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Extreme Weather and Climate Vulnerabilities of the Electric Grid: A Summary of Environmental Sensitivity Quantification Methods

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ABSTRACT

Climate hazards and extreme weather affect all components of the electric grid system, from generation to end use. Increasing temperatures, decreasing water availability, more intense storm events, and sea level rise affect the ability of the electric grid to produce and transmit electricity from fossil, nuclear, and existing and emerging renewable energy sources. Most electricity infrastructure is built for past or current climate conditions. Due to long lifetimes, electricity systems are likely to be exposed more frequently to more extreme climate conditions than those for which they were designed, and may not operate as intended under changing climate conditions. Utilities, regulators, state energy offices, and other electricity system planners are beginning to conduct environmental risk assessments, develop climate resilience plans, and incorporate changing climate conditions into long-term planning processes. Here, we highlight the analytical resources available for sensitivity assessment of electrical grid components under extreme weather and climate, and identify gaps in the literature on quantitative methods available for assessment of component vulnerability.

1. VULNERABILITIES OF THE ELECTRIC GRID TO EXTREME WEATHER

Extreme weather is the leading cause of electric power outage events, especially for the most significant disruptions[45, 76, 74] (Figure 1). Extreme weather and climate-related threats to electrical grid systems include but are not limited to: sea level rise and associated coastal flooding, increasing frequency, intensity and duration of heat waves, changing precipitation patterns, ice storms, lengthening regional droughts and wildfires, and more instances of flooding and damaging winds from severe storms. Climate change has led to an increase in the frequency and intensity of extreme weather events, raising concerns about the resilience of the electric grid to present and future climate and weather hazards. For example, increased severity of extreme weather events was the principal contributor to an observed increase in the duration of U.S. power outages between 2000 and 2012 [56].

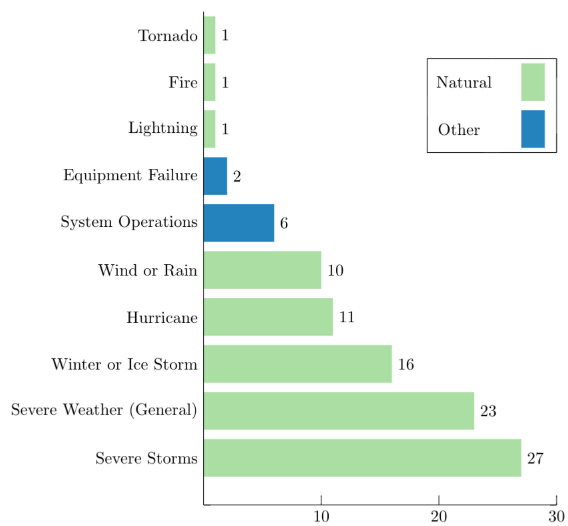


Figure 1. Causes of Large U.S. Electric Disturbance Events Affecting at Least 50,000 Customers (% 2000-2016)

The determinants of vulnerability to climate and weather hazards include exposure, sensitivity and adaptive capacity[84] (Figure 2). *Exposure* refers to the degree to which infrastructure is exposed to hazards, and can change over time as frequency and intensity of hazards change; *Sensitivity* is the degree to which electricity systems and infrastructure are affected by a hazard; and *Adaptive capacity* is the ability to adjust to potential hazards or respond to consequences. This review provides a collection of the most accessible quantification methodologies for determining grid component *sensitivity* to extreme weather and climate hazards, that is, those that quantify the relationship between a potential environmental threat to a specific component and the consequences of that threat to the system (e.g., damaged equipment, duration of outages).

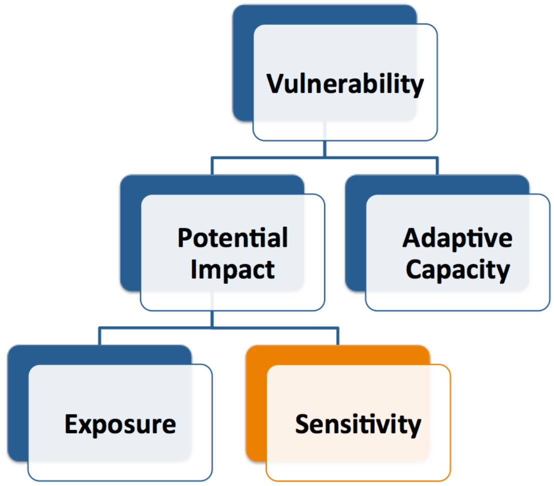


Figure 2. Elements of electric grid system vulnerability. This review focuses on grid component sensitivity.

2. DEFINING RESILIENCE

Resilience is often defined as [106] the "ability to prepare for and adapt to changing conditions and to withstand and recover rapidly from disruptions." System resilience includes characteristics such as flexibility and redundancy, both physically and institutionally, which in turn are associated with such business concerns as continuity of operations. Resilience can be characterized as a function of time with respect to a disturbance event[81]. In this characterization, the two aspects of resilience applicable to the electrical grid system are: 1) operations and 2) infrastructure. Key resilience features on the operational side of the system include: 1) robustness and resistance; 2) resourcefulness, redundancy, adaptive self-organization; and 3) response and recovery. As the operations side of the system copes with the evolving conditions associated with an event according to its capability in these three aspects, the infrastructure must be capable of full recovery.

Several guides to resilience planning[79, 39, 78] provide frameworks for assessing the vulnerability of electric utility assets and operations to climate change and extreme weather and developing appropriate resilience solutions. Within these frameworks, resilience is measured by the degree of robustness to the initial shock, the functionality maintained during the event, and/or the post-event recovery duration. The goal here is to facilitate the development of a comprehensive approach for quantifying both the short-term (i.e., before, during, and after an event) and long-term features of electrical grid resilience at the component level in order to obtain a quantitative understanding of the resilience of the electrical grid system as a whole.

