917<5.26
S Scotland	19.39	19.2<19.393<19.59	-0.05	19.40	17.99<19.402<20.81
N England and N Wales	7.03	6.97<7.03<7.091	-0.12	7.04	6.54<7.038<7.53
S England and S Wales	14.28	14.18<14.276<14.37	0.45	14.21	13.185<14.213<15.24

H-6 Test Case Five - Decrease in Snow Days (40-70%) + 5% Increase in Wind Gusts

Table H-17 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Five)

	Wind Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.21	0.00<0.212<0.699	0.61	0.21	0.00<0.211<0.714
S Scotland	0.46	0.00<0.464<2.241	18.78	0.39	0.00<0.391<2.113
N England and N Wales	0.17	0.00<0.165<0.844	5.15	0.16	0.00<0.157<0.836
S England and S Wales	0.06	0.00<0.061<1.352	-9.82	0.07	0.00<0.067<1.325

Table H-18 - Lightning Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Five)

	Lightning Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.96	0.513<0.962<1.411	1.96	0.94	0.602<0.943<1.284
S Scotland	0.91	0.00<0.91<2.578	-2.60	0.93	0.00<0.934<2.434
N England and N Wales	1.05	0.419<1.051<1.682	2.31	1.03	0.52<1.027<1.534
S England and S Wales	0.86	0.00<0.861<2.088	-1.60	0.88	0.00<0.875<1.967

Table H-19 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Five)

	Other Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.35	0.00<0.354<0.827	-1.44	0.36	0.332<0.359<0.387
S Scotland	0.87	0.00<0.865<2.578	-2.61	0.89	0.82<0.888<0.956
N England and N Wales	0.38	0.00<0.38<1.036	-3.86	0.39	0.367<0.395<0.423
S England and S Wales	0.53	0.00<0.533<1.777	-1.82	0.54	0.503<0.543<0.583

Table H-20 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Five)

	Non-Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	4.88	0.00<4.881<17.411	-0.73	4.92	4.58<4.917<5.26
S Scotland	19.29	0.00<19.29<61.24	-0.58	19.40	17.99<19.402<20.81
N England and N Wales	7.07	0.00<7.071<23.993	0.48	7.04	6.54<7.038<7.53
S England and S Wales	14.18	0.00<14.18<44.62	-0.22	14.21	13.185<14.213<15.24

H-7 Test Case Six - Decrease in Snow Days (40-70%) + 10% Increase in Wind Gusts

Table H-21 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Six)

	Wind Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.19	0.00<0.19<12.7	-8.37	0.21	0.00<0.211<0.714
S Scotland	0.39	0.00<0.39<42.06	0.54	0.39	0.00<0.391<2.113
N England and N Wales	0.16	0.00<0.16<17.213	0.31	0.16	0.00<0.157<0.836
S England and S Wales	0.07	0.00<0.07<30.82	6.44	0.007	0.00<0.067<1.325

Table H-22 - Lighting Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Six)

	Lightning Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.94	0.642<0.943<1.244	-0.05	0.94	0.602<0.943<1.284
S Scotland	0.94	0.00<0.939<2.156	0.51	0.93	0.00<0.934<2.434
N England and N Wales	1.05	0.599<1.052<1.504	2.42	1.03	0.52<1.027<1.534
S England and S Wales	0.88	0.00<0.878<1.795	0.31	0.88	0.00<0.875<1.967

Table H-23 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Six)

	Other Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.38	0.213<0.382<0.551	6.35	0.36	0.332<0.359<0.387
S Scotland	0.84	0.368<0.843<1.318	-5.11	0.89	0.82<0.888<0.956
N England and N Wales	0.38	0.174<0.376<0.579	-4.68	0.39	0.367<0.395<0.423
S England and S Wales	0.53	0.179<0.531<0.883	-2.16	0.54	0.503<0.543<0.583

Table H-24 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (State Test Case Six)

	Non-Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	4.87	4.33<4.875<5.42	-0.86	4.92	4.58<4.917<5.26
S Scotland	19.17	17.29<19.166<21.04	-1.22	19.40	17.99<19.402<20.81
N England and N Wales	7.13	6.38<7.135<7.89	1.38	7.04	6.54<7.038<7.53
S England and S Wales	14.29	12.9<14.29<15.68	0.54	14.21	13.185<14.213<15.24

Appendix I: Failure Rates and Associated Confidence Limits for Sequential Sampling for the Weather Test Cases

This appendix contains the weather histograms for South Scotland, North England and North Wales, and South England and South Wales for the basecase sequential sampling model. As well at the results for the weather tests cases for the weather types not changed.

