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Review

Shedding light on the economic costs of long-duration power outages: A review of resilience assessment methods and strategies

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ABSTRACT

This paper provides a literature review of methods and modeling techniques to estimate the cost of power system outages, along with the value of outage mitigation or system resilience. Regulators, policymakers, and infrastructure owners have a growing need to understand the methods for estimating the benefits of resilience improvements of electric infrastructure against natural and man-made disasters. There is a broad literature that estimates the cost of short-duration outages and a small but developing literature on estimating the cost of long-duration outages. This article reviews the models used to estimate the cost of outages and discusses their relative strengths. Additionally, this paper identifies key questions from stakeholders regarding resilience investment and maps them to the relevant models that would help answer them. We include recommendations for future work to include recent advances in regional economic modeling that can estimate region and demographic-specific costs and the distributional consequences of potential resilience projects.

1. Introduction

Power system resilience research against natural disasters has gained momentum as large outages have increasingly impacted the electrical grid [1]. The resulting service interruptions[1] have spanned from multiple days to weeks [3,4]. Mitigating or avoiding the costs of more frequent and longer-duration service interruptions requires significant investment to improve the resilience of the electrical grid. Power system resilience strategies can include hardened infrastructure, redundant systems, or increasing flexibility [5]. Justifying such investment requires a rigorous understanding of the value of avoiding long-duration power outages.

The term "long-duration outages", however, is inconsistently defined, often without a clear distinction between short and long-duration outages [6–8]. In addition, the costs incurred from long-duration outages are not well documented, particularly how cost varies by location, duration, and scale.

Resilience is also inconsistently defined and is frequently conflated with reliability and mitigation, yet is important when planning a power system [5]. In power systems, reliability is concerned with meeting service standards over a prolonged period. In contrast, power system resilience is the ability of a system to adapt and recover from acute disruptions [9]. The core components of resilience are robustness, redundancy, resourcefulness, and rapidity [9]. Mitigation is defined as

Abbreviations: BPS, Bulk Power System; CBA, Cost-benefit analysis; CDF, customer damage function; CEA, Cost-effectiveness analysis; CGE, Computable General Equilibrium; CIC, commercial and industrial customers; CV, contingent valuation; DCE, discrete choice experiments; DER, Distributed Energy Resources; EPRI, Electric Power Research Institute; EV, Electric Vehicles; GDP, Gross Domestic Product; GE, General Equilibrium; ICE, Interruption Cost Estimator; IO, Input-Output; IRP, Integrated Resource Planning; LEAD, Low-Income Energy Affordability; LOLE, Loss of Load Expectation; LOLP, Loss of Load Probability; REAcct, Regional Economic Accounting Tool; VoLL, Value of Lost Load; WTP, willingness to pay.

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[1] With respect to the IEEE definitions, an outage refers to the failure of equipment to meet the load and an interruption refers to the loss of power to a customer [2].

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activities implemented exclusively before an event that incur a cost regardless of whether a disruption occurs. Intuitively, resilience is understanding the ability of a system to withstand and recover from a disaster [10]. Larsen et al. [11] define resilience as actions that are implemented before *or* after an event with costs that can be incurred before or after the event also. Additionally, mitigation efforts can generally impact the magnitude or frequency of an event while resilience can impact the duration and speed of recovery from an event [11].

Decision-makers such as government and utility officials are presented with several challenges when attempting to assess the risks and costs associated with long-duration outages and resilient investments. This is evident in state resilience assessments like Oregon and North Carolina [12,13]. In these reports, the problem is clear, but how to resolve it is not as well understood. Some of the critical gaps include identifying which model(s) are best suited to their needs, what the degree of uncertainty is in the models, and how they can address changes to society such as climate change and emerging technologies. Stakeholders who may not understand the intricacies and distinctions between different candidate model(s), are left without a clear answer to address their problems.

Given the several unknowns and inconsistencies, attempting to invest in a resilient power system that minimizes the damage from long-duration outages is difficult. This paper aims to close the gap between decision-maker needs and knowledge and the modeling solutions available.

1.1. Overview of outage examples and implications

Within the United States, many natural disasters cause long-duration outages such as hurricanes in the southeast, freezing temperatures throughout the country, and wildfires, heatwaves, and earthquakes in the west. The impacts of these outages are numerous including financial impacts, infrastructural impacts, and societal impacts. Financial impacts of outages include the cost to restore electricity to customers, the cost to repair generation components, and the indirect costs associated with outages such as lost economic activity due to the inability to operate commercial and industrial processes. Impacts to infrastructure include fallen power lines, damaged generation components due to flooding or debris, and damaged transformers.

Some examples of consequential outages include several days in North Carolina [13,14], 2–7 days in Texas [15], 7–51 days in Oregon [12], and nearing 14 days in Louisiana due to Hurricane Ida [16], and ten months in Puerto Rico due to Hurricane Maria [17]. In 2018, 1.7 million utility customers in North Carolina were affected by multi-day outages from Hurricane Michael [14]. Impacts from a Texas arctic blast in 2021 included frozen wind turbines and ice build-up in natural gas pipelines that prevented fuel delivery to many gas-powered plants [18,19]. At the event's peak, about 40 % of the state's power generation capacity was affected [20]. The freeze and subsequent outages affected about 4.5 million customers over a week, particularly historically disadvantaged demographics and communities [18,19]. Louisiana was hit by Hurricane Ida in late August 2021 and dealt with consequential outages until mid-September [16]. At their peak, the outages affected over 1 million customers [16]. The United States Energy Information Administration reported that 30,000 utility poles were damaged, double the number damaged during Hurricane Katrina [16]. The power system was particularly damaged due to already aging transmission lines and damage sustained from storms the previous year [21].