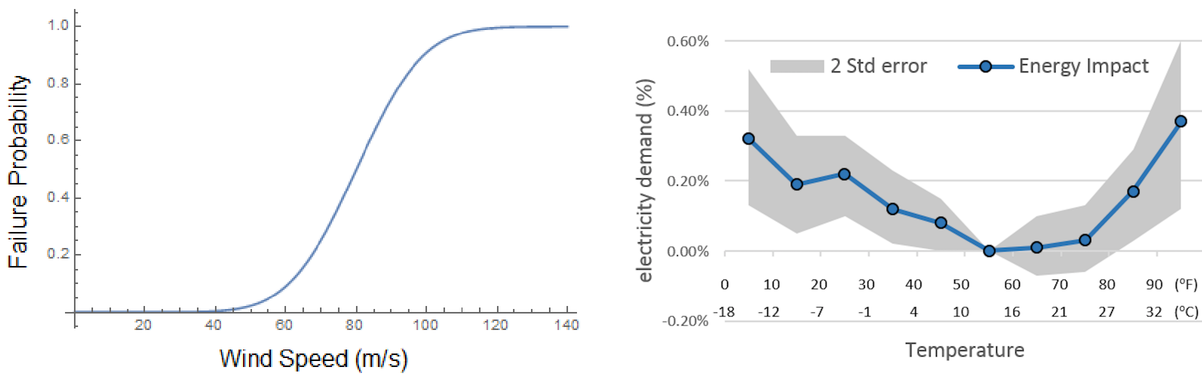
3. QUANTIFYING COMPONENT DEGRADATION AND FAILURE

To determine the vulnerability of different components of the electrical grid system to potential physical or environmental threats, engineering approaches exist in the form of mathematical functions that predict degradation or failure of the components under certain adverse conditions and their intensity, duration and frequency. These functions are commonly referred to as fragility curves, damage functions, or dose-response functions and give electricity system planners the ability to quantify the potential climate vulnerabilities of their energy assets.

Dose-response functions quantify the physical response of a component in the system to its exposure to a climate stress. By relating a specific measure of the impact to the component from the climate stress while controlling for other factors, the role of the stress in causing the impact can be estimated. This estimate can then be used to predict the deterioration of the component corresponding to an increase in exposure to the stress. For example, a dose-response function could answer questions like “How does the maximum capacity of a natural gas combined cycle (NGCC) power plant change as a function of ambient temperature?”

Fragility curves and damage functions, in contrast, give the probability of system or component failure in response to exposure to a single extreme event. For example, a fragility curve might answer the question “What percentage of transmission poles will fail as a function of one-minute sustained wind speed?”[75]

Examples of a fragility curve and a dose-response function are shown in Figure 3. On the left is a sample wind fragility curve for transmission towers, giving the probability of failure as a function of wind speed. In this example, the failure probability is modeled as a lognormal distribution function, although fragility curves can also take other functional forms and can even be discontinuous (e.g., no damage below a certain threshold value). Fragility curves such as this are applied to wide range of phenomena, including wind damage, flooding, earthquakes, and other hazards. On the right is a sample dose-response curve giving changes in residential energy consumption for heating/cooling as a function of temperature. Dose-response curves are also commonly used to quantify degradation of service in response to a weather or climate variable, e.g., capacity deratings for thermoelectric plants in response to high temperatures.



(a) (b)

Figure 3. Example fragility curve for wind damage to utility poles (a) and temperature-response curve for electricity demand (b), recreated from data in [83] and [28], respectively.

Several approaches to the development of fragility curves are outlined in the literature:[100] judgmental, empirical, analytical, and hybrid. Judgmental approaches are based on expert opinion or engineering judgment. Procedures for development of judgmental fragility curves can vary widely in the levels of rigor with which they are implemented. Generally, these approaches are used as a last resort when data are lacking to support an empirical approach. Thus, it is difficult to quantify or even qualify results obtained from a judgmental fragility curve[100].

Empirical approaches are based on observations; that is, measurements and collected data. Fragility curves developed through empirical methods are also fairly specific to the observed structures, making it difficult to use these fragility curves to model the reliability of other structures. Fragility curves developed using an empirical approach generally cannot be confirmed through laboratory testing because it would require bringing multiple physical models to failure, an activity that is regarded as too expensive and too time consuming. However, confirmation of empirical fragility curves can be achieved using damage data from multiple historical disasters occurring in similar locations when such data are available (e.g., Allen et al.[6, 75]). Analytical fragility curves are based on structural models that characterize the performance limit state of the structure. The performance of the structure is a function of some vector of “basic” variables. These variables determine both the capacity of a structure to withstand a load and the demand placed on the structure. Basic variables include material properties, geometry, or dimensions; they could also include environmental variables (such as temperature or humidity) that might in some way affect capacity. A hybrid approach to developing fragility curves uses a combination of two or more of the approaches discussed above in an attempt to overcome their various limitations. Empirical approaches tend to be limited by the availability of observational data; judgmental approaches tend to be limited by subjectivity of expert assessments; and analytical approaches tend to be limited by modeling deficiencies, restrictive assumptions, or computational burdens.

In some cases, the impacts of climate- and weather-related events are poorly understood or not easily quantified. In such cases, exposure to a hazard may be used as an interim proxy for vulnerability until additional data are available to quantify sensitivity. For example, a 2012 California Energy Commission[97] addressed the increased risks of wildfire *exposure* of the California transmission and distribution systems, and also identified some of the potential *impacts* of wildfires (beyond outright destruction of poles and wires). However, the report was not able to quantify all of these impacts (for example, the heat-related capacity derating of transmission lines as a function of wildfire exposure). Recognizing this gap, however, a 2015 study[23] addressed vulnerability of conductors to elevated temperatures due to wildfire proximity including damage to conductors leading to violations of safety clearances between conductor and ground. Their resulting unified model incorporates the radiative and convective heat released due to a progressing wildfire, and allows for dynamically changing the thermal ratings of conductors in the vicinity of a wildfire.