I-1 Sequential Sampling Weather Frequency Distributions

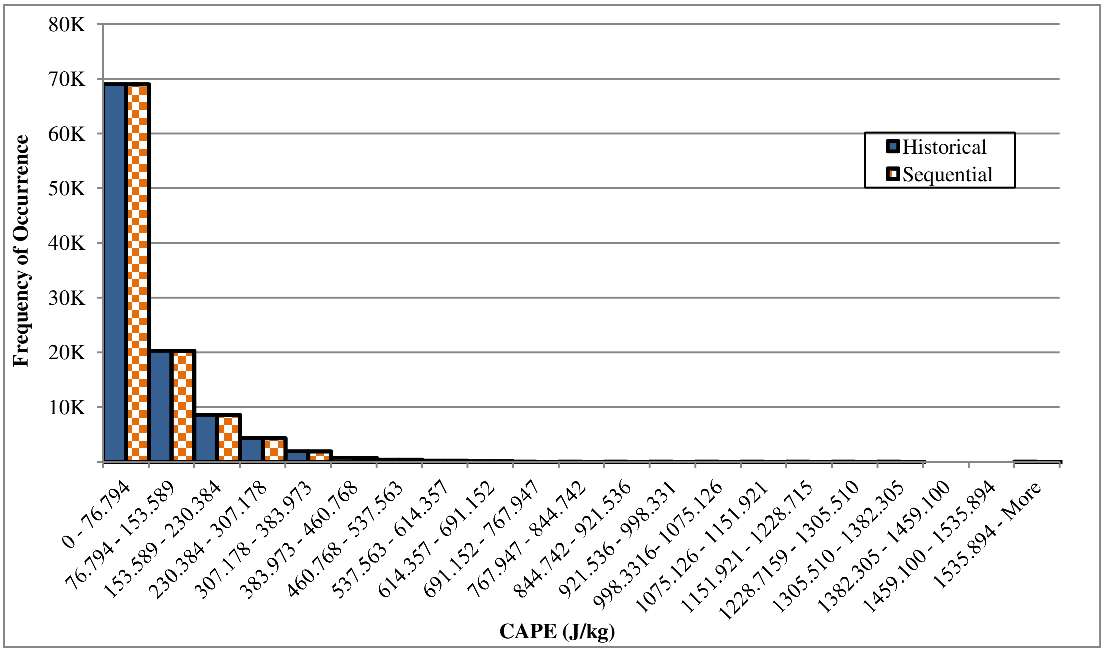


Figure 10-155 - Sequential Basecase and Historical CAPE (J/kg) Distribution, South Scotland

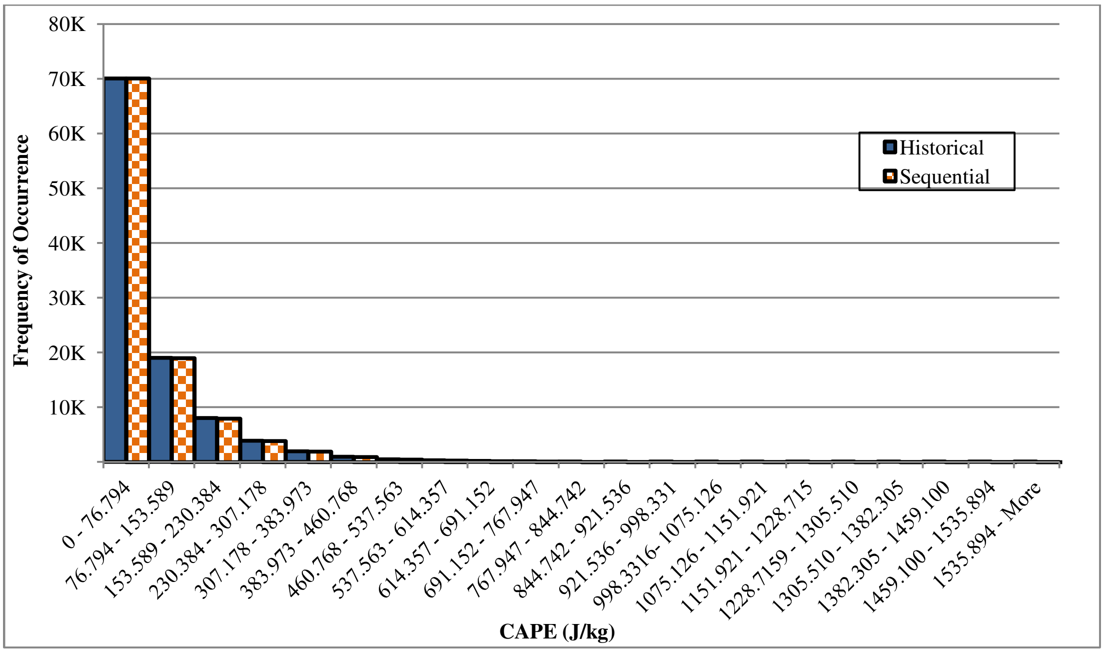


Figure 10-156 - Sequential Basecase and Historical CAPE (J/kg) Distribution, North England and North Wales

