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Weather-related fragility modelling of critical infrastructure: A power and railway case study

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Climate change has led to more frequent and severe extreme weather events which impact critical infrastructure networks such as railway and power systems. Although our infrastructure networks are interdependent, the analysis to understand the impact of weather events on infrastructure systems is usually performed in sector specific silos. Here we present a methodology to examine how the same weather events affect different infrastructure sectors to understand cross-sectoral impact of extreme weather for interconnected regional infrastructure. We use fragility modelling to examine the impact of temperature and rainfall on power and rail system failures using the West Midlands as a case study. The results demonstrate that the impact of temperature is broadly consistent across both infrastructure networks, showing less impact until specific upper and lower thresholds are passed; these thresholds are similar for the different infrastructure networks evaluated however railway infrastructure is impacted more from lower temperatures. A growing correlation between the number of faults on power and railway systems is also found for both rainfall and temperature, indicating the value in coordinating preparation and planning efforts. For infrastructure operators and owners, regional resilience forums, and other decision-makers, this study provides an approach to assess the regional impact of extreme weather across multiple infrastructure sectors. The results give useful insight to inform the allocation of resources in response to extreme weather events.

1. Introduction

Climate change is increasing both the frequency and intensity of extreme weather events such as high temperatures, heavy rainfall, wildfires, and flooding (Seneviratne et al., 2021), and the economic damages associated with such events (Coronese et al., 2019). For example, according to the National Centers for Environmental Information, the US has experienced 372 weather and climate disasters with an adjusted damage cost at or above $1 Billion, with total costs exceeding $2.6 Trillion (NOAA, 2023). These costs included: damage to residential, commercial and municipal buildings, public assets (roads, bridges), electrical infrastructure, etc. The economic cost of weather and climate related extreme events in the Europe between 1980 and 2021 is estimated at €560 billion (EEA, 2023). Quantification of the impact of weather on infrastructure is important to maintain safe and reliable operation in this changing climate.

Within the UK, heavier rainfall events that are often associated with infrastructure damage are increasing (Cotterill et al., 2021). Moreover, temperature extremes are changing at a faster rate than average temperatures (Kendon et al., 2023), and in summer 2022 the maximum temperature exceeded 40°C for the first time, causing significant infrastructure disruption (Dooks, 2023). Extreme temperatures and heavy rainfall cause damage and disruption to power and rail systems that are the focus of this paper. On the railway network, high temperature can cause signalling equipment to overheat and cause sagging of the overhead lines which can cause the pantograph (that connects the train to overhead power) to disconnect (Ferranti et al., 2016). High temperature also causes expansion of structures such as rails and railway bridges, while a decrease in temperature causes contraction. This expansion and contraction may lead to deformation and stress concentrations in the rails, which in turn can cause damage and fractures (Lee et al., 2015). During hot weather events, speed restrictions are introduced to reduce the likelihood of track deformation, and the impact of any potential derailment event. These speed restrictions are also costly, and cause travel disruption (Ferranti et al., 2018). High temperatures also have a considerable impact on the electricity distribution network (Li et al., 2013) and are associated with increased fault rates (Abi-Samra et al., 2010). The direct effect of increased temperature is to limit or reduce the maximum power rating of equipment and increase energy losses (Houghton, 2009). In addition, increased temperatures lead to increased loads on electrical equipment, which increases the risk of equipment overload, a notable cause of distribution network failures (Houghton, 2009).

Considering heavy rainfall, this can lead to flooding of railway infrastructure and water damage to electrical and communication equipment, while too little precipitation can lead to soil drying and cracking that can misalign tracks (Palin et al., 2021). Intense rainfall can cause landslides to damage rail infrastructure (Liu et al., 2021). Intense rainfall may increase the risk of surface flooding, which may have direct or indirect effects on the power system (Wang et al., 2022). For example, the rainstorm that affected China in 2005 led to the collapse of more than 60 high-voltage transmission towers (Xie and Zhu, 2011). Often, infrastructure repairs and maintenance cannot be undertaken until flood water has receded, meaning the impact of a flooding event can persist long after the rain has finished falling (Ferranti et al., 2017)

As our infrastructure networks are connected, failures can have impacts beyond the location affected by extreme weather, particularly when failures occur on critical infrastructure. For example, flooding of the railway line south of Birmingham in 2012 created knock-on delays from Penzance to Edinburgh amounting to 4900 delay minutes, along with many cancellations (Jaroszweski et al., 2021). Similarly, a problem with a pantograph near Manchester in 2018 during extreme temperature led to 19,000 delay minutes as knock on delays affected services as far away as London, Glasgow, Cardiff and Newcastle (Ferranti et al., 2018). Flooding of an electric power station in Lancaster in 2016 led to power loss and the collapse of several critical infrastructure systems within the city including communication, road and rail, education and health (Ferranti et al., 2017). It is therefore imperative that infrastructure owners and operators work together to manage infrastructure interdependencies, cascade failures, and propagating delays.

Over the last decade, academic and practitioner research within the UK has made significant progress in understanding weather and climate change risks to infrastructure (Jaroszweski et al., 2015). Several studies have also tried to predict infrastructure fault rates associated with extreme weather. For example, logistic regression prediction model was used for predicting distribution transformer faults by analysing the correlation between weather data and historical distribution transformer fault data (Ko et al., 2020). Vulnerability and exposure were used to assess the risk posed by current and future weather to railway infrastructure (Palin et al., 2021). A number of multiple regression models are applied to analyses the impact of weather on railway network delays (Brazil et al., 2017). Fuzzy Bayesian Reasoning was used to quantify the climate risk faced by the railway system, and the results showed that heavy precipitation and flooding are potential climate threats (Wang et al., 2020). Other studies have considered infrastructure fragility for specific weather conditions or disasters such as earthquakes. Fragility curves depict the likelihood of failure of specific infrastructure, or infrastructure within a region, for a particular set of conditions. For example, in the power sector, fragility curves have been applied to earthquakes, flooding, ice-storms, lightning, wildfires and windstorms (Serrano-Fontova et al., 2023). Donaldson et al (2022) use fragility curves to explore the regional variation in wind impact on power system fault rates and develop unified thresholds for fault risk management. Others have developed fragility curves for overhead power lines (Dunn et al., 2015, Jamieson et al., 2020). In the rail sector, fragility analysis been applied to extreme flood events in order to estimate the likelihood of railway bridge failures during extreme flood events (Lamb et al., 2019, Martinović et al., 2016). Martinović et al. (2016) use fragility curves to understand how slope vulnerability along railway embankments may vary under a changing climate.

Despite the progress in understanding infrastructure risk and vulnerability to weather and climate change, and the need to consider and minimise the risks associated with infrastructure interdependencies (Ferranti et al., 2017, Rinaldi et al., 2001) the majority of weather and climate analysis studies are undertaken in sector specific silos. Few studies have considered how extreme weather impacts multiple interdependent and co-located infrastructure networks. Accordingly, this paper presents: (1) A methodology for concurrent evaluation of fragility across critical infrastructure for joint planning. (2) Demonstration of the methodology using a case study for power system faults and railway fault events based on weather factors in the West-Midland region of the UK. Application of the proposed methodology can allow better alignment of the regional preparation for infrastructure faults due to weather, enabling identification of consistent hazard thresholds to provide advance notice of potential risks.