Here, we compile known damage functions, dose-response and fragility curves of climate- and weather-related impacts on electrical grid system components (Table 2), to serve as a resource for use by system planners in modelling, risk assessments, cost-benefit analyses, and long-term integrated resource planning. Additionally, we identify gaps where more research is needed to develop quantitative damage functions.

4. KEY FUNCTIONS FOR SENSITIVITY ASSESSMENT

Because weather related outages have increased significantly over the years, many empirical evaluations regarding outages due to equipment failure as a result of extreme weather events have been performed. These evaluations have led to the development of overall mathematical descriptions of various components' degradation and failure primarily under conditions of high temperature and high wind. Evaluations have focused mostly on frequency of these events rather than on duration. They have also focused on single events in specific geographic regions. However, as both climate and infrastructure vary significantly in different U.S. regions, systems located in these regions can react differently to local climate.

Electrical grid system components generally fall into one of three subsectors: i) generation, ii) transmission and distribution and iii) end use. These components, with potential impacts of various climate and weather hazards on them, are shown in Table 1. Extreme weather events considered include high temperature, high winds, floods, drought, wildfire and ice. Additional vulnerability of coastal energy infrastructure is considered with regard to sea level rise. Finally, impacts of change in electricity demand with changing weather conditions are addressed.

Table 1. Implications of Climate/Weather Hazards to Electricity Sector Components

Component	Hazard	Potential Impacts
Electricity Generation: Thermoelectric	High ambient air temperatures	Reduction in plant efficiency and available generation capacity
	High water temperatures	Reduction in plant efficiency and available generation capacity; increased risk of exceeding thermal discharge limits
	Drought and water availability issues	Reduction in available generation capacity; impacts on coal, natural gas, and nuclear fuel supply chains
	Storms, sea level rise, and storm surge	Increased risk of physical damage and disruption to coastal facilities
	Flooding	Increased risk of physical damage and disruption to inland facilities
Electricity Generation: Hydropower	High ambient air temperatures and evaporative losses	Reduction in available generation capacity and changes in operations
	Changes in precipitation and decreasing snowpack	Reduction in available generation capacity and changes in operations
	Flooding	Increased risk of physical damage and changes in operations
Electricity Generation: Wind energy	Variations in wind patterns	Uncertain impacts on resource potential
Electricity Generation: Solar energy	High ambient air temperatures	Reduction in potential capacity
	Extreme weather	
Transmission and Distribution: Transformers	High ambient air temperatures	De-rating, decreased capacity, accelerated aging, loss of life
Transmission and Distribution: Power Lines	High ambient air temperatures	Reduction in transmission efficiency and available transmission capacity
	Wildfires	Increased risk of physical damage and decreased transmission capacity
	Storm events, including ice storms	Increased risk of physical damage
Transmission and Distribution: Poles	High Winds	Line damage, failure
	Wildfires	
End Use: Demand	High ambient air temperatures	Increased electricity demand for cooling, increased adoption of air conditioning
	Extreme heat events	Reserve margin vulnerability

5. VULNERABILITIES IN ELECTRICITY GENERATION

5.1 High Temperature

High ambient air and water temperatures reduce both the efficiency and available generating capacity of thermoelectric power plants[77, 38]. Coal, nuclear, concentrated solar power (CSP), biomass, geothermal, and some natural gas power plants use steam turbines that are affected by higher coolant temperatures, because the efficiency of thermal electricity generation is proportional to the temperature difference between the steam inlet and the condenser temperature[30, 59, 46, 42, 48]. For plants with once-through cooling systems, hotter cooling waters remove less heat from the plants' steam cycle, decreasing the system's cooling efficiency[44]. Efficiency losses are generally more pronounced in wet-recirculating and air-cooled systems[13]. Capacity deratings also occur because the higher ambient air temperatures result in lower mass density of intake air, resulting in less fuel mass that can be ignited, and therefore reduced power output. Similar effects apply to natural gas combustion turbines and natural gas combined cycle plants[9, 64, 26]. Published information on the performance of thermoelectric generation with respect to ambient temperature conditions can be found in technical publications,[27] empirical studies,[30, 59, 46, 42, 48, 44, 13, 9, 64] and is sometimes included in publications from the original equipment manufacturer[104].

Response functions are generally linear, in the form of a constant decrease in power output per degree change above a reference temperature. Some studies develop separate response functions for efficiency loss and capacity derating[52]. For example, one study conducted by the California Energy Commission (CEC) found that natural gas combined cycle power plant capacity decreases by 0.3-0.5 percent for each 1°C increase above a reference temperature of 15°C[97]. The CEC study developed separate temperature-response functions for NGCC and NGCT plants based on geographic region to account for location-specific factors, in addition to temperature. They found that plants operating in mountainous regions had lower reference operating capacity owing to the decreased ambient air density at higher elevations. Similar studies examining the temperature response of nuclear power plant output have found a decrease of approximately 0.1-0.5 percent for every 1°C increase in ambient air temperature[30, 59, 46, 90]. In addition, a rise in ambient air temperature might give rise to higher temperatures at working locations within the power plant, influencing the proper functioning of safety related equipment like the emergency diesel generators[90].

Operating temperature also decreases both the electrical efficiency and the power output of a solar photovoltaic (PV) module. The traditional relationship between the output and operating temperature of a solar cell is typically given by a linear function expression the solar energy conversion efficiency as a function of cell operating temperature[36]. For example, Radziemska[91] finds that power output decreases by 0.66% per 1°C increase above a reference temperature of 25°C for crystalline silicon solar cells. However, the operating temperature of the solar cell depends on a range of factors, including ambient air temperature, wind speed, solar radiation flux/irradiance, and material and system-dependent properties. While establishing a direct relationship between solar PV performance and ambient temperature and other weather variables is challenging, solar PV temperature response functions have been reviewed and presented[29].