Across these events and ones like it, utility customers in vulnerable socio-economic classes were hit especially hard [19,22]. Low-income communities experience more frequent blackouts and less reliable electricity. Determining who pays for reliability and resilience improvements present difficulties. At-risk communities already pay larger proportionate energy bills and have lower willingness-to-pay and ability-to-pay for improvements due to lower income. However, requiring high-income households to pay for improvements that they receive no benefit from may see public backlash [23]. These events and their consequences have complex implications for electricity customers and further complicate the problem being presented to decision-makers.

Additionally, the needs of systems vary based on the community make up and natural disasters experienced. For example, North Carolina's Climate Risk Assessment and Resilience Plan [13] is identifies a need for legislators to develop resiliency metrics to quantify the economic consequences of power outages to inform power sector infrastructure planning, investments, and operations. A major resilience goal in North Carolina is to ensure no critical infrastructure, especially hospitals, police stations, and fire stations, are left without power for >48 h. Similarly, Oregon's Resilience Plan specifies pressing climatological risks in the state and outlines potential action to improve the infrastructure resilience against natural disasters for the next 50 years [12]. For example, a major earthquake has the potential to cause severe infrastructure damage, death, and major economic consequences [8]. In Oregon, resilience is highly dependent on the status of the critical energy infrastructure hub, which spans 6 miles along the Willamette River, where several ports, pipelines, substations, and storage facilities are located [3]. Each region has a range of resilience threats and goals but addressing them requires an understanding of the value of long-duration outages.

This paper aims to address multi-faceted issues decision-makers face about resilience investments to moderate the cost of long-duration outages. To do this, we review the types of models used to estimate the economic cost of long-duration outages and highlight the strengths and weaknesses of the different models. In addition, we include a brief discussion of short-duration outages to provide context and contrast them to the models used for long-duration outages. We also discuss how model estimates can be used for resilience infrastructure planning and classify which models are best suited to address stakeholder questions identified as part of the literature review. The scope is limited to a review of resilience to electricity outages. We do not include literature on resilience for other infrastructure such as water supply and sea-level rise. We exclude the literature on the economic benefits of electrification such as in [24–26].

The remainder of this paper is organized as follows. Section 2 of this paper discusses and explains various models and methods used to estimate the economic cost of short-duration outages. Section 3 discusses models used to quantify long-duration outage costs. Section 4 outlines how model outputs relate to resilience and mitigation infrastructure investment. Section 5 links common stakeholder questions with the appropriate models to answer them. Finally, Section 6 summarizes the gaps and underdeveloped research areas and suggests the next steps.

2. Models used to estimate the costs of short-duration electrical outages

The direct costs of an electrical outage are defined as the economic consequences that result from not having access to electricity, typically lost production or consumption [27]. Estimates of direct outage costs are generalized and summarized using customer damage functions (CDFs). The simplest CDF describes outage costs as a function of the duration of the outage. CDFs can also be generalized to be a function of additional outage attributes such as time of day, day of the week, season, etc., customer characteristics and demographics such as business size, household income, presence of backup equipment, and external features such as temperature, and whether the outage was caused by a natural disaster or is man-made.

2.1. Commercial and industrial customers

Outage costs to commercial and industrial customers (CICs) are primarily tangible and measurable and are calculated as the lost profit to the business caused by the outage. The changes in profit may come from additional costs imposed from extra labor costs, replacing damaged equipment, lost revenue from reduced production, and may also include some offsets from reduced energy or labor costs [27]. Several studies have been conducted that survey businesses on their costs during outages. Regression models are then used to estimate the average costs as a function of outage duration and other attributes by the size of the business [7,25,40]. These estimates can be used for utility planning to estimate the benefit of grid improvements to reliability and resilience.

For a single location, a comprehensive CDF that separates costs into fixed, flow, and stock costs can be estimated using a detailed inventory [28]. This method is most useful for determining whether installing infrastructure at the location being studied would be beneficial. The primary difference is that this is a private decision rather than one being made by a utility or public planner for many customers.

2.2. Residential customers - stated preference surveys

For residential customers, there are significant costs imposed from non-monetary and intangible sources such as fear, inconvenience, lack of comfort, lost leisure, and inability to heat or cool homes [29]. Stated preference (SP) surveys have been developed to assess people's willingness to pay (WTP) for goods and services that are not bought and sold on markets, so they are well suited to capture monetary and non-monetary costs. SP methods have been used in the United States [6,30–37], Europe [29,38–40], developing countries [41,42], and elsewhere [43–45] to estimate short-duration outage costs to residential customers.

SP surveys use a highly structured format to ask respondents whether they would prefer to prevent an outage with an associated cost or have the outage occur with no additional cost. WTP is then estimated from the survey responses using discrete choice models. For more detail on the general theory and practice of stated preference surveys, see [46,47]. For a discussion of SP surveys related to estimating the cost of power outages, see [42,48,49]. The major concern with SP estimates is that they may suffer from hypothetical bias, where respondents may not answer truthfully or accurately compared to how they may behave in an actual outage scenario. Johnson et al. [43] discuss best practices that have been developed to mitigate the potential for hypothetical bias.

2.3. Metrics for resource adequacy

In power system planning, resource adequacy assessments are developed to determine how much investment in capacity is needed to achieve specified reliability (and potentially resilience) outcomes [50]. There are monetary and non-monetary metrics that can be used to determine adequate resource requirements, some of which are discussed in this section [51].

The most common monetary metric is the Value of Lost Load (VOLL), which describes the customers' willingness to pay to avoid the loss of one unit of power and is usually expressed in \$/kWh or \$/MWh [52]. The planner will add capacity to the system up to the point where the marginal cost of adding capacity matches the VOLL. Fig. 1 shows a map of some estimated values from studies across the globe. The values vary significantly by country, sector, and outage duration. More dimensions of this data are available in the SI-1.