2. Methodology

The methodology to concurrently assess infrastructure fragility to weather includes data collection and pre-processing, integration of data, fragility curve creation, and analysis of cross-sector correlation. This is summarised in Figure 1, and each of the core steps are detailed below.

2.1 Dataset Collection and Preprocessing

The first step is to select the region of interest and collect historical data for use in assessing infrastructure fragility for weather variables of interest. This requires two primary data sources: weather data and infrastructure faults. The infrastructure data should contain fault location, asset type, and the time of the fault. This can then be linked spatially with the corresponding weather variables such as temperature or rainfall, though the exact weather variables of interest will vary depending on the climate of the region of interest. The amount of historical data necessary will also differ by region and use case, due to variations in the number of historical faults and data availability. Some general guidance when collecting this data is to balance the spatial resolution with the quality of the data available. For example, when considering the reliability of distribution networks, IEEE Standard 1366 proposes that from a statistical point of view, the more data used to calculate thresholds, the better. However, as distribution systems expand, the stochastic processes that generate the data change. Using too much historical data can dampen the effects of these changes. Five years of data provides an appropriate balance between these considerations (IEEE, 2022). Similarly, for the methodology proposed in this paper, five years is recommended as a minimum duration to evaluate cross-sector impacts.

After the data is collected, it should be screened to identify outliers, or other extreme values in the data. Rather than removing these values, they should be identified for consideration in the later analyses as they could provide valuable insight into the response of networks under extreme events.

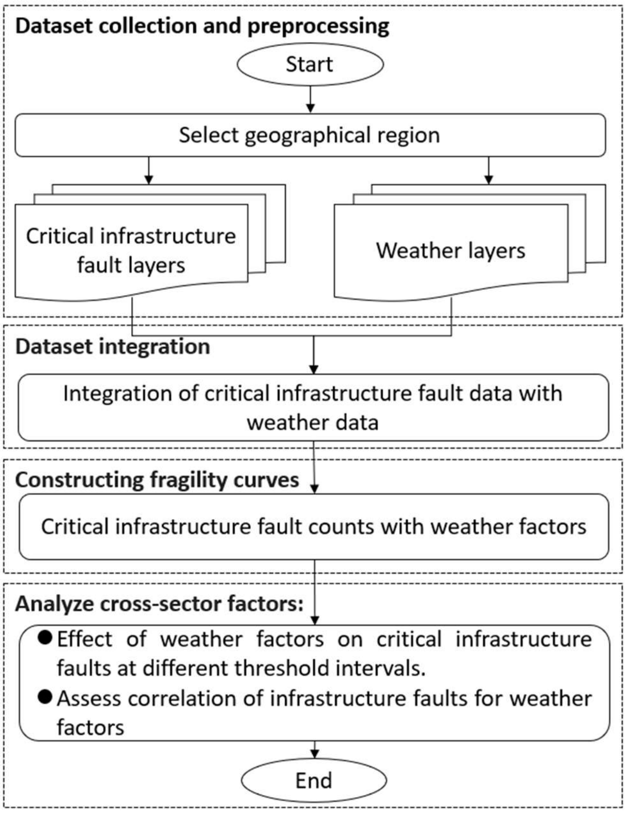


Figure 1. Methodology to concurrently assess critical infrastructure fragility to weather related failure.

2.2 Dataset Integration

The second step is to combine the collected critical infrastructure fault data with the weather data, as follows:

1) Aggregate faults to match the temporal resolution of the weather data. Then determine the best means to align the weather data to match the spatial resolution of interest. The process will differ depending on whether point-based weather station data or gridded data is used and the availability of data. Examples of both approaches to fragility can be seen from the literature with Donaldson et. al. (2022) and Ferranti et al (2016, 2018) using data from individual weather stations and Wilkinson et. al. (2022) using gridded weather data.
2) Spatially join weather and infrastructure fault time series to obtain a complete dataset that contains spatio-temporal weather and fault information. In this step, the decision must be made whether to use specific weather information for each fault location, or an aggregation of weather for the entire region. Both approaches have advantages and uncertainties. When using specific weather information for each fault location, weather conditions are included at the highest granularity. This may be appropriate for rainfall, which can have high spatial variability across a region. For temperature, the increased granularity may or may not be indicative of the temperature associated with asset failure, for temperature can be highly localised and individual location factors (e.g., tree shade) may be affecting the asset, but not the reported temperature (Ferranti et al., 2016), leading to false precision. When using aggregated weather data for a whole region, the spatial variation in weather conditions that may impact the asset (e.g., localised heavy rainfall) can be lost in the averaging process. However, regional weather information is more commonly used for regional decision-making (e.g., Resilience Forums, railway maintenance sectors), and so analysis employing regional averages may be better suited to support decision-makers. This is because the analysis output (e.g., fragility curves) is at a resolution comparable to the information provided for response management. When using this approach, taking maximum values of weather variables (rather than averages) ensures that localised extreme weather conditions (e.g., a heavy rainfall event, high wind gust) that are often associated with infrastructure failures are part of the aggregation process.

2.3 Fragility Curves

Fragility curves are commonly used in hazard modelling to define the probability of exceeding a given damage state as a function of environmental change (Dunn et al., 2018). Fragility curves can help distribution network operators (DNOs) and railway network operators to predict and estimate the number of faults that may occur in their service area (Donaldson et al., 2023, Bellè et al., 2022, Palin et al., 2021, Quinn et al., 2018, Wilkinson et al., 2022, Serrano-Fontova et al., 2023). In this paper, the objective is to determine the relationship between weather and fault counts, to produce a mathematical model to model the fragility function that can be used to compare the performance of multiple infrastructure networks exposed to the same weather conditions. This is done for each weather variable of interest. These variables can either be an individual weather variable such as windspeed or temperature, or a composite variable that includes a combination of several weather factors.

Extreme events can have a disproportionate impact on the overall fault count adversely impacting the validity of the resulting fragility function. Although outliers may impact the value of the mean, the median is not adversely affected and is a robust statistic that can effectively cope with outliers in the data. Therefore, to reduce the influence of outliers on the overall fragility curve, the median of the number of faults for each value of weather variable is used to calculate the fragility curve as opposed to the average. The number of observations at the extrema of the curve will also be limited and can bias the curve to the systems performance to a specific event. Such extreme event response is of interest but may lead to improper conclusions of the overall fragility at these values due to the lack of sufficient observations Therefore, curves should be produced with and without these values to inform the overall performance of the networks.

To translate the individual points into a fragility curve, a polynomial regression model is used as polynomial regression models are flexible and can be adapted to different forms of data (Ostertagová, 2012). The use of higher order polynomial regression may face disadvantages such as overfitting and increased model complexity, while making it difficult to interpret the meaning of each coefficient in the model. In this paper, second-order polynomials are used. The equation for polynomial regression is:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_n x^n + \varepsilon \qquad (1)$$

where y is the dependent variable, x^n is the independent variable, β_n is the coefficient of the regression equation, representing the weights of the different power terms and ε is the unobserved random error.