Heat waves can also affect electricity generators, potentially causing physical damage above a certain temperature threshold or forcing curtailment to avoid safety hazards[16]. One approach for assessing generator vulnerabilities to heat waves assigns each generator a heat wave vulnerability level based on its geographic location (coastal or inland), the type of generator (thermal or other) and the cooling method (presence of a cooling tower)[16].

High water temperatures can also cause threshold impacts. For example, plants may be forced to curtail operations partially or completely when the intake cooling water exceeds operating design temperatures[103]. Additionally, plants are typically not allowed to discharge cooling water above a certain temperature, to avoid harming fish and other wildlife. Thermal discharge limits vary by world geopolitical region but in the U.S., surface water is typically required to remain under 32.23°C. Plants that use once-through cooling technologies typically return water to the source at a temperature that is 8 to 12°C warmer than the original intake water temperature[61].

5.2 Drought and Water Availability

Thermoelectric generation accounts for approximately 40% of freshwater withdrawals across all water use sectors[53]. Plants with once-through cooling systems are particularly vulnerable to water availability stressors, as they require more cooling water per electricity produced (10,000-60,000 gallons/MWh, depending on the fuel type) than plants with recirculating systems (250-1,800 gallons/MWh)[77, 60]. Severe drought can cause water levels to drop below the level of intake valves that supply cooling water to power plants, causing plants to stop or reduce power production. In a study of 423 thermoelectric power plants, 43% were identified as having cooling-water intake heights of less than

10 feet below the typical water level of their cooling water source[54]. The U.S. Electric Power Research Institute has developed a water sustainability risk index to identify power plants in counties with “at risk” water supplies, using a set of five criteria: growth in water demand, susceptibility to drought, available precipitation, groundwater use, and water storage limitations[35]. In general, threshold impacts such as water levels falling below the level of intake valves depend on plant-specific features, making general response functions or fragility curves challenging to develop. Plant operators may need to rely on individual plant operating requirements and geography-specific features in order to assess susceptibility to drought and water availability issues.

Hydropower generation is also responsive to climate and weather variables that impact water availability. Many studies have found a linear relationship between annual runoff and generation[50, 96]. Some have found a strong linear correlation between streamflow anomalies, expressed as deviations from historic averages, and generation anomalies[8]. However, the relationship between runoff and climate and weather variables such as temperature and precipitation is complicated by evaporation loss (from high ambient temperatures) and watershed storage, including snowpack. Some plant-specific impact functions have been developed. For example, in the U.S., Hoover Dam loses 5-6 MW of capacity for every foot decline in Lake Mead, due to a loss of water pressure to drive the turbines and the potential for air bubbles to form[22]. Similarly, some U.S. region-specific functions, as in one for the Colorado River Basin, show that every 1% decrease in streamflow causes power generation to decrease by 3%[51].

5.3 Flood

Storm events, sea level rise, and inland flooding pose a risk to inland and coastal power plants. Flood risks to electricity generation are a consequence of the need for most thermoelectric plants to be close to sources of cooling water. Very little research specifically focuses on damage functions for power plants; however, damage curves are generally believed to be similar to those for the general building stock[98, 87]. In this case, flood damage is typically expressed as a percentage of damage to a facility in response to the depth of inundation. For example, a damage level of 100% would require the complete replacement of the facility. Hazus®, a risk/loss assessment tool developed by the US Federal Emergency Management Agency (FEMA), includes a flood model with default fragility curves for power plants, including a threshold depth at which functionality may be impaired. (The Hazus Technical Manual[43] notes that more detailed damage and loss estimates for electric power systems will be developed in a later edition. Additionally, Hazus allows users to replace the default fragility curves with custom curves based on facility-level data.)

5.4 High Wind

Most work on electricity generation vulnerability to wind has focused on wind turbines. Wind turbines are vulnerable to hurricanes because the maximum wind speeds in those storms can exceed the design limits of wind turbines. Failure modes can include loss of blades and buckling of the supporting tower[93]. In many areas being actively considered by developers of offshore wind farms, for instance, nearly half the turbines in a given farm are likely to be destroyed in a 20-year period[93]. The distribution of the number of wind turbine towers buckled by hurricanes can be modelled using parameters estimated as combined probabilities of multiple single wind turbine tower buckling along with the probability of an area receiving winds of hurricane magnitude.

6. VULNERABILITIES TO TRANSMISSION/DISTRIBUTION

The U.S. transmission and distribution system includes approximately 697,000 circuit-miles of transmission lines, 6.3 million miles of distribution lines, and 21,500 substations consisting of transformers, circuit breakers, and other control equipment[2, 3]. Climate- and weather-related vulnerabilities include impacts from extreme temperatures, wildfires, wind, flood, ice storms, and other extreme weather.

6.1 High Ambient Air Temperature

Transformers and power lines are particularly vulnerable to high ambient air temperature. Persistent extreme temperatures can lead to deratings, shorter lifetimes, and abrupt failure of these components[111]. The response of efficiency and maximum capacity of power transformers to ambient temperature is usually represented as a linear relationship with varying inclinations (i.e. slopes). In general, the average power output decreases 0.7% to 1% per 1°C increase in air temperature, above a reference temperature (usually taken to be 20°C)[57, 63, 105].

Additionally, the lifetime of a transformer can be significantly degraded by high ambient temperatures. The lifetime of a transformer is limited by the "hot spot" temperature, the highest temperature within the windings of the transformer, which can be much greater than the ambient temperature. For example, a 30°C ambient temperature can correspond to a 120°C hot spot temperature[97]. However, the hotspot temperature is also affected by total load and other factors such as wind, which affect the transformer's ability to shed excess heat. Over time, the insulation in a transformer breaks down, eventually leading to transformer failure. Exposure to high temperatures can accelerate this aging process. Empirical studies of transformer lifetimes have found that an increase of 7°C in the hotspot temperature can double the aging acceleration factor[14]. In some cases, the combination of extreme heat and increased demand for electricity for cooling can lead to catastrophic failure, as when 2,000 distribution line transformers failed during a July 2006 heat wave in California[109].