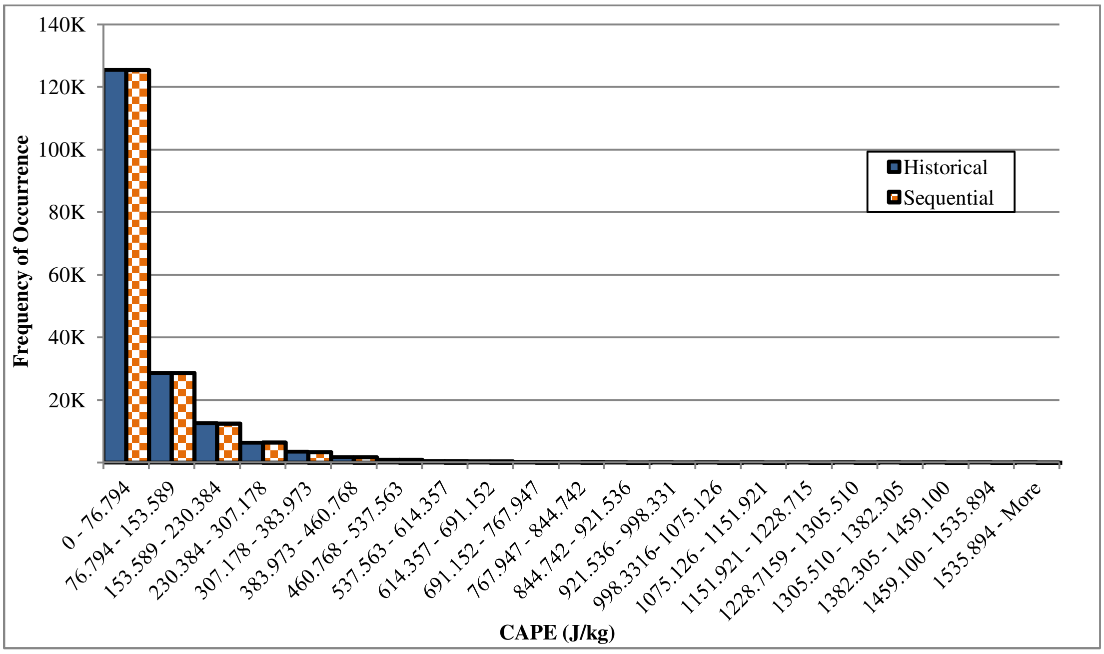


Figure 10-157 - Sequential Basecase and Historical CAPE (J/kg) Distribution, South England and South Wales

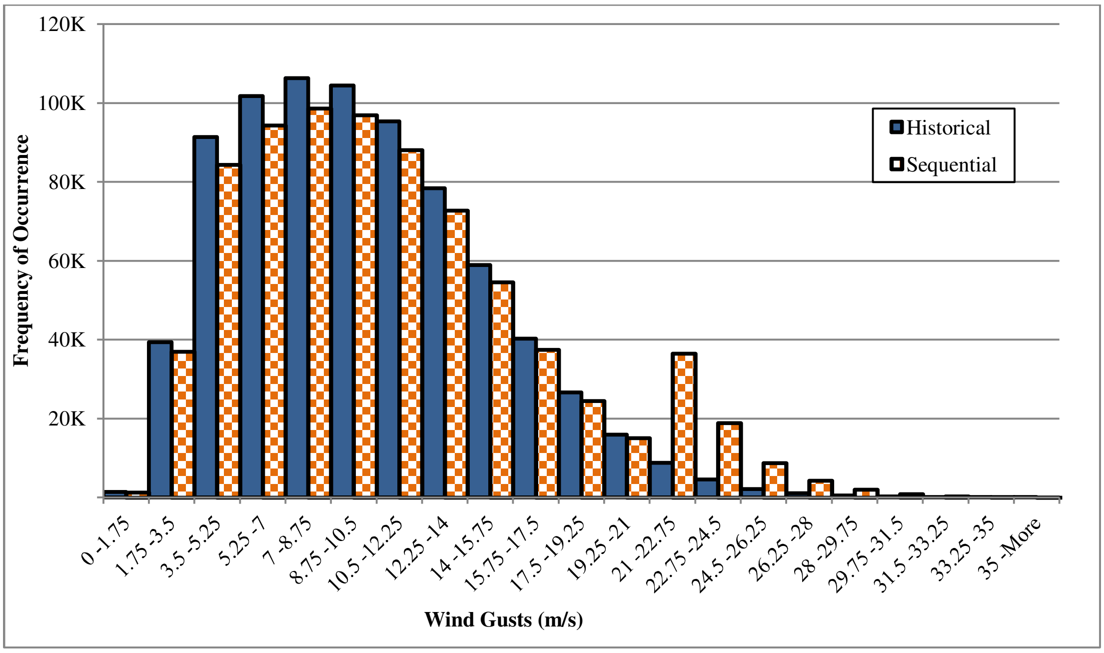


Figure 10-158 - Sequential Basecase and Historical Wind Gusts (m/s) Distribution, South Scotland