2.4 Analysis of Cross Sector Impacts

After production of individual fragility curves for each infrastructure sector, the resulting curves are plotted for the same period and weather variable for visual comparison of the shape, magnitude, and trend. This provides for a qualitative comparison. In addition to this qualitative evaluation, the correlation between infrastructure layers for intervals of each weather parameter provides a quantitative measure of the relationship. This is done using Pearson correlation coefficient (Sedgwick, 2012).

3. Case study and results

For this analysis, a fault constitutes an asset failure either on the power system logged by Western Power Distribution (WPD, now NGED) or on the railway logged by Network Rail's Fault Management System (FMS). The FMS is a central data repository managed by Network Rail. (CGI, 2013). To demonstrate the proposed methodology, a case study is conducted for the West Midlands region of the UK, considering two critical infrastructure sectors: railway and electrical power distribution. The UK electricity network consists of two main components: the high voltage transmission network and the low voltage distribution network, with the DNO (Distribution Network Operator) operating the low voltage distribution network and delivering electricity from the high voltage transmission network to homes and businesses (nationalgridESO, 2022). As can be seen from Figure 2, the study area covers seven districts within the West Midlands, Birmingham, Gloucester, Hereford & Ludlow, Stoke-on-Trent, Telford, Tipton, and Worcester, respectively. To conduct a unified assessment, railway system faults are collected for the same area from Network Rail. Following the process outlined in Section 2, data logged by Western Power Distribution (WPD, now NGED) and Network Railis collected including all power system faults and all railway fault events in the West Midlands from 1st April 2009 to 31st March 2014. A total of 73,286 electric power distribution and 45,153 railway faults are considered in the analysis.

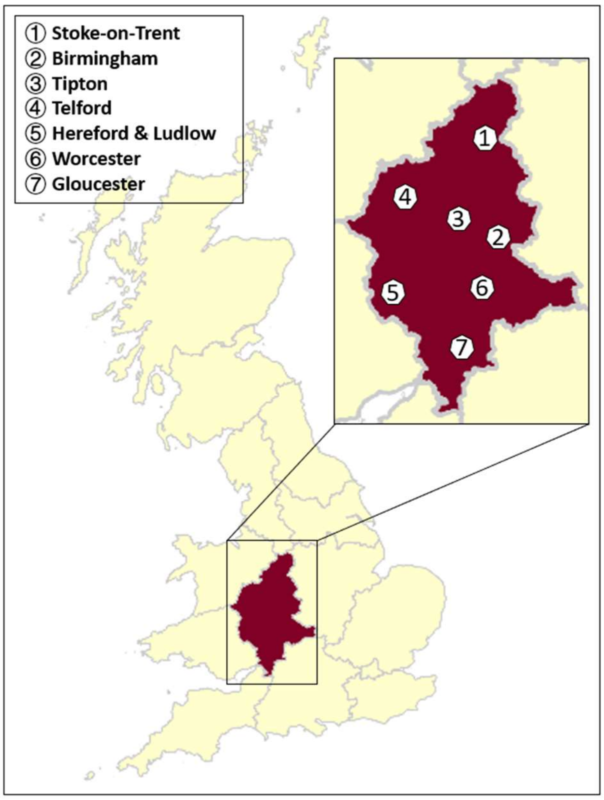


Figure 2. Great Britain Distribution Network Operators (DNOs) with the West Midlands area of National Grid Electricity Distribution (NGED, show in red) and location of districts used in the analysis.

Meteorological data (Maximum daily temperature and total daily rainfall) on a 12-km grid for the period April 1, 2009, to March 31, 2014, were obtained from the HadUK-Grid gridded climate observations provided by UK Met Office (MetOffice, 2022). As the weather data contains the maximum daily temperature and rainfall value on a 12km grid over the locations of the faults, first the fault data is aggregated to daily counts of faults for each of the two infrastructure sectors. For this case study, the intended application is to provide initial insight into decision-making for a wider region where local authorities may not have access to granular outage location information but rather aggregated data. To reflect this, the weather data for the region is averaged over the study area to form a single weather series against which to compare the regional infrastructure performance. More granular resolution could also be utilised to evaluate more localised impacts, which would involve taking the weather variables from the 12km square in which the fault occurred.

The historical faults are plotted to provide insight into the dispersion of the number of faults in power system and railway system across temperature and rainfall (as shown in Figures 4 and 6). Each grey point corresponds to the number of faults occurring on a single day and the corresponding maximum temperature. The median number of faults is shown in black. Error bars are produced which reflect the standard deviation in faults for each value of the weather variable. Plotting the standard deviation shows that the fit is well constrained in for some temperature ranges, but much less so for low temperature extremes.

Each of the steps in the asset fragility curves analysis are shown in Figure 3. Figure 5(a) shows the fragility curves for power and railway with respect to temperature. Evaluation reveals that the number of power system faults and railway fault events are approximated by a straight line in the interval of 8°C-25°C. In this temperature range, the number of faults in the power system is about 38 per day and the number of railway faults is about 25 per day. Below 7°C (including 7 °C), the number of faults increases as the temperature decreases. For each degree Celsius decrease in temperature, the number of power system faults increases by 2.1 and the number of railway system faults increases by 6.1. After 26°C (including 26°C), the number of faults increases as the temperature rises. For each degree Celsius rise in temperature, the number of power system faults increases by 2.4 and the number of railway fault events increases by 2. The fragility functions that map the relationship between infrastructure (power and railway) faults and temperature are shown below:

$$f_p(T) = 0.064T^2 - 1.581T + 43.47 \tag{7}$$
$$f_r(T) = 0.0923T^2 - 3.124T + 46.32 \tag{8}$$

where f_p is power system faults fragility function and f_r is railway fault events fragility function. T is temperature.