Alternatively, non-monetary metrics that include the Loss of Load Probability (LOLP), the Loss of Load Expectation (LOLE), and the Expected Unserved Energy impose a performance benchmark on the power system [53]. The system will be designed then to meet a prescribed level of LOLP (e.g., 5 %) or LOLE (e.g., 1 day in 10 years). While both monetary and non-monetary metrics are theoretically equivalent, their use varies depending on the planning domain – bulk power system (BPS), distribution, or demand-side – and on how investment decisions are made.

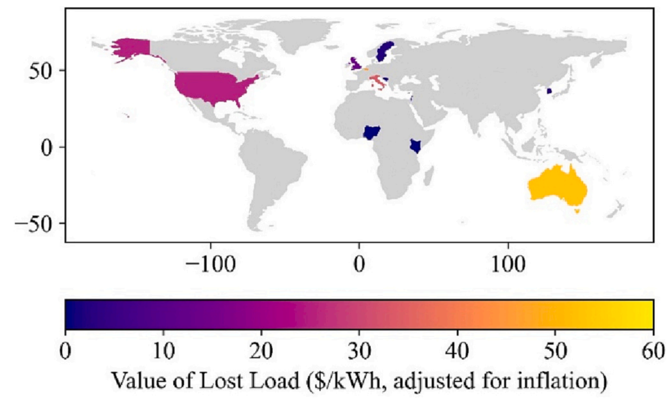

Fig. 1. Value of Lost Load around the world.

2.4. Summary of short-duration outage cost estimates

Küfeoğlu and Lehtonen [54] have reviewed the academic literature on short-term outage customer interruption costs based on customer surveys, case studies, and power quality events. La Commare et al. [55] estimate that the total cost of sustained power interruptions is \$44 billion per year (in 2015\$) and that commercial customers bear the largest share with 70 % of the costs. Fig. 2 shows the spread of the estimated outage values over several years and multiple sectors. A general trend in the results is that outage costs increase as outage duration increases but that the per-hour costs decrease with longer duration. This trend is more visible in the Appendix.

Sullivan et al. [8] conducted a meta-analysis of studies conducted by utility companies in the United States that estimated the value of service reliability. They obtained separate estimates for residential, small commercial, and medium and large commercial customers. Their results show that WTP increases with the length of outage duration for all customers. WTP increases with income for residential customers, and for commercial customers, WTP increases with the size of the business affected, typically measured by electricity demand. However, WTP does not increase linearly with firm size. Increasing electricity use by a factor of 10 increases the interruption cost by approximately 2.5.

The meta-analysis and econometric models are the basis for the

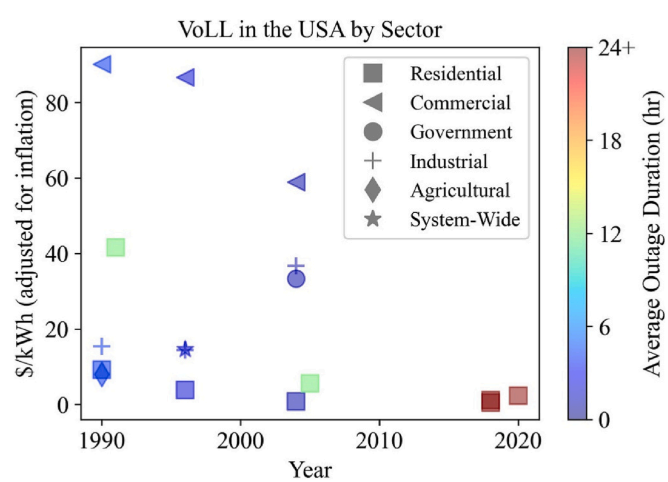

Fig. 2. Value of Lost Load in the United States, by sector, year, and average outage duration.

Interruption Cost Estimate (ICE) calculator.[2] The calculator includes costs for the different customer types as well as adjustments for regional attributes. The damage function, spanning an approximate 24-hour period, is slightly sigmoidal with an inflection point in the 8th hour, providing higher expected per-hour outage costs in the convex region (first 8 h) than the later hours [56]. Some limitations of the calculator are that customer interruption cost surveys that formed the basis of the meta-analysis are only in the United States and were limited to certain geographical regions and that GDP per industry type, or cost by class, is made at the county level.

3. Models used to estimate the cost of long-duration electrical outages

The cost of long-duration outages includes direct and indirect costs. The indirect costs of outages are defined as the spillover effects of disruptions to other sectors and other changes in economic activity, such as price increases that result from shortages [57]. This section discusses some models that have been used to estimate indirect damages in addition to direct damages. The damage is typically measured as a change to gross product at the spatial level under consideration (i.e., gross domestic product, gross state product, etc.).

Regional economic models are the most common type of models used to estimate indirect costs. Their use in modeling electricity disruptions is reviewed in [57,58]. Shuai et al. [59] briefly review models to estimate direct and indirect losses of electricity outages. Our review is more in-depth, provides more analysis of the models, and addresses resilience and how to apply the results to public planning. Regional economic models are simulation-based and typically include many sectors of the economy interacting through a set of equations. The model types are distinguished by how the equations are derived and how the sectors interact. These differences are discussed below.

Long-duration outages have not been studied as completely as short-duration outages. Larsen et al. [11] organized an expert workshop in 2019 to bring the issue of a limited portfolio of research on long-duration outages into the limelight and has facilitated meaningful conversation in these research fields.