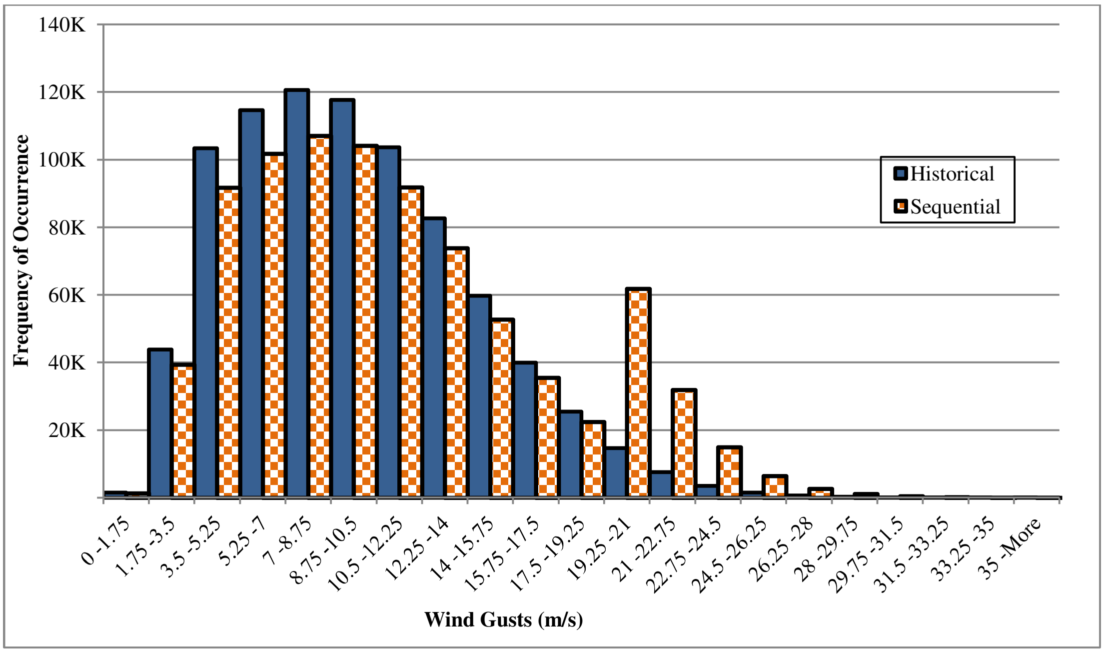


Figure 10-159 - Sequential Basecase and Historical Wind Gusts (m/s) Distribution, North England and North Wales

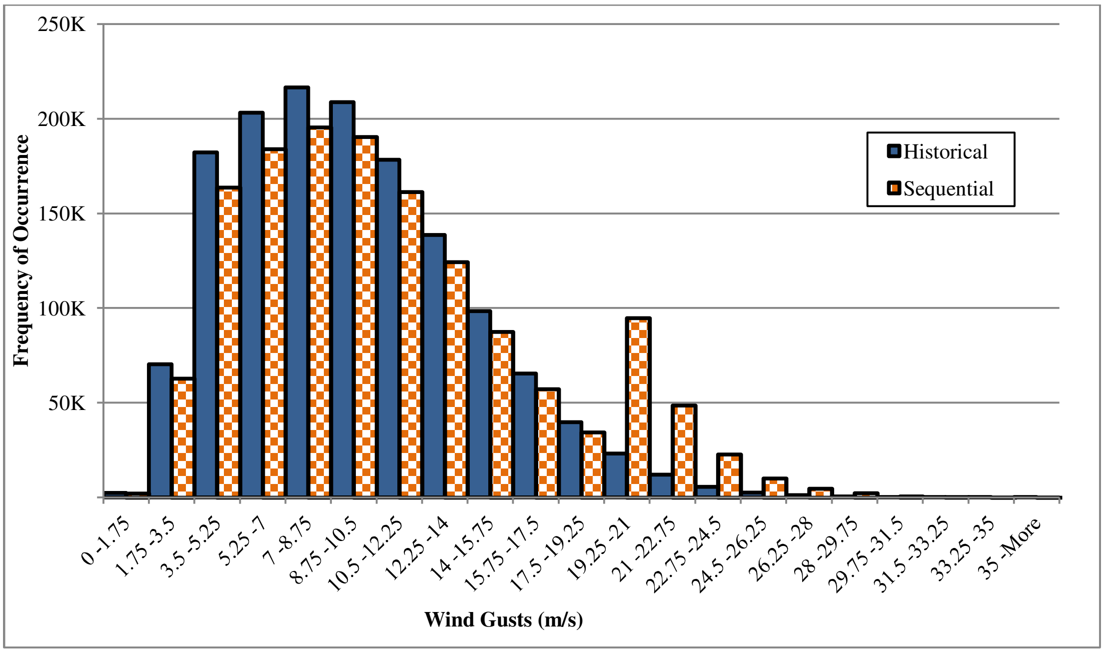


Figure 10-160 - Sequential Basecase and Historical Wind Gusts (m/s) Distribution, South England and South Wales