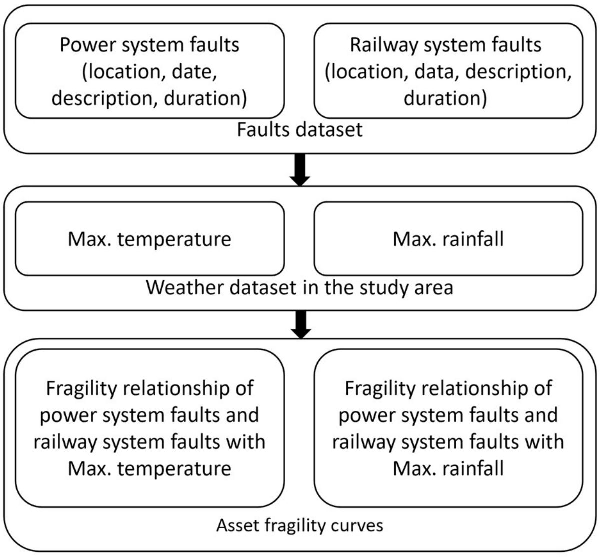
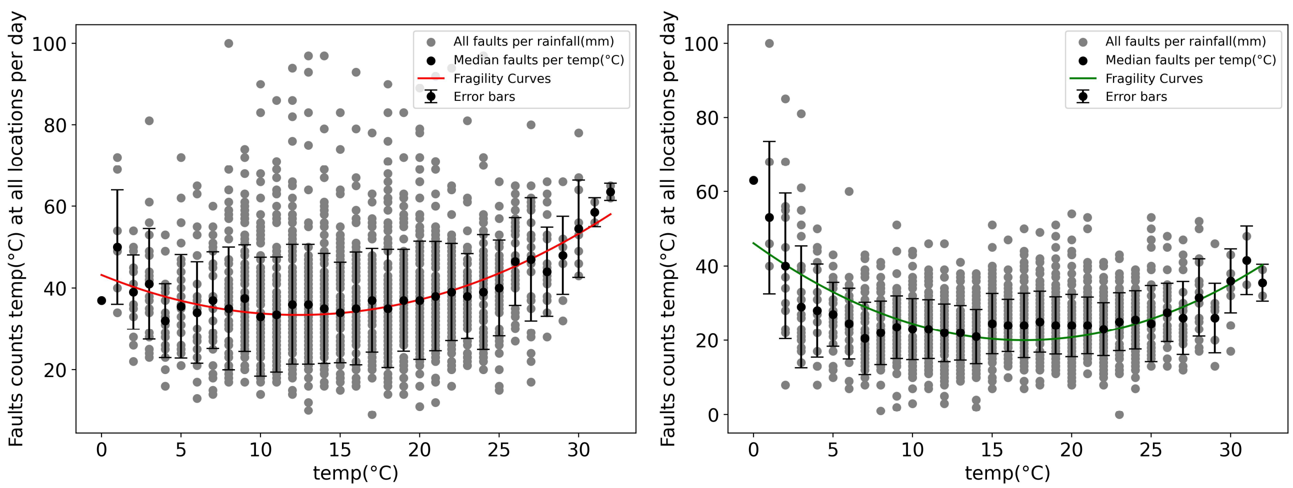
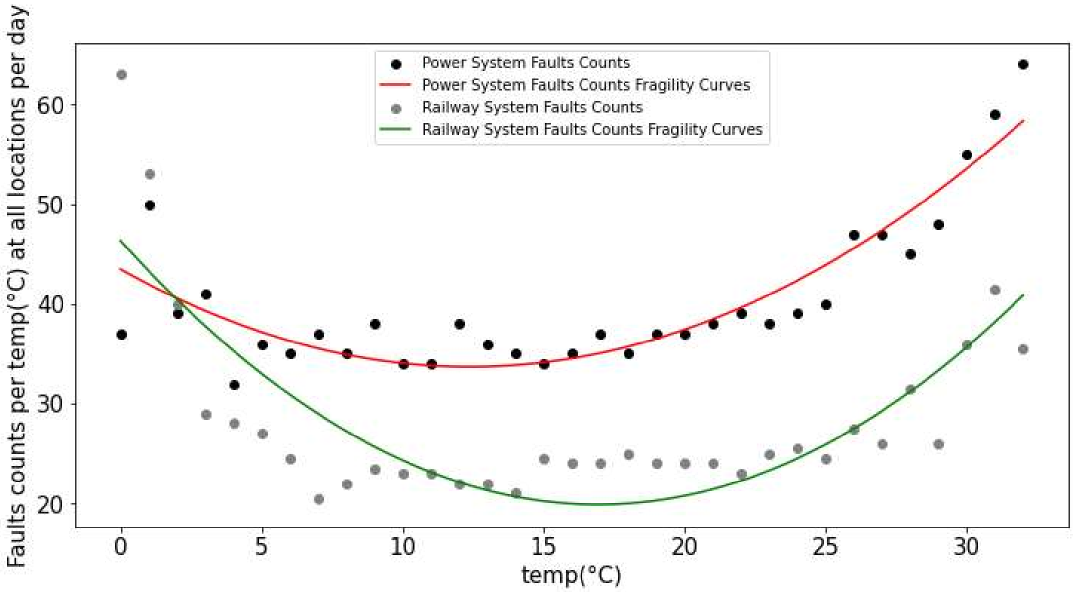


Figure 3. Steps in asset fragility curves analysis

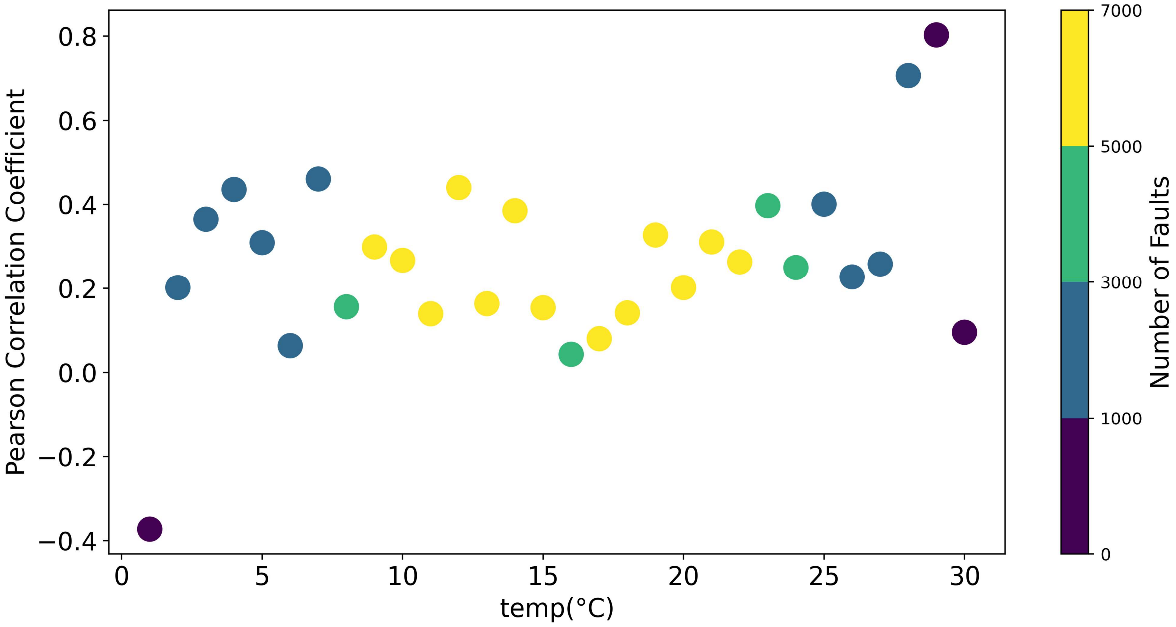


(a) **(b)**

Figure 4. (a) Number of all power system faults (grey points) and median number of faults (black points) recorded at different temperatures (max) at all locations. (b) Number of all railway fault events (grey points), and median number of faults (black points) recorded at different temperatures at all locations.