3.1. Surveys for long-duration outages

Few studies have used SP surveys to estimate the cost of long-duration outages. In principle, adjusting the questions to include outage durations >24 h is straightforward. However, practitioners have concerns that, since few customers have prior experience with long-duration outages, their responses are hypothetical rather than retrospective [6,48].

Baik et al. [6] is the first study to use stated preference survey methods to value long-duration (>24 h) outages for residential customers. They assess the WTP for resilience to a 10-day power disruption. They use a CV survey method for residents of the northeastern United States and find that respondents are willing to pay \$1.7–2.3 per kWh to sustain their critical electricity demand, defined with a 20A threshold. This estimate is on the low end per kWh of estimates reported across studies in Sullivan et al. [56] but on the high end of total WTP per outage. In addition, the survey asked whether the respondent had experienced a long-term outage to determine the potential impact of prior experience on WTP. The study finds that WTP does not change significantly if the respondent has prior experience with long-term outages, an encouraging finding for future studies that assess long-duration outage costs using SP methods.

Another study that uses a stated preference survey to estimate the benefits of community resilience to long-duration outages is Hotaling et al. [60]. They estimate WTP for a local microgrid. They vary the services connected to the microgrid across the survey respondents to determine the WTP for different services and levels of operation.

Hotaling et al. [60] found that respondents had the largest WTP for access to water, shelter, and full emergency services at \$3.77, \$2.80, and \$4.44 per month, respectively. WTP was lowest for retail services at \$1.16 per month. They also included intermediate levels of operation in the survey for hospitals and emergency services (i.e., partial emergency services). They found WTP was not statistically different for the intermediate scenarios compared to no service. Two differences between this study and Baik et al. (2020) [6] are that (1) the microgrid in Hotaling's study would power community services but not the survey takers' homes, and (2) Hotaling estimates WTP as an addition to their monthly electricity bill, while Baik et al. (2020) [6] estimate the cost after an outage has occurred. Comparison of these estimates requires assumptions about the probability of an outage and preferences over the time value of money.

Recently, there have been efforts to employ commercial and industrial cost surveys to estimate costs of power interruptions ranging from short- and localized events to widespread and long-duration events. One prominent example of these efforts is Baik et al. [6], which used customer interruption cost surveys across Cordova Electric Cooperative's service territory. The researchers took the following four steps: 1) presenting respondents with power interruption scenarios that could occur (ranging from common events to the worst possible scenario); 2) eliciting WTP estimates from residential customers and calculating the sum of interruption-related costs and savings; 3) constructing duration-dependent customer damage functions for each customer segment, and; 4) using the customer damage functions to estimate the *average interruption costs* per customer.

3.2. Input-Output models

Input-Output (IO) models are the simplest macroeconomic model used to estimate indirect economic losses. IO models use coefficient matrices to capture interdependencies across sectors of the economy. When used to study electrical outages or natural disasters, IO models assume that sector(s) of the economy become inoperable, preventing their input to other sectors downstream in the supply chain. Using these techniques, the ripple effects of a disaster can be simulated, and the direct and indirect losses can be computed and compared [57,61].

There are a few significant shortcomings to IO models. First, the coefficients in the matrix are fixed, so any adaptive behavior or other resilience measures are not captured. Due to this, IO models typically overestimate the indirect losses, but their estimates can be used as an upper bound on economic losses. Second, IO models are less accurate for shorter-duration outages. The minimum required duration to use an IO model is 24 h and estimates of outages lasting several days are more accurate [57].

Rose et al. [62] is an example of using an IO model to estimate the economic impact of a long-duration electrical outage. They examine the economic impact of an earthquake, and subsequent 15-week loss of power in Memphis, TN. Their simulation shows that cross-sector supply bottlenecks can reduce output to 79 % below the baseline when indirect effects are included during week zero and 8.6 % below baseline over the 15-week timeframe. They also simulated the same scenario with the reallocation of scarce electricity to the sectors with the most significant bottleneck, and they found that losses can be dramatically lowered to 12.5 % in week zero and 0.58 % overall.

Rose and Lim [63] have used a different IO model to estimate the economic impact on businesses in Los Angeles from the Northridge earthquake. This paper is one of the first to incorporate resilience measures within an IO model analysis. The IO model cannot directly incorporate resilience measures but can be run under assumptions such as power rationing that allow important industries to remain in operation. They estimate that a 35-hour outage incurs a cost of \$227 million with no resilience measures, but this can be reduced to \$9.2 million with

[2] https://icecalculator.com/home.

the resilience measures incorporating production shifting, time-of-day adjustments, and electricity importance adjustments. This highlights the magnitude of the inter-sectoral impacts that resilience infrastructure can provide. Restoring power quickly to the most important sectors can spillover and alleviate a large portion of the cost to other sectors.

The city of New York commissioned a study [64] following hurricane Sandy that sought to assess the costs of future electrical outages and how the costs would change under different climate change scenarios. This model bridges some of the gap between Integrated Assessment Models, commonly used to assess the long-term costs of climate change, and the IO and computable general equilibrium (CGE) models commonly used to evaluate singular disaster events. This study estimates electrical losses from flooding and varies the probability of these flood events using outputs from a climate model. They find that several hardening and resilience projects outlined by FEMA would have positive and sometimes substantial societal benefits.

Industrial Economics also conducted a study in New York City [65]. They study the resilience benefits of installing a microgrid for one neighborhood in Nassau County that includes about 3000 residential buildings and 535 commercial and service buildings. Their analysis considers the possibility of 100 % economic activity loss compared to a microgrid that fully restores economic activity. The area's economic output is estimated at $1.2 billion annually, and the benefits of preventing outages of 1–7 days are estimated to be $5.5–$36 million. They include additional analysis that assumes some percent of power is restored during the outage (e.g., 50 % power output after three days during a 5-day outage). However, they do not include any analysis where the microgrid does not satisfy 100 % of the baseline power needs.