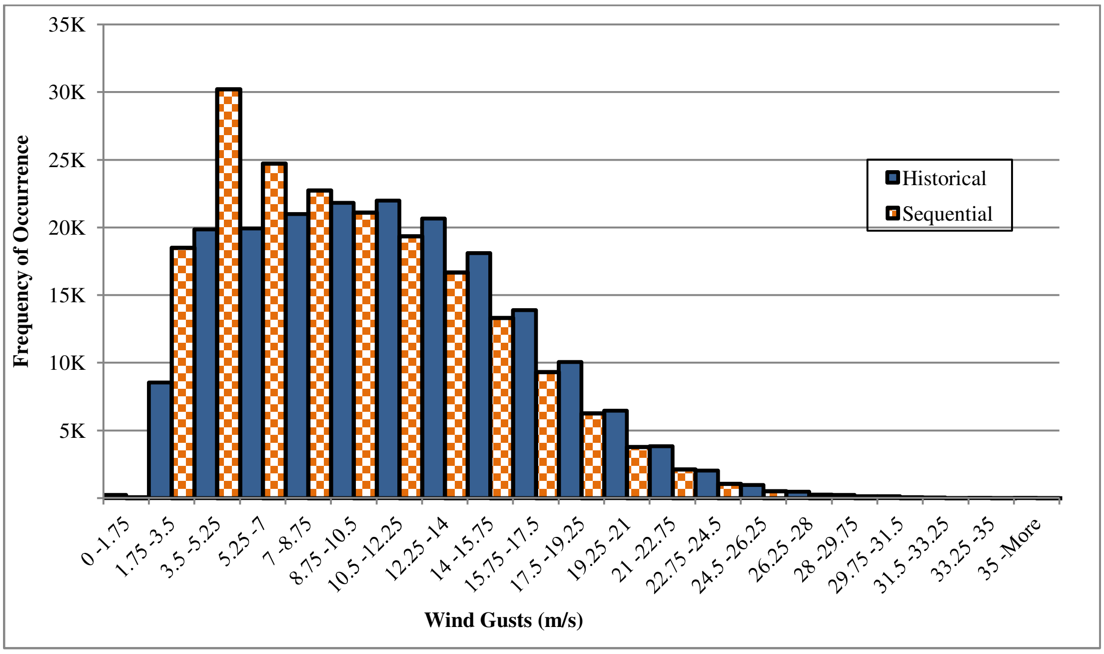


Figure 10-161 - Sequential Basecase and Historical Wind Gusts on Snow Days (m/s) Distribution, South Scotland

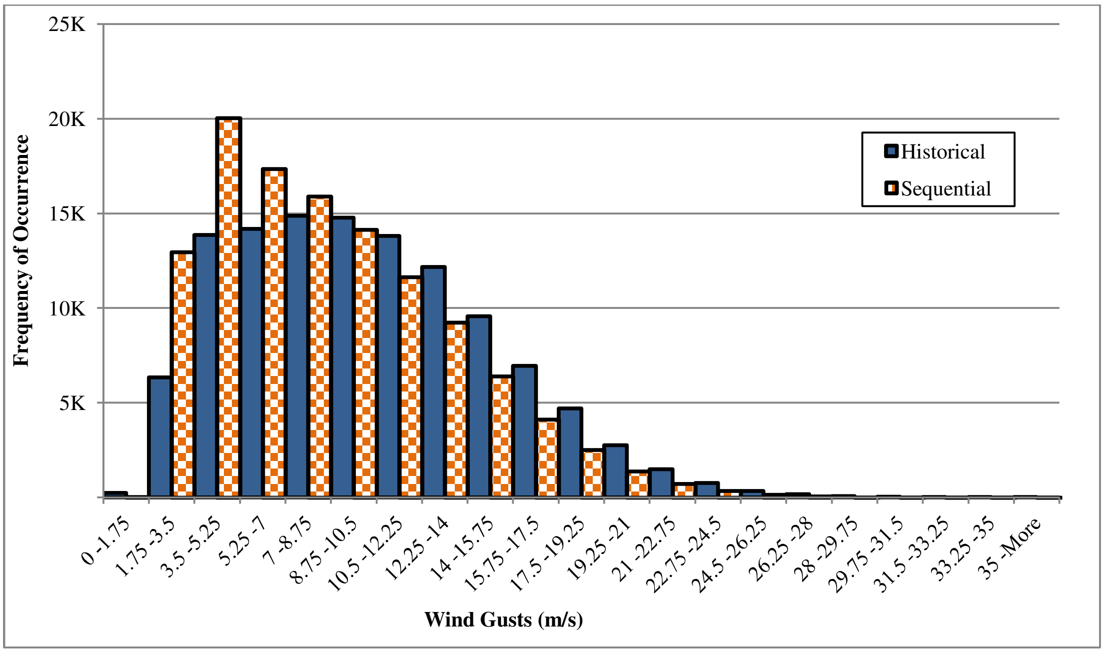


Figure 10-162 - Sequential Basecase and Historical Wind Gusts on Snow Days (m/s) Distribution, North England and North Wales