(a)

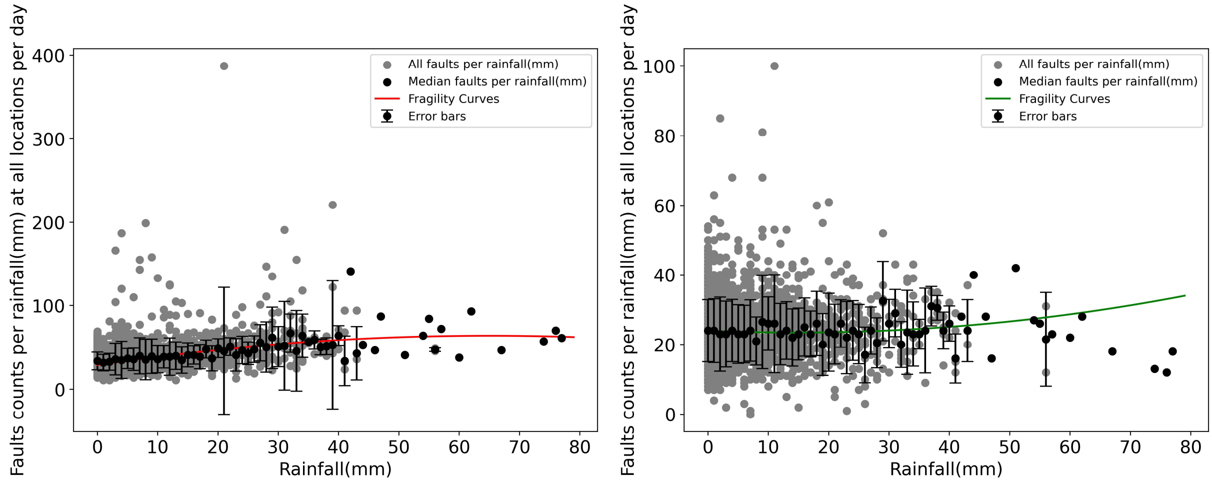


(b)

Figure 5. (a) Fragility curves of power system and railway system fault counts with temperature. (b) Correlation coefficient for power vs railway system faults at different temperatures.

Figure 5(b) provides the correlation between power and railway faults at each value of temperature using the Pearson correlation coefficient. Apart from extreme temperatures, it can be observed that as the temperature increases, the strength of the correlation between the number of rail and power faults increases with correlation ranging from 0.2 to 0.8 after 25 degrees. The average correlation between rail and power for all faults occurring at 25 degrees or above is 0.5 with a p-value of 0.03. This indicates a moderate correlation that is statistically significant. Figure 5(b) also indicates that power system faults and railway system faults are mainly concentrated in the range of 1°C-30°C (Figure 5(a)).

Similar to Figure 5(a), Figure 9 shows the distribution of the number of failures for different rainfall amounts. It should be noted that the number of power system faults is mainly concentrated in the range of 0mm-43mm of rainfall; there was only one day with more than 43mm of rainfall with a fault during the study period (figure 6(a)). For railway faults, there is only one day of data per rainfall point on average after more than 43 mm of rainfall (figure 6(b)). This illustrates the scarcity of data at high rainfall levels. For power and railway system faults under different rainfall amounts, they are mainly concentrated between 0 mm – 29 mm (Figure 7). Accordingly, data from days where rainfall exceeds 30 mm will not be used for analysis. The result after removing the days with a scarcity of data is shown in Figure 8.



(a) **(b)**

Figure 6: (a) Number of all power system faults (grey points) and median number of faults (black points) recorded at different rainfall (mm) at all locations (including outliers). (b) Number of railway fault events (grey points), and median number of faults (black points) recorded at different rainfall (mm) at all locations (including outliers).

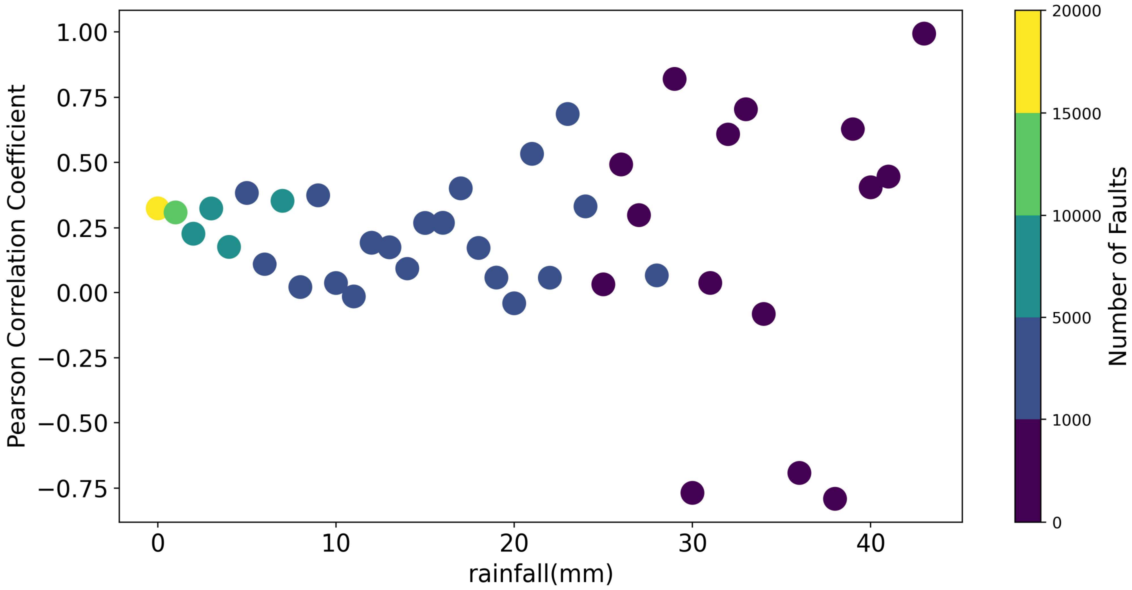
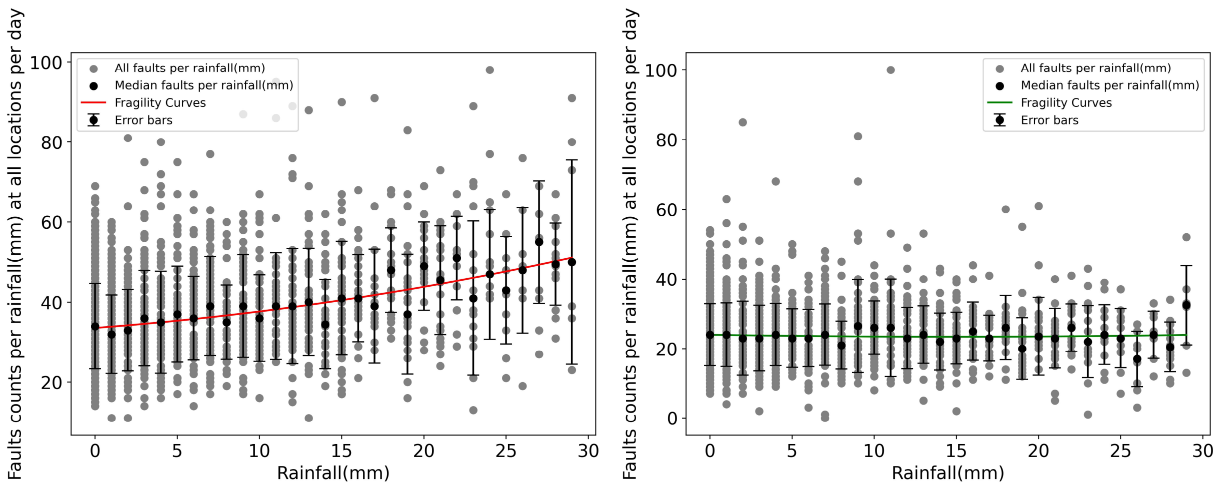


Figure 7: Correlation coefficient for power vs railway system faults at different rainfall.