High temperatures also increase transmission and distribution line losses and reduce carrying capacity. Average electricity transmission and distribution losses are about 5% in the United States[32]. The resistance of power lines increases with temperature, leading to greater resistive loss[47]; however, the impact of ambient temperature on resistive losses is generally considered to be negligible compared to impacts on total carrying capacity[97]. The line capacity is limited by the maximum normal operating temperature, typically 80°C. The operating temperature of the line depends on several factors, including the ambient temperature, current in the line, and wind speed, which affects the ability of the line to get rid of excess heat, and is generally much higher than the ambient temperature. (The IEEE Standard for Calculating the Current-Temperature of Bare Overhead Conductors (IEEE 738-2006) gives line operators a method for modeling transmission line temperature.) Higher line operating temperatures can also cause excessive sag of power lines due to thermal expansion[77]. Sagging power lines pose many risks, including fire and safety hazards, and increased chance of lines contacting trees or the ground. In order to avoid excessive sag and maintain operating temperatures within design limits, system operators may manually reduce line capacity[58]. For example, the CEC study found that an ambient temperature of 37.78°C resulted in 7-8% capacity loss below normal design ratings[97].

6.2 High Wind

High winds can snap towers and down power lines causing widespread electricity customer outages. A variety of fragility curves and statistical methods have been developed to analyse past power outage data during adverse weather events to identify recurrent patterns in the power outage data in order to understand the vulnerability of the existing power grid. For instance, fragility curves have been constructed to characterize, during hurricanes, the relationship between wind speed and resulting power outages[6]. For these curves, real-time power outage data and wind speed data are used to derive statistical relationships. These 'as built' relationships are then compared to the 'as designed' engineering fragility curves to improve risk assessment and outage forecasting during future high wind events.

The physical response of towers and power lines to high winds is commonly represented as a function of line failure probability in response to wind speed[83]. These fragility curves are usually taken to be a lognormal distribution, where the probability of being in, or exceeding, a damage state ds is described by the lognormal function:

$$P[ds|S_d] = \Phi[\frac{1}{\beta_{ds}} ln(\frac{S_d}{\bar{S}_{d,ds}})]$$

where: $\bar{S}_{d,ds}$ is the median value of engineering parameter (e.g., displacement or stress) at which the tower or power line reaches the threshold of the damage state ds; β_{ds} is the standard deviation of the natural logarithm of engineering demand parameter at which the asset reaches the threshold of the damage state ds; and Φ is the standard normal cumulative distribution function. This type of fragility curve can also be used to characterize damage in response to other hazards (e.g., earthquakes) or damage to other kinds of infrastructure. In 2007, Entergy used an empirical fragility curve showing the probability of pole failure based on wind speed and pole type (wood, concrete, lattice steel, or tubular steel) to address potential damages to distribution poles from projected hurricane events[33]. They further calculated direct costs of damage to the poles based on the number of poles damaged.

6.3 Flood

Electricity transmission and distribution lines and substations are at risk of damage from flooding, sea level rise, and storm surge events[77]. In recent recognition of this risk, the US utility that serves Massachusetts, New York and Rhode Island (states that suffered unprecedented damage from 2012 Hurricane Sandy) has begun upgrading vulnerable transmission substations to be able to withstand a 1,000-year flood event[86]. FEMA has developed default fragility curves for substations and distribution circuits for use in their Hazus loss estimate/risk assessment model[43]. These curves estimate the percent damage as a function of flooding depth.

Some research has also focused on the risks to underground transmission and distribution systems from flooding and sea level rise[17, 18, 71, 41]. In general, underground lines have a shorter useful life than overhead lines and are more susceptible to corrosion than overhead lines[72] are. Water from inundation or flooding may follow electrical lines back to underground conduits and vaults, damaging underground substations, and underground wires may also be vulnerable to damage from saltwater intrusion associated with sea level rise[71, 41]. However, quantitative fragility curves for underground lines are limited.

6.4 Wildfire

Large fires can cause a range of physical impacts on transmission and distribution systems, including damage to towers and poles leading to potential collapse of power lines. However, line damage is not restricted to the destruction of the support structures. Power lines supported by wooden poles–typically lower voltage, lower capacity lines–are more likely to be directly destroyed by a wildfire. Additionally, the transmission capacity of a line can be affected by the heat, smoke, and particulate matter from a fire even if there is no actual damage to the physical structure. For example, the insulators that attach the lines to the towers can accumulate soot, creating a conductive path and causing leakage currents that may force the line to be shut down. Ionized air in smoke can act as a conductor, causing arcing between lines or between lines and the ground. Fire retardant from aircraft dumping can foul lines and reduce line capacity[97]. Lines exposed to high fire temperatures, even without excessive load, can expand and sag, leading to violations of safety clearances between power lines and the ground, or a reduction in line capacity by operators (per radiative and conductive heating calculation following the IEEE standard equation [23, 24]).

6.5 Ice

Ice storms can lead to ice accumulation on power lines, stressing the lines and increasing the probability of line breakage under moderate wind exposure. As a result of an ice storm in the southern United States in December 2002, the weight of ice on trees and power lines caused power outages lasting more than a week in some areas, and the damage to infrastructure in the region was large enough to be compared to Hurricanes Hugo (1989) and Fran (1995). Using data from the 2002 ice storm, researchers have developed a model that allows utilities and emergency managers to estimate the radial ice accretion thickness using publicly available data from the Automated Surface Observing System (ASOS)[49]. Damage caused by ice storms is a function of both radial ice accumulation and windspeed. To characterize the physical damage and resulting outages from ice storms, researchers in Oklahoma developed the five-tiered Sperry-Piltz Ice Accumulation Damage Index$^{\text{TM}}$–analogous to the Fujita Scale for tornadoes–that categorizes the severity of the damage as a function of radial ice accretion, total precipitation, and wind speed[67].