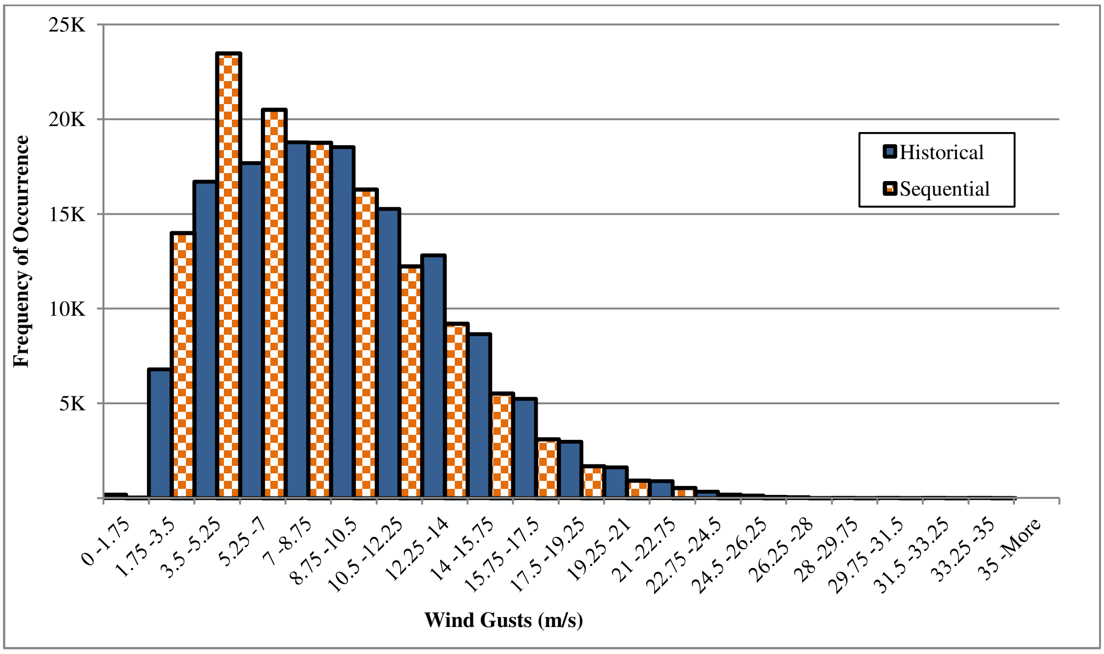


Figure 10-163 - Sequential Basecase and Historical Wind Gusts on Snow Days (m/s) Distribution, South England and South Wales

I-2 Test Case One - 5% Wind Gust Increase

Table I-1 - Lightning Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case One)

	Lightning Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.51	0.485<0.514<0.544	-3.24	0.53	0.5<0.532<0.563
S Scotland	0.50	0.462<0.496<0.529	-8.84	0.54	0.507<0.544<0.58
N England and N Wales	0.44	0.419<0.435<0.452	0.83	0.43	0.415<0.432<0.448
S England and S Wales	0.38	0.362<0.379<0.396	1.27	0.37	0.359<0.374<0.39

Table I-2 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case One)

	Snow Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.09	0.08<0.092<0.105	-12.96	0.11	0.091<0.106<0.121
S Scotland	0.16	0.141<0.159<0.178	11.03	0.14	0.126<0.144<0.161
N England and N Wales	0.10	0.088<0.096<0.105	11.26	0.09	0.08<0.086<0.093
S England and S Wales	0.02	0.014<0.017<0.021	-17.65	0.02	0.017<0.021<0.025

Table I-3 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case One)

	Other Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.09	0.076<0.088<0.1	-14.29	0.10	0.09<0.102<0.115
S Scotland	0.14	0.119<0.136<0.152	-6.88	0.15	0.128<0.146<0.163
N England and N Wales	0.09	0.087<0.095<0.102	-3.32	0.10	0.089<0.098<0.106
S England and S Wales	0.13	0.116<0.125<0.135	-1.62	0.13	0.118<0.127<0.137

Table I-4 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case One)

	Non-Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	1.10	1.059<1.101<1.144	-2.48	1.13	1.089<1.129<1.17
S Scotland	3.17	3.102<3.174<3.247	0.38	3.16	3.079<3.162<3.246
N England and N Wales	0.79	0.767<0.789<0.811	3.25	0.76	0.743<0.764<0.786
S England and S Wales	1.48	1.441<1.476<1.511	-2.82	1.52	1.482<1.519<1.557

I-3 Test Case Two - 10% Wind Gust Increase

Table I-5 - Lightning Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Two)

	Lightning Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.57	0.537<0.57<0.603	7.12	0.53	0.5<0.532<0.563
S Scotland	0.56	0.526<0.557<0.587	2.43	0.54	0.507<0.544<0.58
N England and N Wales	0.45	0.43<0.448<0.466	3.76	0.43	0.415<0.432<0.448
S England and S Wales	0.37	0.349<0.366<0.382	-2.37	0.37	0.359<0.374<0.39

Table I-6 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Two)

	Snow Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.09	0.08<0.092<0.104	-13.77	0.11	0.091<0.106<0.121
S Scotland	0.14	0.12<0.136<0.151	-5.51	0.14	0.126<0.144<0.161
N England and N Wales	0.09	0.084<0.091<0.099	5.63	0.09	0.08<0.086<0.093
S England and S Wales	0.02	0.015<0.019<0.023	-11.76	0.02	0.017<0.021<0.025

Table I-7 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Two)

	Other Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.09	0.079<0.091<0.102	-11.34	0.10	0.09<0.102<0.115
S Scotland	0.14	0.117<0.135<0.153	-7.25	0.15	0.128<0.146<0.163
N England and N Wales	0.10	0.091<0.098<0.105	0.17	0.10	0.089<0.098<0.106
S England and S Wales	0.13	0.122<0.13<0.139	2.27	0.13	0.118<0.127<0.137

Table I-8 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Two)

	Non-Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	1.13	1.079<1.126<1.173	-0.30	1.13	1.089<1.129<1.17
S Scotland	3.19	3.112<3.193<3.274	0.97	3.16	3.079<3.162<3.246
N England and N Wales	0.79	0.767<0.788<0.809	3.14	0.76	0.743<0.764<0.786
S England and S Wales	1.47	1.433<1.466<1.499	-3.51	1.52	1.482<1.519<1.557