Bhattacharyya et al. [66] used an Inoperability IO model to estimate the cost of power outages in the U.S. Rather than modeling a specific scenario, they estimate the GDP loss for 1 % of inoperability to the utility sector. They find that each 1 % inoperability results in $11.6 billion of GDP losses with a standard deviation of $3.5 billion. They found the industries most affected are utilities, professional and technical services, wholesale trade, and construction.

He et al. [67] use an IO model to estimate economic losses due to several different levels of hypothetical electrical outages in China. They use sectoral data from China's economy to model cross-sector interdependencies. They assume an initial shock to production in the energy supply sector and then model the reduction in output in other sectors. Their model includes 42 industrial sectors but does not include the consumer side of the economy.

They find that the sectors most affected are those that are electricity-intensive and those that generate important inputs to other sectors of the economy, such as mining, mineral processing and smelting, and production and supply of water. They also find that the ranking of which sectors are most severely affected does not change with the quantity of power lost and that resilience measures such as reserve capacity are more effective at reducing costs for smaller outages.

Sandia National Laboratories developed the Regional Economic Accounting Tool (REAcct) tool that uses IO modeling to estimate economic losses, expressed in losses in GDP and employment, from natural disasters [68–70]. Like ICE, REAcct uses county-level data to assign GDP per industry type with the percentage of industry type allocated by employment numbers of a specific zip code. Again, high-resolution study areas would require greater care in assessing actual losses. The tool uses GIS information to provide spatially relevant results to the disaster being analyzed. The model uses IO multipliers at the county level that are obtained from the U.S. Bureau of Economic Analysis to estimate the corresponding industry-level indirect impact [71]. The tool can be used for many types of disasters, and a grid outage can be modelled as a power plant(s) disruption. The tool is useful for decision-making within federal agencies, but other authors have not widely adopted it within the peer-reviewed literature.

3.3. Computable general equilibrium models

CGE models are another class of models used to estimate indirect losses. CGE models use a framework of demand and supply equations for various markets in equilibrium. The impacts of outages are simulated by changing the relative price(s) and quantities of goods and services. Because CGE models use supply and demand relationships, they can account for behavioral effects such as price changes and substitution among inputs. CGE models are generally considered to provide more accurate estimates of long-run losses from disasters than IO models due to this flexibility [57,72]. However, it has also been argued that CGE models understate costs because they assume a frictionless economy and perfectly rational behavior, which may not be realistic, particularly during disasters and electrical outages. Because CGE models assume frictionless adaptation, their estimates are considered a lower bound on economic losses. The range of losses can be estimated by combining the lower bound from a CGE model with an upper bound from an IO model [57].

CGE models face limitations similar to IO models, that they are only accurate for longer-duration outages. Additionally, CGE models have some disadvantages compared to IO models. First, CGE models are typically more complex and computationally demanding, requiring considerably more time and money to set up and run. Second, CGE models require many input parameters, each requiring a value that must be assumed. If the input assumptions are incorrect or measured with high uncertainty, the model outputs will not be reliable [73]. Third, the assumption that all markets are in equilibrium is tenuous during long-duration outage scenarios.

Rose et al. [74] have used a CGE model to study an outage in Los Angeles County caused by a hypothetical terrorist attack. They examine indirect effects that increase outage costs and resilience measures that can reduce them. They look at resilience measures, including adaptive electricity substitution, electricity conservation, electricity importance direction, alternative generation, and production rescheduling. They find that the indirect effects add 23.8 % to the direct costs but that using all resilience options could reduce the negative impacts by 86 % [74]. This result highlights again that resilience infrastructure can dramatically reduce the cost of outages across multiple sectors. CGE models face limitations similar to IO models, that they are only accurate for longer-duration outages. Additionally, CGE models have some disadvantages compared to IO models. First, CGE models are typically more complex and computationally demanding, requiring considerably more time and money to set up and run. Second, CGE models require many input parameters, each requiring a value that must be assumed. If the input assumptions are incorrect or measured with high uncertainty, the model outputs will not be reliable [73]. Third, the assumption that all markets are in equilibrium is tenuous during long-duration outage scenarios. Rose et al. [74] have used a CGE model to study an outage in Los Angeles County caused by a hypothetical terrorist attack. They examine indirect effects that increase outage costs and resilience measures that can reduce them. They look at resilience measures, including adaptive electricity substitution, electricity conservation, electricity importance direction, alternative generation, and production rescheduling. They find that the indirect effects add 23.8 % to the direct costs but that using all resilience options could reduce the negative impacts by 86 % [74].

Hu et al. [75] looked at the costs of snowstorms in China in 2008. They model the economic losses from a snowstorm using both an IO model and a CGE model. Their difference of 29 % demonstrates how much price changes and substitution behavior can reduce the impact of an outage. Hu et al. [75] claim that the difference between the two models represents the benefits of resilience. However, this would only represent adaptive resilience, and this method is not useful for estimating the benefits of dynamic resilience such as grid or infrastructure improvements.

Timilsina and Steinbuks [76] estimated the cost of electrical load shedding in Nepal using a CGE model, and found that losses were >6 %

of the country's GDP. This study estimated the impact of electric supply shortages over a long-time horizon due to a lack of generation capacity rather than a sudden outage. Due to the length of outages, the damages are higher in percentage terms than other studies.