7. POTENTIAL IMPACTS TO END USE/DEMAND

Electricity demand for space conditioning is climate-sensitive, and temperature in particular is a significant determinant of the electricity consumed. Demand for heating and cooling, which accounts for as much as half of residential and a third of commercial energy use[31], fluctuates hourly, daily, and seasonally in response to outdoor ambient temperatures. As a general rule, energy demand for space heating and cooling increases as ambient temperatures depart from a reference temperature. The temperature dependence of electricity demand has been examined from three distinct directions: impacts to overall energy consumption, impacts to peak demand, and impacts on deployment of air conditioners.

Various models for calculating overall demand for a region include as critical components the spatial distribution of residential and commercial consumers, projections for future changes in those distributions, and historical and projected changes in the distribution of temperatures[11]. Some studies have also looked at electricity use as a function of latitude[7], while others have examined the adoption of air conditioning in more northern regions in response to increases in overall average temperature[15, 95, 92].

Hourly load data at the level of load balancing authorities has also been used to parameterize the relationship between average and peak electricity demand and temperature[12]. Because electricity planners in the U.S. often use reserve margins (capacity requirements above forecast peak load) of 15 to 20%, the response of peak load to extreme temperatures can translate directly into increases in capital costs, even if the average generation impacts are not large. The study found that temperature response curves for both average and peak load roughly resemble parabolas, with minimum load occurring when the average daily temperature is between 15°C and 18.34°C. Additionally, peak load increases faster in response to temperature than average load.

8. GAPS AND RESEARCH OPPORTUNITIES

This survey has shown that while there are many useful infrastructure component vulnerability quantifications available, they are primarily empirical and single-event driven. Additionally, environmental impacts on some specific components of the electrical grid are understudied, such as underground powerlines. Mathematical formulations that have emerged from these studies tend mostly to describe infrastructure and end user response to higher ambient and extreme temperature, low water availability or wind and flooding from storms. Little attention has been given to asset maintenance under wildfire risk and to issues due to cold weather extremes such as icing. We also note a lack comprehensive assessment of cumulative damages from multiple extreme weather and climate events to specific and multiple components of the electric grid. As the frequency and intensity of extreme weather and climate events are expected to rise in future, understanding the sensitivity of specific components of electricity systems and their collective vulnerability to climate and weather hazards is crucial to long-term planning.

9. ACKNOWLEDGEMENTS

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Table 2. Environmental Sensitivity Quantification and Sources

Component	Hazard	Equation	Source
Electricity Generation	Heat waves	The heat wave vulnerability level for a generator (VG) is calculated as follows: $$VG = TG \times WG \times CG$$ where TG is a binary variable representing whether the generator is a thermal power plant (1 if yes, 0 if no), WG is a binary variable representing whether the power plant draws from an inland water source (1 if yes, 0 if no), and CG is a variable representing whether the power plant has a cooling tower (0.5 if yes, 1 if no). Together, these variables provide an estimate of a generatorâĂŹs heat wave vulnerability. $$M_{(V,s)} = \sum_{(n=1)}^{N} V_{(G,n)} \times M_{(G,n)}$$ where $M_{(V,s)}$ is the magnitude of vulnerable generation capacity attached to substation s, N is the number of generators attached to substation s, $V_{(G,n)}$ is the vulnerability of generator n (calculated according to the equation above), and $M_{(G,n)}$ is the total generation capacity of generator n	Ref[16]
	High Temperature	Manufacturer design specifications with temperature-response curves for both heat rate and capacity for GE natural gas combined cycles	Ref[104]
		Decrease in the maximum capacity and conversion efficiency of crystalline photovoltaics of 0.66%/°C and 0.08%/°C, respectively	Ref[91]
		Technical manual that consolidates manufacturer design specifications for natural gas combined cycle and combustion turbines, including temperature response curves for capacity and heat rate	Ref[27]
		Separate temperature-response curves for both dry-cooled and wet-cooled natural gas combined cycle (NGCC) plants across four different climate regions in California. Found that plant capacity decreases by 0.3-0.5% for each 1°C increase	Ref[64]
		The impact of 1°C increase in cooling water temperature results in a decrease of 0.45% and 0.12% in the power output and the thermal efficiency, respectively, of a model pressurized-water nuclear power plant	Ref[42]
		Empirical temperature-response curve for natural gas combustion turbines (NGCT), finding an efficiency loss of 0.1%°C above ideal operating conditions	Ref[26]
		Theoretical change in capacity for nuclear power plants as a function of changes in temperature and empirical data identifying parameters. Under design climatic conditions for a nuclear plant, the plant will produce an output equal to $\eta_D \times f_D$ where η is thermal efficiency, f is fuel input, and D denotes design conditions. As the condenser temperature (T_c) deviates from design conditions by 1°C, capacity utilization Y will deviate as follows: $$\frac{dY}{dT_c} = [\frac{d\eta}{dT_c} \frac{f}{\eta_D \times f_D} \frac{df}{dT_c} \frac{\eta}{\eta_D \times f_D}] \times 100$$ % points where the first term in the square bracket is the result of changes in the actual thermal efficiency, and the second term in the square brackets is the result of changes in actual fuel input. Based on empirical data for one nuclear plant, this study finds a reduced output of 0.3-0.4% per 1°C for ambient temperatures between -7°C and 20°C. For temperatures higher than 20°C, output decreases by 0.96-1.10% per 1°C	Ref[59]
		Decrease in nuclear power plant efficiency of 0.1%/°C.	Ref[90]
		Decrease in power output and efficiency of a pressurized water reactor nuclear power plant of 0.39% and 0.16%, respectively, per 1°C increase in the coolant temperature	Ref[46]
		Historical performance data for 39 coal and natural gas plants with once-through and recirculating cooling systems determines the response of efficiency to coolant, dry-bulb, and wet-bulb temperatures. For once-through systems, there is an efficiency decline of at most -0.11%/°C rise in coolant temperature, and a smaller response to dry-bulb temperature. The effect of wet-bulb temperatures on recirculating systems is small, ranging from -0.06%/°C to +0.04%/°C.	Ref[44]