I-4 Test Case Three - 25% CAPE Increase

Table I-9 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Three)

	Wind Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.27	0.24<0.268<0.295	5.25	0.25	0.231<0.254<0.277
S Scotland	0.40	0.365<0.401<0.436	-0.39	0.40	0.368<0.402<0.436
N England and N Wales	0.11	0.098<0.111<0.124	-6.69	0.12	0.107<0.119<0.131
S England and S Wales	0.05	0.041<0.048<0.055	-10.04	0.05	0.047<0.053<0.06

Table I-10 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Three)

	Snow Failure Rates			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.11	0.093<0.106<0.119	0.00	0.11	0.091<0.106<0.121
S Scotland	0.16	0.145<0.164<0.183	14.34	0.14	0.126<0.144<0.161
N England and N Wales	0.10	0.09<0.098<0.106	13.70	0.09	0.08<0.086<0.093
S England and S Wales	0.01	0.011<0.015<0.018	-30.39	0.02	0.017<0.021<0.025

Table I-11 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Three)

	Other Weather Failure Rates			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.08	0.073<0.084<0.096	-17.65	0.10	0.09<0.102<0.115
S Scotland	0.16	0.142<0.163<0.183	11.59	0.15	0.128<0.146<0.163
N England and N Wales	0.10	0.089<0.097<0.105	-0.83	0.10	0.089<0.098<0.106
S England and S Wales	0.12	0.111<0.121<0.13	-5.02	0.13	0.118<0.127<0.137

Table I-12 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Three)

	Non-Weather Failure Rates			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	1.17	1.125<1.167<1.209	3.31	1.13	1.089<1.129<1.17
S Scotland	3.12	3.044<3.122<3.2	-1.27	3.16	3.079<3.162<3.246
N England and N Wales	0.78	0.756<0.777<0.799	1.70	0.76	0.743<0.764<0.786
S England and S Wales	1.49	1.457<1.489<1.522	-1.95	1.52	1.482<1.519<1.557

I-5 Test Case Four - 50% CAPE Increase

Table I-13 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Four)

	Wind Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.28	0.253<0.28<0.307	10.32	0.25	0.231<0.254<0.277
S Scotland	0.42	0.38<0.42<0.459	4.33	0.40	0.368<0.402<0.436
N England and N Wales	0.12	0.108<0.121<0.133	1.50	0.12	0.107<0.119<0.131
S England and S Wales	0.05	0.047<0.054<0.061	0.77	0.05	0.047<0.053<0.06

Table I-14 - Snow Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Four)

	Snow Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.09	0.08<0.093<0.106	-12.55	0.11	0.091<0.106<0.121
S Scotland	0.15	0.132<0.15<0.169	4.78	0.14	0.126<0.144<0.161
N England and N Wales	0.09	0.085<0.092<0.1	6.75	0.09	0.08<0.086<0.093
S England and S Wales	0.02	0.015<0.019<0.023	-10.78	0.02	0.017<0.021<0.025

Table I-15 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Four)

	Other Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.08	0.07<0.083<0.096	-18.91	0.10	0.09<0.102<0.115
S Scotland	0.15	0.13<0.146<0.161	0.00	0.15	0.128<0.146<0.163
N England and N Wales	0.10	0.089<0.097<0.105	-0.83	0.10	0.089<0.098<0.106
S England and S Wales	0.12	0.114<0.124<0.134	-2.91	0.13	0.118<0.127<0.137

Table I-16 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Four)

	Non-Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	1.14	1.102<1.143<1.184	1.22	1.13	1.089<1.129<1.17
S Scotland	3.27	3.189<3.273<3.356	3.49	3.16	3.079<3.162<3.246
N England and N Wales	0.79	0.766<0.789<0.812	3.23	0.76	0.743<0.764<0.786
S England and S Wales	1.50	1.459<1.495<1.532	-1.57	1.52	1.482<1.519<1.557

I-6 Test Case Five - Decrease in Snow Days (40-70%) + 5% Increase in Wind Gusts

Table I-17 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Five)

	Wind Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.29	0.261<0.29<0.318	13.87	0.25	0.231<0.254<0.277
S Scotland	0.41	0.374<0.406<0.439	1.05	0.40	0.368<0.402<0.436
N England and N Wales	0.12	0.106<0.118<0.131	-0.27	0.12	0.107<0.119<0.131
S England and S Wales	0.05	0.044<0.051<0.058	-4.63	0.05	0.047<0.053<0.06

Table I-18 - Lightning Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Five)

	Lightning Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.52	0.486<0.52<0.553	-2.27	0.53	0.5<0.532<0.563
S Scotland	0.55	0.518<0.555<0.592	2.04	0.54	0.507<0.544<0.58
N England and N Wales	0.44	0.427<0.443<0.459	2.59	0.43	0.415<0.432<0.448
S England and S Wales	0.39	0.369<0.387<0.405	3.30	0.37	0.359<0.374<0.39

Table I-19 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Five)