Sue Wing and Rose [77] have developed an analytical general equilibrium (GE) model to examine economic losses of long-duration power outages and how resilience measures could reduce losses. The model is more straightforward than the computable models, using only two sectors. However, the analytical tractability clarifies the mechanisms involved and highlights the importance mitigation investment and substitutability can play in reducing losses. They also compare the results of the analytical model to a computable model and show they are relatively similar. They also compare the GE model results to summing WTP estimates obtained from consumer surveys across the relevant population and find that CGE estimates are substantially lower. They claim that the survey estimates are likely higher due to the biases inherent in survey-based research.

A recent paper by Baik et al. [78] has outlined a hybrid approach to estimating the value of resilient power systems and the costs of outages, both long and short term. Utilities rely primarily on customer surveys as they require less time and expertise to implement than IO or CGE models, even though they do not estimate indirect costs. They propose that CGE models calibrated by surveys be used in the future by utilities as part of their planning for outage prevention and resilience. They also propose the hybrid approach to improve one of the main shortcomings of CGE models—that the model requires many input parameters, mostly elasticities of production that must be assumed. They propose calibrating these parameters using customer surveys. This would allow the model to be more accurate for the specifics of electrical outage studies and would also allow the model to capture regional differences in costs and input substitution. The paper does not include a case study to compare how the numerical results change with the hybrid method, but that appears to be forthcoming in subsequent analysis.

3.4. Other models

Macroeconometric models such as structural vector autoregression have been used extensively to forecast macroeconomic variables (GDP, inflation, unemployment, etc.), but their use in estimating losses due to disasters and electrical outages, etc. has been more limited. These models have seen little use in recent years as they have been supplanted by IO and CGE models that are considered more accurate. Greenberg et al. [79] provide an example of this type of analysis, looking at the costs of a terrorist attack in New Jersey. One feature that their model incorporates is the potential relocation of firms. Output typically returns to baseline shortly after an outage. However, if the high frequency of outages causes firms to relocate, the effects could persist for years. Relocation may be an essential regional consideration for areas that may be prone to an increase in disasters due to climate change. Areas such as the southeastern United States that may expect more frequent and severe hurricanes in the future may wish to consider the impact of firm relocation in addition to traditional measures of economic loss.

The losses due to natural disasters are typically more extensive than losses solely due to electrical power, including damage to capital and infrastructure. However, a significant portion of economic damage during a disaster is the reduction in economic activity, similar to the loss of activity during long-duration outages. For example, Superstorm Sandy cost an estimated $30–50 billion USD. Of the total cost, $7–20 billion USD (14–66 %) is assumed to be lost economic activity [80]. The economic impact of natural disasters has been reviewed by Botzen et al. [72].

The natural disaster literature can provide a source of innovation for estimating the cost of long-duration outages and resilience measures to reduce their impact. The natural disaster literature has used similar IO and CGE models to estimate the indirect losses. Recent methodological innovations in the natural disaster literature have sought to mitigate the shortcomings of IO models. Multi-regional impact assessment models are a recent advancement in IO modeling that can include spatial substitution effects that allow output to increase in regions that are not directly affected [81]. In addition, adaptive regional economics models allow for price changes and sector-specific supply constraints to be included in the model, helping to bridge the gap between CGE and IO models [82].

The second type of model innovation that could be transferred from the natural disaster literature is the use of empirical models (i.e., [83]). These models use microeconometric estimation techniques that attempt to isolate the causal effect of a natural disaster on GDP or GDP growth. See Lazzaroni and van Bergeijk [84] for a review of these studies. These models capture both direct and indirect effects. A major reason why these have not typically been used to study electrical outages is that they use regression-based models with GDP as the dependent variable, which is not typically measured on the finer spatial and temporal scales of power outages. Studies using these techniques typically used national scale data that would not transfer to the smaller scales of electrical outages. Modern empirical studies [85] have begun to explore the use of datasets that measure economic output at a finer spatial scale and incorporate geography into their estimates. These techniques could provide richer outage cost estimates and help understand which locations would benefit the most from resilience infrastructure.

A significant feature of empirical models is that they identify causal estimates from actual outages rather than using simulation [72]. This places a limitation on empirical studies. They cannot simulate hypothetical changes to determine on the benefits of resilience measures or policy responses that have not previously been implemented [72]. The other limitation they face is that they cannot disentangle the costs of the electrical outage from other tangential costs. However, empirical studies could contribute significantly to this field of study by validating estimates from IO and CGE models, and helping to determine which input assumptions yield the most accurate results [72]. Following up on studies such as Timilsina and Steinbuks [76] that simulated costs at a national scale with empirical estimation would provide more confidence in results from IO and CGE studies and reduce some of their drawbacks. Table 1 provides a summary of the models discussed in this section. The table briefly describes each model and the duration(s) where it is appropriate to use.

4. How to justify investments based on resilience improvements?

Literature estimating outage costs has a major application in prevented economic damage as the benefits of an investment that reduces or provides resilience against such losses. Several types of infrastructure upgrades can mitigate or provide resilience to electrical outages in different ways. Eyer and Rose [86] discuss mitigation and resilience trade-offs, specifically within power system planning. They model business interruptions to minimize overall impact and measure the benefits associated with different options. The difference between the outages with resilience measures in place and those without are compared and can inform the value of resilience. Estimating the benefits of resilience improvements allows decision-makers and public planners to make more informed decisions about the optimal level of investment in resilience, reliability, or mitigation. This section discusses different types of resilience investments.

4.1. Types of resilience investments

When identifying resilience improvements, there are a few standard options. The first is electrical grid hardening which reduces the risk of outages. Some examples of electrical grid hardening strategies include reinforcing delicate and vulnerable power system components (ex., power lines), undergrounding power lines, and building flood walls for nuclear power plants [87]. Panteli and Mancarella [5] used Monte Carlo

Table 1
Summary of models used to estimate costs of long-duration outages. *X indicates the model possesses the characteristic.