(a) (b)

Figure 8: (a) Number of all power system faults (grey points) and median number of faults (black points) recorded at different rainfall (mm) at all locations. (b) Number of railway fault events (grey points), and median number of faults (black points) recorded at different rainfall (mm) at all locations.

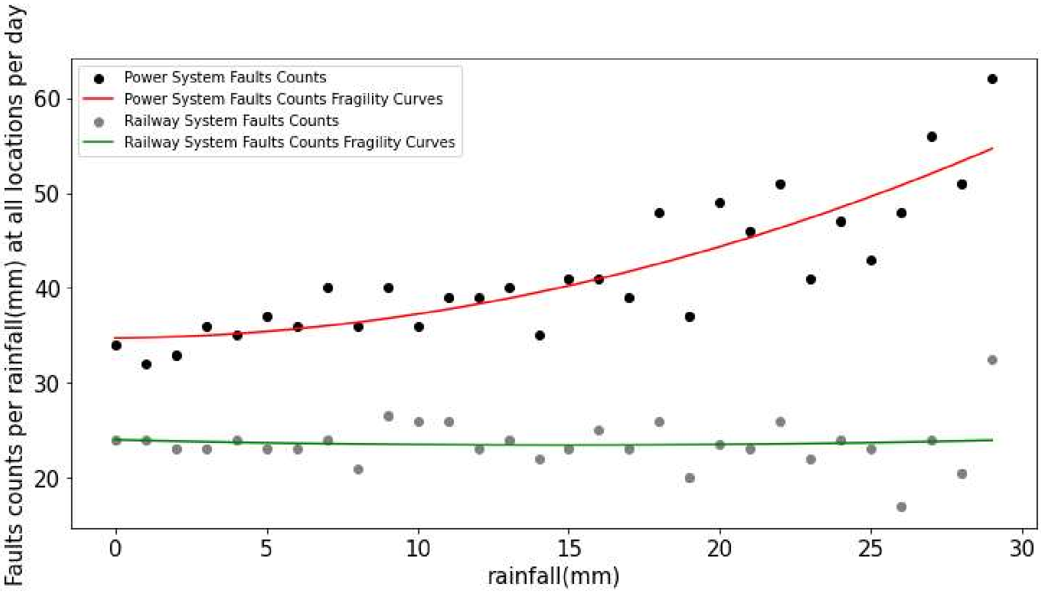


Figure 9: Fragility curves of power system and railway system faults counts with rainfall.

With increased rainfall, the number of power system faults also increases (Figure 9). The number of power system faults increases by one for every one mm increase in rainfall. However, the number of failures on the railway system remained essentially the same as the amount of rainfall increased. The fragility functions between power system faults and railway fault events and rainfall are shown below:

$$f_p(F) = 0.023F^2 + 0.022F + 32.73 \qquad (9)$$
$$f_r(F) = 0.003F^2 - 0.077F + 24.00 \qquad (10)$$

where f_p is power system faults fragility function and f_r is railway fault events fragility function. F is rainfall value.

Table 1. Coefficient of determination for power system and railway system for weather factors

Weather factors	Power System	Railway System
Rainfall (mm)	0.76	0.10
Temperature (°C)	0.83	0.66

Through figure 5(a) and figure 9 it can be observed that there is a difference in fragility curves of power system and railway system faults counts with temperature and rainfall. Fragility curves of power system and railway system faults counts with temperature have a minimum value at medium temperature and increase at both ends (higher/lower temperature). However with increase in rainfall the faults are increased for power system, but the railway system may be less directly affected by rainfall. Overall, this shows that the trend of the fragility curves for the power system and the railway system is the same for different temperatures, which implies that the critical infrastructure failures are similar for temperature factors. However, for the rainfall factor, a different trend is presented, with power system faults showing an incremental trend with increasing rainfall, but rail system faults are largely unaffected by increasing rainfall.

Table 1 shows the coefficients of determination (R^2) for the power system and the railway system for different weather factors. The number of faults in the power system have a relatively high goodness of fit of the regression with rainfall, with an R^2 of about 0.76, and a high goodness of fit of the regression with the temperature factor, with an R^2 of about 0.83. The goodness of fit statistics between temperature and number of faults in the railway system is more moderate, with R^2 about 0.66, while the goodness of fit with the rainfall factor is lower, with R^2 only 0.10. These results show that temperature has a clear influence on power system and the railway system fault rates. The relationship between fault rates and rainfall is less clear.

4. Discussion

This study shows that temperature and rainfall impact power and railway systems in similar ways through qualitative evaluation of the fragility curves. Temperature has a stronger explanatory strength for both power system and railway faults (R^2 = 0.83; R^2 = 0.66, respectively) with rainfall showing weaker impact (R^2 = 0.76; R^2 = 0.10, respectively). However, this paper sets up a time frame spanning five years for this comparison, and accordingly data is sparse for lower frequency more extreme weather events such as very heavy rainfall and high extreme temperatures. Future work could consider analysis of more time frames, i.e., analysing the effects of temperature on power system faults and railway system faults over multiple five-year ranges. One other trade-off present in the case study was the aggregation of weather parameters for regional decision-making. While this may be suitable for temperature, for rainfall there is much more spatial uncertainty and as such, using the regional maximum daily rainfall over a region may not be suitable for localised fragility evaluation. This may contribute to the lower R^2 values for rainfall. Future research should use longer time periods to increase the variety of meteorological conditions to which the infrastructure assets are exposed. Alongside evaluation of more historical data, variation of the spatial resolution should also be explored to better understand the trade-offs between regional aggregation for decision-making and the granularity of measurement necessary for accurate fragility modelling. Sensitivity testing would identify the most useful and robust approach to combining infrastructure fault data with weather data. Moreover, the most appropriate approach may vary for different regions, different infrastructure fault sets, and for different infrastructure decisions. Increasing the resolution of weather data used may also improve the strength of the correlation.

Infrastructure owners are actively working to improve their resilience and ensure they can adapt to the challenges of higher temperatures (Dooks, 2023).UK Electricity DNOs have collaborated on research and development over the years in a variety of activities, including climate change impacts on assets and asset design or rating work (Powergrid, 2015). Network Rail is also involved in various climate change risk assessments and has developed a weather risk management policy to provide infrastructure that can operate effectively in a changing climate (Rail, 2011). In July 2022, temperatures within the West Midlands exceeded 38.7°C for the first time, and climate projections indicate that these summer temperatures will be increasingly common in the future (Mike Kendon, 2022). Furthermore, high temperatures tend to affect a wider area than other climate factors such as flooding. NGED noted in the Adaptation to Climate Change-Second Round Report that temperature increases are progressive, and they found that 11,000-volt and 33,000-volt wood pole lines are most vulnerable to temperature changes of among all pole line types. In response to projected future high temperatures, NGED has been designing new overhead lines since 2011. Now, most poles are now used that are 0.5 m-1.0 m taller than previous designs, which allows these devices to operate at temperatures up to 55 °C, thus reducing the impact of temperature increases on their ratings (WesternPowerDistribution, 2015). With climate change, rail failures associated with cold temperatures are expected to decrease, while the effects of high temperatures will increase (NETWORKRAIL-LIMITED, 2021). High temperatures can cause rail buckles, Temporary Speed Restrictions (TSRs), overheated electrical components. To reduce temperature-related impacts, London North East and East Midlands Route have replaced 51 km of jointed track with continuously welded rail (CWR) to avoid buckling in extreme hot temperature and consider temperature when installing signalling and telecommunications and electrical equipment in buildings (NETWORKRAIL-LIMITED, 2021).