		Literature review of temperature-response functions for photovoltaic (PV) electrical efficiency. Most functions take the form of the Evans-Florschuetz equation $$\eta_c = \eta_{Tref}[1 - \beta_{ref}(T_c - T_{ref})$$ η_{ref} is the module's electrical efficiency at reference temperature Tref at solar radiation of 1000 W/m^2 and β_{ref} is the temperature coefficient. η_{Tref} and β_{ref} are normally given by the PV manufacturer. T_c is the cell temperature.	Ref[29]
	Wind	The probability that a single wind turbine tower is buckled by a 10-min sustained hub-height wind speed u is modeled using a log-logistic funciton with a scale parameter α and a shape parameter β. $$D(u) = \frac{(u/\alpha)^\beta}{1 + (u/\alpha)^\beta}$$ Values for α and β are given for two cases in which the turbine is pointed into the wind and the turbine is pointed perpendicular to the wind. The number of turbine towers buckled by a single hurricane in a wind farm of n turbines is modeled as a beta-binomial distribution with parameters α_B and ${}_B$. The probability that X, the number of turbine towers that buckle out of n total, equals a particular value x is given by: $$Pr(X = x) = \binom{N}{k} \frac{B(x + \alpha_B, n - x + \beta_B)}{B(\alpha_B, \beta_B)}$$ where $B()$ is the beta function.	Ref[93]
	Flood	Flood microscale damage function g relates the relative damage r of an item i to the hazard magnitude x: $$r_i = g(x - \lambda_i)$$ the damage is conditional on the exceedance of the item-specific hazard threshold λ_i. In other words, a single item will suffer damage only if its hazard threshold is exceeded. The collective storm-damage function for flood over a portfolio of assets in a given geographic area is given as: $$d_{expl}(x) = \sum_j f(\lambda_j) g(x - \lambda_j)$$ where $f(\lambda_j)$ represents a discrete frequency distribution of damaged assets, and where the sum runs over all discretized threshold values λj.	Ref[87]
		Default fragility curves for small, medium and large power plants	Ref[37]
	Water Availability	Linear relationship between annual hydropower generation and annual runoff for eighteen power river basins with federal hydropower	Ref[50]
Transmission/Distribution	High Temperature	Fragility curves, which give the transformer aging rate as a function of the hot-spot temperature–the highest temperature on the transformer windings–for three different transformer types based on the transformer windings insulation. The hot-spot temperature is given as a function of the transformer load: $$\Theta_{HS} = \Theta_{TO} + \Delta\Theta_{HR}(\frac{I}{I_R})^{2m}$$ where Θ_{HS} is the hot-spot temperature, Θ_{TO} is the top-oil temperature, $\Delta\Theta_{HR}$ is the rated hot-spot temperature rise above top oil, I is the load current, I_R is the rated current, and m is the winding exponent.	Ref[14]
		Decrease in maximum capacity for both distribution and transmission transformers of approximately 1%/°C above a reference temperature of 20°C	Ref[63]
		Temperature response curve for transformer load capability: capacity decrease of 0.7%/°C for temperatures above 30°C	Ref[97]

	Wind	Power line wind fragility from empirical results (1) and engineering curve (2) $$y = 4.732e^{0.048x} \quad (1)$$ $$y = 5.1519e^{0.0546x} \quad (2)$$ where y=per cent of county customers without power, x=one minute maximum wind gusts at nearest measurement station in knots.	Ref[6]
		Fragility curves for both transmission lines and towers given as: $$P_{L,T}(w) = \begin{cases} \bar{P}_{L,T}, if w < w_{critical} \\ P_{L,T_{hw}}(w), if w_{critical} \leq w < w_{collapse} \\ 1, if w \geq w_{collapse} \end{cases}$$ where $P_{(L,T)}(w)$ refers to the line (L) or tower (T) failure probability as a function of the wind speed w. $\bar{P}$ is the "good weather conditions" failure rate, taken to be zero for towers and 10^{-2} for lines. P_{hw} is the failure rate under high wind speed, after some critical threshold $w_{critical}$ is reached. The wind speed beyond which the survival of transmission lines/towers is negligible is given by $w_{collapse}$. The study provides sample assumptions for $w_{critical}$ and $w_{collapse}$. This study also develops empirical fragility curves for loss of load frequency (LOLF) and expected energy not served (EENS) as a function of maximum wind speed for a particular electric grid.	Ref[83]
		Comparison of storm damage functions: 1) Generic exponential damage function, 2) Probabilistic power law damage function, 3) Cubic excess-over-threshold damage function, 4) Probabilistic claim-based damage function. Notes scale-appropriateness of different functions.	Ref[88]
	Wildfire	Modifies the IEEE standard (IEEE 738-2006) that allows line operators to model transmission line temperature, by incorporating the radiative and convective heating due to a progressing wildfire. Line temperature is determined by: $$RI^2 + Q_s + Q_{r,f} + Q_{c,f} = Q_r + Q_c$$ where $Q_{r,f}$ and $Q_{c,f}$ are wildfire radiative and transfer rates per unit area of the conductor, respectively.	Ref[97]
	Flood	Default fragility curves for three types of substations and three types of distribution circuits as a function of flood depth.	Ref[37]
	Ice Storm	Sperry-Piltz Ice Accumulation Damage Index^{TM} for powerline icing (a numerical scale similar to the Fujita Scale for tornadoes that categorizes the severity of damage to transmission and distribution systems as a function of radial ice accretion and wind speed)	Ref[67]
		Storm severity quantified in terms of the equivalent uniform radial ice thickness using data from ASOS weather stations. The radial ice thickness R_{eq} can be calculated from samples of ice on branches and wires. The mass m of a measured length L of the ice sample from a wire or branch of diameter d is measured. The radial ice thickness is determined by solving the equation for the mass of an annulus of ice: $$m = \rho_i \pi L(dR_{eq} + R_{eq}^2)$$ for R_{eq}, and two independent methods of inferring R_{eq} from ASOS data are described.	Ref[49]
End Use: Demand Increase	High Temperature	National electricity demand curve for space heating/cooling in response to ambient temperature.	Ref[28]