	Other Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.08	0.07<0.083<0.096	-18.91	0.10	0.09<0.102<0.115
S Scotland	0.14	0.123<0.14<0.157	-3.99	0.15	0.128<0.146<0.163
N England and N Wales	0.10	0.088<0.096<0.104	-1.82	0.10	0.089<0.098<0.106
S England and S Wales	0.13	0.118<0.128<0.137	0.16	0.13	0.118<0.127<0.137

Table I-20 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Five)

	Non-Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	1.15	1.111<1.152<1.193	2.02	1.13	1.089<1.129<1.17
S Scotland	3.19	3.114<3.192<3.271	0.95	3.16	3.079<3.162<3.246
N England and N Wales	0.80	0.779<0.803<0.827	5.05	0.76	0.743<0.764<0.786
S England and S Wales	1.50	1.467<1.5<1.532	-1.26	1.52	1.482<1.519<1.557

I-7 Test Case Six - Decrease in Snow Days (40-70%) + 10% Increase in Wind Gusts

Table I-21 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Six)

	Wind Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.27	0.246<0.273<0.3	7.45	0.25	0.231<0.254<0.277
S Scotland	0.40	0.373<0.403<0.433	0.26	0.40	0.368<0.402<0.436
N England and N Wales	0.13	0.112<0.125<0.138	5.33	0.12	0.107<0.119<0.131
S England and S Wales	0.06	0.051<0.058<0.065	8.49	0.05	0.047<0.053<0.06

Table I-22 - Lightning Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Six)

	Lightning Failure Rates			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.55	0.518<0.546<0.574	2.75	0.53	0.5<0.532<0.563
S Scotland	0.54	0.502<0.536<0.57	-1.46	0.54	0.507<0.544<0.58
N England and N Wales	0.44	0.421<0.437<0.453	1.24	0.43	0.415<0.432<0.448
S England and S Wales	0.38	0.36<0.378<0.396	1.05	0.37	0.359<0.374<0.39

Table I-23 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Six)

	Other Weather Failure Rates			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.09	0.073<0.086<0.1	-15.55	0.10	0.09<0.102<0.115
S Scotland	0.14	0.119<0.136<0.152	-6.88	0.15	0.128<0.146<0.163
N England and N Wales	0.10	0.092<0.1<0.107	1.99	0.10	0.089<0.098<0.106
S England and S Wales	0.13	0.118<0.128<0.138	0.32	0.13	0.118<0.127<0.137

Table I-24 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Six)

	Non-Weather Failure Rates			**Basecase**	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	1.11	1.06<1.107<1.154	-1.98	1.13	1.089<1.129<1.17
S Scotland	3.23	3.142<3.228<3.314	2.09	3.16	3.079<3.162<3.246
N England and N Wales	0.80	0.776<0.799<0.821	4.48	0.76	0.743<0.764<0.786
S England and S Wales	1.50	1.468<1.5<1.532	-1.25	1.52	1.482<1.519<1.557

I-8 Test Case Seven - Decrease in Snow Days (40-70%) + Increased Snow Duration + 10% Increase in Wind Gusts

Table I-25 - Wind Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Seven)

	Wind Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.28	0.255<0.283<0.31	11.17	0.25	0.231<0.254<0.277
S Scotland	0.42	0.38<0.419<0.457	4.07	0.40	0.368<0.402<0.436
N England and N Wales	0.12	0.104<0.116<0.129	-1.91	0.12	0.107<0.119<0.131
S England and S Wales	0.05	0.046<0.053<0.059	-1.54	0.05	0.047<0.053<0.06

Table I-26 - Lightning Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Seven)

	Lightning Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.58	0.543<0.577<0.611	8.58	0.53	0.5<0.532<0.563
S Scotland	0.52	0.483<0.517<0.551	-4.85	0.54	0.507<0.544<0.58
N England and N Wales	0.43	0.413<0.431<0.448	-0.23	0.43	0.415<0.432<0.448
S England and S Wales	0.37	0.357<0.374<0.392	0.00	0.37	0.359<0.374<0.39

Table I-27 – Other Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Seven)

	Other Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	0.09	0.074<0.086<0.098	-15.97	0.10	0.09<0.102<0.115
S Scotland	0.15	0.132<0.151<0.17	3.62	0.15	0.128<0.146<0.163
N England and N Wales	0.10	0.089<0.097<0.104	-1.33	0.10	0.089<0.098<0.106
S England and S Wales	0.12	0.111<0.12<0.13	-5.66	0.13	0.118<0.127<0.137

Table I-28 – Non-Weather Failure rates, per area, per year, per 100km, Mean 95% Confidence Limits and Percentage change from the Basecase (Sequential Test Case Seven)

	Non-Weather Failure Rates			Basecase	
Area	Failure Rates	Mean 95% Confidence Limits	Percentage Change from the Basecase	Failure Rates	Mean 95% Confidence Limits
N Scotland	1.11	1.066<1.106<1.147	-2.02	1.13	1.089<1.129<1.17
S Scotland	3.19	3.114<3.189<3.264	0.83	3.16	3.079<3.162<3.246
N England and N Wales	0.78	0.756<0.777<0.799	1.72	0.76	0.743<0.764<0.786
S England and S Wales	1.46	1.43<1.463<1.496	-3.69	1.52	1.482<1.519<1.557