Based on the results of this study, there are two key points for infrastructure owners and operators. Firstly, the fragility curves calculated in this work show that without adaptation, the number of power system and railway faults will increase in the future. Resilience can be increased via increase maintenance of assets, increased capacity to respond to during an emergency, and “building back better”, i.e., when updating infrastructure assets, using those which are designed for future warmer climates. Secondly, this study demonstrates that fragility curves provide a transferable means to compare infrastructure resilience to different weather parameters at a regional level across different infrastructure sectors. Extreme weather rarely impacts one system in isolation, and interdependencies exist between infrastructure systems. Aside from the ability to predict an extreme event, the correlation analysis for temperature and rainfall indicates that days which have high number of faults are correlated across these sectors and the correlation grows at extremes of temperature and rainfall. As a result, organisations with regional responsibility for resilience such as Local Resilience Forums, Lead Local Flood Authorities or Combined Authorities could work with infrastructure operators to develop regional fragility curves for different weather types or climate indices and thereby provide a consistent regional approach to understanding vulnerability to extreme weather. This would support the management of cascade failures, often linked to energy supply (Ferranti et al., 2017, Guo et al., 2020, Liu et al., 2022) by allowing all operators within the region to have a shared understanding of the potential impact of different types of weather on the systems with which they are interdependent. This would also feed into emergency response and recovery planning for infrastructure failures such as power faults, communication interruption, or traffic disruptions caused by extreme weather events.

5. Conclusion and Future Work

This paper presents a process for the concurrent evaluation of the fragility of infrastructure to weather related failure. The methodology is demonstrated using a case study that examines the effects of temperature and rainfall on power and rail systems in the West Midlands, UK. Specifically, for this region, joint analysis indicates that power and rail are both adversely affected by temperature extremes and more importantly that the daily number of faults across these areas show correlation. Therefore, collaboration across sectors is necessary to ensure successful adaptation and planning for such events. They are anticipated to become more frequent in the future due to the changing climate.

More broadly, this study demonstrates the continued need for government agencies, distribution network operators, rail operators, urban planners, and other relevant stakeholders to continue to monitor and understand the relationship between weather and infrastructure faults. The resulting fragility curves show that although the failure modes may differ across infrastructure types, such as railway and power distribution systems, the response to rainfall and heat can have similar relationships. This highlights the importance of inter-operator collaboration to develop appropriate policies and measures to ensure the sustainability and resilience of critical infrastructure.

While, this paper focused on temperature and rainfall impacts across power distribution and railway networks, future studies could investigate concurrent fragility curves for other meteorological parameters such as wind (Donaldson et al., 2023), different climate indices such as warm nights, warm days, heatwave days, hot days (Greenham et al., 2023) or other related critical national infrastructure.

6. References

ABI-SAMRA, N., FORSTEN, K. & ENTRIKEN, R. Sample Effects of extreme weather on power systems and components, part I: Sample effects on distribution systems. IEEE PES general meeting, 2010. IEEE, 1-3.

BELLÈ, A., ZENG, Z., DUVAL, C., SANGO, M. & BARROS, A. 2022. Modeling and vulnerability analysis of interdependent railway and power networks: Application to British test systems. *Reliability Engineering & System Safety,* 217**,** 108091.

BRAZIL, W., WHITE, A., NOGAL, M., CAULFIELD, B., O'CONNOR, A. & MORTON, C. 2017. Weather and rail delays: Analysis of metropolitan rail in Dublin. *Journal of Transport Geography,* 59**,** 69-76.

CGI. 2013. *Case study on Network Rail's Fault Management System Made Safe and Simple* [Online]. NETWORK RAIL - CGI. Available: https://www.cgi.com/sites/default/files/files_uk/casestudies/case_study_-_network_rails_fault_management_system_made_easy_new.pdf [Accessed 22 Nov 2023].

CORONESE, M., LAMPERTI, F., KELLER, K., CHIAROMONTE, F. & ROVENTINI, A. 2019. Evidence for sharp increase in the economic damages of extreme natural disasters. *Proceedings of the National Academy of Sciences,* 116**,** 21450-21455.

COTTERILL, D., STOTT, P., CHRISTIDIS, N. & KENDON, E. 2021. Increase in the frequency of extreme daily precipitation in the United Kingdom in autumn. *Weather and Climate Extremes,* 33**,** 100340.

DONALDSON, D. L., FERRANTI, E. J., QUINN, A. D., JAYAWEERA, D., PEASLEY, T. & MERCER, M. 2023. Enhancing power distribution network operational resilience to extreme wind events. *Meteorological Applications,* 30**,** e2127.

DOOKS, T. C. 2023. Progress in adapting to climate change 2023 Report to Parliament.

DUNN, S., WILKINSON, S., ALDERSON, D., FOWLER, H. & GALASSO, C. 2018. Fragility curves for assessing the resilience of electricity networks constructed from an extensive fault database. *Natural Hazards Review,* 19**,** 04017019.

DUNN, S., WILKINSON, S., GALASSO, C., MANNING, L. & ALDERSON, D. 2015. Development of empirical vulnerability curves for electrical supply systems subjected to wind hazard.

EEA. 2023. *Extreme summer weather in a changing climate: is Europe prepared?* [Online]. European Environment Agency. Available: https://discomap.eea.europa.eu/climatechange/ [Accessed 10 Oct 2023].

FERRANTI, E., CHAPMAN, L., LEE, S., JAROSZWESKI, D., LOWE, C., MCCULLOCH, S. & QUINN, A. 2018. The hottest J uly day on the railway network: insights and thoughts for the future. *Meteorological Applications,* 25**,** 195-208.

FERRANTI, E., CHAPMAN, L., LOWE, C., MCCULLOCH, S., JAROSZWESKI, D. & QUINN, A. 2016. Heat-related failures on southeast England's railway network: Insights and implications for heat risk management. *Weather, Climate, and Society,* 8**,** 177-191.

FERRANTI, E., CHAPMAN, L. & WHYATT, D. 2017. A Perfect Storm? The collapse of Lancaster's critical infrastructure networks following intense rainfall on 4/5 December 2015. *Weather,* 72**,** 3-7.

GREENHAM, S., FERRANTI, E., POWELL, R., DRAYSON, K. & QUINN, A. 2023. The impact of heat on London Underground infrastructure in a changing climate. *Weather,* 78**,** 170-175.

GUO, J., FENG, T., CAI, Z., LIAN, X. & TANG, W. 2020. Vulnerability Assessment for power transmission lines under typhoon weather based on a cascading failure state transition diagram. *Energies,* 13**,** 3681.

HOUGHTON, J. 2009. *Global warming: the complete briefing*, Cambridge university press.

IEEE. 2022. *1366-2022 - IEEE Guide for Electric Power Distribution Reliability Indices* [Online]. IEEE: IEEE Std. Available: https://ieeexplore.ieee.org/document/9955492?denied= [Accessed 10 Oct. 2023].

JAMIESON, M. R., STRBAC, G. & BELL, K. R. 2020. Quantification and visualisation of extreme wind effects on transmission network outage probability and wind generation output. *IET Smart Grid,* 3**,** 112-122.