	Demand for cooling as a function of cooling degree days (CDD) is given by: $$d_c = k_c(CDD \cdot \eta \cdot R + IG)[1 - exp(-\frac{ln2}{\mu_i}\frac{i}{P_c})]$$ Working from left to right, k_C is a unitless calibration coefficient. The expression in parentheses is the satiated level of cooling services. CDD is the number of cooling degree days. η is the thermal conductance of the building envelope (in GJ/m^2day °C) and R is the unitless average surface-to-floor area ratio that translates floorspace into the total surface of the building in contact with the ambient atmosphere. IG is the internal gain (GJ/m^2) from heat released by equipment in the building. The term in brackets gives the fraction of satiated demand that is met: P_C is the average price of cooling technology; i is per capita income; and μ_i is the degree of demand satiation given a particular level of affordability.	Ref[34]
	Temperature response curves from hourly load data for both average demand and peak demand, for each of 166 load balancing authorities.	Ref[12]
	Per cent increase in electricity demand for a county due to temperature rise is calculated: $$J = (5.33 - 0.067L_{centroid} * \Delta T$$ with J = per cent increase in electricity demand per customer, $L_{centroid}$ = the latitude in degrees at the centroid of the county and ΔT equal to the change in maximum annual temperature in °F.	Ref[7]

Table 3. Table of References

Component	Hazard	Region	# of Studies	Pub Year	Quantification
Electricity Generation	Heat waves	US[8], Europe[16, 55], Global[5]	4	2017[8], 2016[16], 2015[5], 2013[55]	Empirical Equation[8], Qualitative[5, 16], Index[55]
	High Temperature	US[44, 13, 61, 38, 75, 103, 42, 40, 27, 64, 36], Australia[4], South America[9] Europe[90, 85, 30, 91], Asia[26], World[29, 69, 104, 107]	25	2016[75, 112, 44], 2014[38, 46, 13, 4], 2013[61, 29], 2012[103, 107], 2011[59, 90, 26], 2010[85, 69], 2009[42], 2006[40, 30, 27, 64], 2005[9], 2003 [91], 2001[104], 1977[36]	Conceptual[13, 38, 75, 103, 112, 40], Empirical Equation[44, 46, 4, 29, 90, 26, 85, 42, 30, 27, 64, 9, 91, 104, 107, 59], Economic Analysis[61, 69, 36]
	Wind	US[89, 93]	2	2013[89], 2012[93]	Qualitative [89], Statistical Analysis[93]
	Flood	Europe[87], US[37]	2	2015[87], 2013[37]	Threshold Exceedance[87, 37]
	Drought	US[7, 110, 50, 96, 22, 60, 51, 54, 53], Europe[85]	10	2016[7, 110], 2015[50], 2012[96], 2011[22, 60], 2010[85], 2009[51, 54, 53]	Statistical Analysis[7, 110, 50, 96, 85, 51], Empirical Analysis[22, 60, 54, 53]
	Sea Level Rise	US[17, 62]	2	2015[17], 2014[62]	Spatial Quantification[17, 62]
Transmission and Distribution	High Temperature	US and Canada[77, 111, 109, 21, 97, 35, 57, 58], Europe[85, 63, 73], Asia, Global[1]	15	2014[73], 2013[77, 21], 2012[111, 109], 2011[97, 35], 2010[85], 2008, 2007[14, 63], 2005[57], 2001[105], 1995[1], 1989[58], 1948[25]	Conceptual[73, 77, 111, 109, 21, 35, 1, 58], Empirical Equation[85, 57, 105], De-rate[14], Magnitude[97, 63, 25]
	Wind	US[75, 101, 6, 33], Europe[88, 83, 85]	8	2016[75, 83], 2015[88, 101], 2014[6], 2010[85, 100], 2007[33]	Empirical Equation[88], Statistical Analysis[6], Qualitative[75, 101, 83, 85, 100, 33]
	Drought	Europe[85]	1	2010[85]	Economic Analysis[85]
	Wildfire	US[97]	2	2015[23], 2011[97]	Statistical Analysis[97], Empirical Equations[23]
	Flood	US[71, 108, 41, 19, 98], Europe[18]	7	2016[71, 108], 2013[41], 2012[19], 2008[18], 2006[98]	Qualitative[71, 108, 19], Empirical[98], Economic Analysis[41, 18]
	Ice	Canada, US[20, 68, 49]	3	2007[20], 2008[68], 2004[49]	Index[68, 49], Empirical[20]
End Use: Demand Increase	High Temperature	US[6, 11, 66, 92, 48, 97, 12, 28, 51, 70, 15, 95, 94], Asia[34], Europe, world[10]	16	2017[12], 2015[66], 2014[6, 92, 48], 2012[11, 34], 2011[97, 28], 2009[51, 10], 2008[70, 15], 2003[95], 2002[80], 2001[94]	Conceptual[10, 80], Empirical Equations[6, 11, 66, 48, 97, 34, 12, 28, 51, 70, 95, 94], Economic Analysis[92, 15]
General	Extreme Events		14	2017[3, 39], 2016[79], 2015[**?**, 78, 81, 82], 2012[99, 111], 2009[45, 65], 2007[84], 2005[102], 1997[43]	

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