	Residential surveys - stated preference	Commercial and industrial surveys	Input-output (IO)	Computable general equilibrium (CGE)	Empirical
Simulation-based method			X	X	
Empirical-based method	X	X			X
Estimation across multiple industries		X	X	X	X
Long-duration outages		X	X	X	X
Short-duration outages					
Time/data intensive			X	X	X
Costs calculated as function of duration	X	X			
Adaptive behavior incorporated	X	X		X	
Resilience measures incorporated	X	X			

simulations in a time sequential model and found that a hardened network was the most resilient compared to redundant or highly responsive networks.

Another power system resilience strategy is islanding or microgrids. Microgrids enable an area to maintain access to electricity even if the primary power grid experiences a power outage [88]. A Sandia National Laboratories report [89] estimated the resilience benefits of 159 proposed microgrids in Puerto Rico. Through extensive analysis, they were able to determine the optimal microgrids to implement, as well as the benefits (both social and economic) they would have provided during a resilience-testing event such as Hurricane Maria. If physical changes to the electrical grid are not possible, another avenue to explore is load management techniques, also known as electrical traffic optimization. Though not as commonly explored as a resilience technique in the literature, various methods are adopted throughout the United States, especially for peak load management [90].

Two primary challenges with resilience benefits are that there is no "one size fits all" solution and no one way to measure resilience [91]. Every system has unique customer breakdowns, load patterns, weather patterns, budgets, regulations, and system configurations, and each plan must consider the unique factors relevant to a system. When potential resilience investments are proposed, their resilience cannot be readily quantified and hasn't been in some resilience proposals [92]. Another challenge is identifying which resilience efforts will serve which resilience concerns. For example, undergrounding power lines may help prevent power line failure. However, it may not serve to protect against cyberattacks directly [93]. As research in this area advances, the findings can be applied to power system models to determine the optimal set of investments.

4.2. Reliability and resilience metric applications in power system planning and investing

BPS investment decisions are determined through (i) regulated planning processes in vertically integrated jurisdictions (e.g., integrated resource planning or IRP[3]) or (ii) organized markets in restructured states. A key difference between both processes is that organized markets procure energy and capacity in separate markets, while regulated planning processes are used to procure both simultaneously. This has led to IRP generally utilizing non-monetary metrics to determine adequacy, as the monetary metrics are used to determine an optimal energy mix [94]. In contrast, some organized markets use the VOLL to directly or indirectly set or guide the capacity price, which, as described earlier, is a commonly used monetary metric to identify power system investment needs. Midcontinent Independent System Operator (ISO) utilizes the VOLL as a cap for their energy and operating reserve market prices [95], while Electric Reliability Council of Texas uses a VOLL to set its scarcity price [96]. However, other entities such as ISO-New England and Pennsylvania New Jersey and Maryland ISO use non-monetary metrics to define capacity needs and build a residual demand curve for capacity to procure these needs on a capacity market. In general, the risk of choosing an incorrect VOLL – underinvestment in capacity that could lead to interruptions – and the complexity of determining the VOLL that changes across customers, seasons, and time of day, limits its use in BPS planning processes.

The VOLL remains scarcely utilized outside the bulk power system planning process [97]. In theory, distribution system planning could use the VOLL to determine optimal investments. However, similarly to IRP, distribution system planning is a least-cost exercise in which the utility looks to meet prescribed levels of reliability and service. Distribution utilities use metrics such as the System Average Interruption Duration Index and its equivalent in frequency to plan their investments. Demand-side management planning uses cost-benefit analysis to identify demand-side resources for implementation. Five U.S. states' guidelines for cost-benefit analysis recognize reliability and resilience benefits; four of these states – Connecticut, Massachusetts, Rhode Island, and New York – use the VOLL to assess the reliability benefits of technologies [97]. In contrast to least-cost planning processes, cost-benefit analysis is more amenable to using the VOLL to monetize the benefits of improvements in reliability. More comprehensive application of the VOLL may require more granular estimates across customers and methods to extend its application from reliability to resilience by reflecting the impacts of widespread and long-duration events.

4.3. Energy justice and equity

Another avenue for research is the development of energy justice and its application to resilience assessments. A consistent shortcoming of existing results is the lack of estimates differentiated based on socio-economic factors. Carvallo et al. [98] combined blackout data with demographic data at the census block group level and found that areas with a high share of minority population were more than four times more likely to suffer a blackout, but that income was not a factor. Future studies should further investigate this finding to explore whether this effect is persistent across other outages and locations. If the effects are persistent, multi-regional versions of IO and CGE models could be used to predict the economic consequences to various communities.

Even though the same resources may serve multiple communities from the same utility, some communities are more vulnerable to greater economic and social losses than others. Various factors such as electricity dependency and private infrastructure unique to the customer (ex. solar panels and backup generators) can influence these disparities. Some data that could help inform analyses in this field are available in the Low-Income Energy Affordability Data Tool (LEAD) [99]. Existing models used for energy resilience analysis could be used with LEAD, and

[3] IRP determines the least-cost and risk-managed expansion portfolio for a given utility for a 10-to-20-year horizon. IRP implements a capacity expansion modeling process to determine the least-cost portfolio, and an accompanying resource adequacy assessment to ensure this portfolio complies with reliability standards.

other energy justice-focused data could provide much-needed examples of the distributional consequences of outages.