JAROSZWESKI, D., HOOPER, E., BAKER, C., CHAPMAN, L. & QUINN, A. 2015. The impacts of the 28 June 2012 storms on UK road and rail transport. *Meteorological Applications,* 22**,** 470-476.

JAROSZWESKI, D., WOOD, R. & CHAPMAN, L. 2021. Chapter 4: Infrastructure. *The Third UK Climate Change Risk Assessment Technical Report.[Betts, RA, Haward, AB, Pearson, KV (eds)] Prepared for the Climate Change Committee, London. Available at: https://www. ukclimaterisk. org/independent-assessment-ccra3/technical-report*.

KENDON, M., MCCARTHY, M., JEVREJEVA, S., MATTHEWS, A., WILLIAMS, J., SPARKS, T. & WEST, F. 2023. State of the UK Climate 2022. *International Journal of Climatology,* 43**,** 1-83.

KO, E. H., DOKIC, T. & KEZUNOVIC, M. Prediction model for the distribution transformer failure using correlation of weather data. 5th International Colloquium on Transformer Research and Asset Management, 2020. Springer, 135-144.

LAMB, R., GARSIDE, P., PANT, R. & HALL, J. W. 2019. A probabilistic model of the economic risk to Britain's railway network from bridge scour during floods. *Risk analysis,* 39**,** 2457-2478.

LEE, K.-C., JANG, S. Y., JUNG, D.-K., BYUN, H.-K., PARK, H.-K. & YANG, T.-S. Rail-structure interaction analysis of sliding slab track on bridge. ASME/IEEE Joint Rail Conference, 2015. American Society of Mechanical Engineers, V001T01A010.

LI, G., ZHANG, P., LUH, P. B., LI, W., BIE, Z., SERNA, C. & ZHAO, Z. 2013. Risk analysis for distribution systems in the northeast US under wind storms. *IEEE Transactions on Power Systems,* 29**,** 889-898.

LIU, H., WANG, C., JU, P. & LI, H. 2022. A sequentially preventive model enhancing power system resilience against extreme-weather-triggered failures. *Renewable and Sustainable Energy Reviews,* 156**,** 111945.

LIU, K., WANG, M. & ZHOU, T. 2021. Increasing costs to Chinese railway infrastructure by extreme precipitation in a warmer world. *Transportation Research Part D: Transport and Environment,* 93**,** 102797.

MARTINOVIĆ, K., GAVIN, K. & REALE, C. 2016. Assessing the vulnerability of Irish Rail network earthworks. *Transportation research procedia,* 14**,** 1904-1913.

METOFFICE. 2022. *HadUK-Grid gridded and regional average climate observations for the UK* [Online]. Available: https://catalogue.ceda.ac.uk/uuid/4dc8450d889a491ebb20e724debe2dfb [Accessed 15 Dec 2022].

MIKE KENDON, M. O. N. C. I. C. 2022. *Unprecedented extreme heatwave, July 2022* [Online]. MET OFFICE. Available: https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/weather/learn-about/uk-past-events/interesting/2022/2022_03_july_heatwave_v1.pdf [Accessed 20 Mar 2023].

NATIONALGRID. 2023. *National Grid Electricity Distribution* [Online]. Available: https://connecteddata.nationalgrid.co.uk/dataset/ [Accessed 19 Jun 2023].

NATIONALGRIDESO. 2022. *GIS Boundaries for GB DNO License Areas,* [Online]. Available: https://data.nationalgrideso.com/system/gis-boundaries-for-gb-dno-license-areas [Accessed 15 Dec 2022].

NETWORKRAIL-LIMITED. 2021. *Network Rail Third Adaptation Report* [Online]. Available: https://www.networkrail.co.uk/wp-content/uploads/2022/01/Network-Rail-Third-Adaptation-Report-December-2021.pdf [Accessed 10 Sep. 2023].

NOAA. 2023. *NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2023).* [Online]. Available: https://www.ncei.noaa.gov/access/billions/ [Accessed].

OSTERTAGOVÁ, E. 2012. Modelling using polynomial regression. *Procedia Engineering,* 48**,** 500-506.

PALIN, E. J., STIPANOVIC OSLAKOVIC, I., GAVIN, K. & QUINN, A. 2021. Implications of climate change for railway infrastructure. *Wiley Interdisciplinary Reviews: Climate Change,* 12**,** e728.

POWERGRID, N. 2015. *Adapting to Climate Change* [Online]. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/478920/clim-adrep-northern-powergrid-2015.pdf [Accessed June 2015].

QUINN, A. D., FERRANTI, E. J., HODGKINSON, S. P., JACK, A. C., BECKFORD, J. & DORA, J. M. 2018. Adaptation becoming business as usual: A framework for climate-change-ready transport infrastructure. *Infrastructures,* 3**,** 10.

RAIL, N. 2011. *Network Rail Climate Change Adaptation Report* [Online]. Available: https://webarchive.nationalarchives.gov.uk/ukgwa/20130124005554mp_/http://archive.defra.gov.uk/environment/climate/documents/adapt-reports/06road-rail/network-rail.pdf [Accessed 30 Apr 2011].

RINALDI, S. M., PEERENBOOM, J. P. & KELLY, T. K. 2001. Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE control systems magazine,* 21**,** 11-25.

SEDGWICK, P. 2012. Pearson's correlation coefficient. *Bmj,* 345.

SENEVIRATNE, S. I., ZHANG, X., ADNAN, M., BADI, W., DERECZYNSKI, C., DI LUCA, A., GHOSH, S., ISKANDER, I., KOSSIN, J. & LEWIS, S. 2021. Weather and climate extreme events in a changing climate (Chapter 11).

SERRANO-FONTOVA, A., LI, H., LIAO, Z., JAMIESON, M. R., SERRANO, R., PARISIO, A. & PANTELI, M. 2023. A comprehensive review and comparison of the fragility curves used for resilience assessments in power systems. *IEEE Access*.

WANG, C., JU, P., WU, F., PAN, X. & WANG, Z. 2022. A systematic review on power system resilience from the perspective of generation, network, and load. *Renewable and Sustainable Energy Reviews,* 167**,** 112567.

WANG, T., QU, Z., YANG, Z., NICHOL, T., DIMITRIU, D., CLARKE, G., BOWDEN, D. & LEE, P. T. 2020. Impact analysis of climate change on rail systems for adaptation planning: A UK case. *Transportation Research Part D: Transport and Environment,* 83**,** 102324.

WESTERNPOWERDISTRIBUTION. 2015. *Adaptation to Climate Change-Second Round Report* [Online]. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/474340/climate-adrep-western-power.pdf [Accessed 12 May 2023].

WILKINSON, S., DUNN, S., ADAMS, R., KIRCHNER-BOSSI, N., FOWLER, H. J., OTÁLORA, S. G., PRITCHARD, D., MENDES, J., PALIN, E. J. & CHAN, S. C. 2022. Consequence forecasting: A rational framework for predicting the consequences of approaching storms. *Climate Risk Management,* 35**,** 100412.

XIE, Q. & ZHU, R. 2011. Earth, wind, and ice. *IEEE Power and Energy Magazine,* 9**,** 28-36.