Another challenge with energy justice is determining who pays for resilience investments. For example, all utility customers paying for resilience investments that will only serve specific entities or communities may frustrate those who front the cost without reaping the benefits. Additionally, Baik et al. [6] find that WTP is increasing with income, indicating that requiring a flat fee for all households would disproportionately burden low-income households. This introduces an important distinction between WTP and ability to pay – customers who may want to pay more to avoid interruptions may not be able to do so given financial restrictions limiting what they can afford. Another Baik et al. study [6] found that although the WTP increased with income levels, the proportion of the WTP amount to the household income decreased with income levels. Implementing a per-usage charge rather than a flat fee can help alleviate this issue but may still require some households to bear a cost burden greater than their WTP. Despite varying WTP values across income levels, all customers deserve the services the same. Therefore, determining how to equitably distribute the cost burden for investments that provide mitigation and resilience to power outages is a challenging but important research question.

4.4. Community resilience

The current capabilities to restore power supply mostly rely upon a top-down restoration approach. The "Last mile" recovery, which depends upon the repairs in low/mid voltage power distribution systems, often takes several days. The delayed restoration especially affects low-income and underserved communities, which may lack backup options [98,100]. Fortunately, recent advances in distribution systems [101,102], including integrating distributed energy resources (DERs) such as distributed solar and storage, provide a potential means to improve system resilience if applied purposefully and methodically. Potential solutions include using DERs and microgrids to form flexible-boundary islands in preparation for an upcoming event and continue to supply critical loads within the island [103,104]. The proactive isolation/islanding feeder sections can also prevent cascading failures and reduce the number of affected customers. Several studies have also investigated the use of DERs to provide operational flexibility for resilience by enabling automated bottom-up restoration [105–110], and examined the use of grid-forming inverters in providing black-start services and other critical bulk-grid services such as frequency and voltage support [111].

Effective management of critical infrastructure systems disruptions requires long-term resilience planning [112,113]. The existing resilience planning methods propose different stochastic optimization models that aim to identify optimal investments for disruption management to reduce the grid impacts of extreme weather events [114]. However, the existing studies on using DERs to improve resilience primarily focus on technical solutions rather than the cost-benefit tradeoffs of the proposed solutions. These tradeoffs are even more important to analyze when extreme weather events are of concern, and the planning solutions need to be driven by resilience requirements and not persistent costs. To this end, incorporating DERs/microgrids into utilities' portfolio of infrastructure planning activities requires appropriate models for quantifying the risk of future events on the power grid and determining how those risks can be reduced cost-effectively. Additional work is needed on evaluating the value propositions to quantify direct cost savings and the value of improved service levels that DERs provide. The solutions to these problems should also provide important insights regarding the tradeoffs of the disparate planning activities to reveal their risk-avoidance potential.

5. Mapping stakeholder questions to the most appropriate model

When stakeholders such as utility owners and operators, policymakers, and regulators ask resilience-related questions, they need a guide for how they can begin to get answers and link questions to models. These answers may be unclear for modeling-based questions, such as determining which model(s) are appropriate for a specific resilience assessment. There is often a disconnect between the knowledge needed to ask stakeholder questions and the knowledge needed to execute the answers. This section aims to provide a clear map from stakeholder questions to appropriate model(s). The questions included in this analysis were selected based on a review of resilience and risk assessment reports [12,13,115], as well as common research gaps the authors identified. These questions were chosen based on frequency in state resilience reports and author expertise and experience from working directly with customers with resilience concerns. Additionally, the selected questions represent decision-maker concerns in instances where they are familiar with the problem and possible solutions but are unfamiliar with the models and tools available to appropriately and effectively value, assess, and identify the best solution given their system. Table 2 introduces the question themes and presents an overview of our findings linking valuation methods previously discussed in this paper to a discussion of their general capabilities.

5.1. What are the distributional and environmental justice impacts of resilience strategies?

An important consideration of any project with community impacts is how the project will serve people across varying socio-economic demographics [115]. It is best practice to design and implement equitable solutions. Environmental justice has not been explored in the context of estimating the cost of electrical outages or the benefits of resilience infrastructure. There are two distinct intersections for how environmental justice and electrical outages intersect.

The first intersection is estimating the costs to different populations and socio-economic groups at sufficient granularity to discern disparate impacts meaningfully [116]. The models previously discussed that have been used to quantify the cost of outage events have separated costs by industry. There have been advancements in IO modeling to include regional-specific estimates [82] that could be applied to long-term electrical outages. There have also been studies that extend CGE models to estimate regional and distributional impacts of policies and economic shocks [117] that have the potential to be applied to future studies of electrical outages. Region-level cost estimations can

Table 2
Mapping valuation methods to general stakeholder questions. This table summarizes which models are suitable for addressing the stakeholder question. "✔" Indicates the model is suitable for addressing the stakeholder concern, "×" denotes the model cannot address the concern, and "∼" indicates "situational," where the model does not directly address the issue but can provide some insight with ex-post analysis.

Stakeholder concern	Residential surveys	IO	CGE	C&I surveys	Empirical
Accounts for energy and environmental justice	∼	∼	∼	×	×
Uncertainty and future	×	✔	✔	✔	×
Estimates inter-sectoral effects	×	✔	✔	×	∼
Suitable for customer-level analyses	✔	×	×	✔	×
Suitable for economy-wide analyses	×	✔	✔	×	✔
Considers transportation networks and impact of electric vehicles	✔	✔	✔	×	×

unintentionally camouflage disparate impacts on marginalized or disadvantaged population segments.

The second intersection is how to apply equity concerns within a cost-benefit analysis (CBA). A CBA is a commonly used tool to quantify all benefit streams to estimate both the costs and benefits and determine the optimal level of investment where the net benefits of a policy (benefits-costs) are maximized [118]. CBA in the U.S. government does not typically include distributional weights, but it has been adopted by the World Bank and in the UK [119]. There are different functional forms for weights that can be used within a CBA framework that provide more prominence to values from lower income demographics [119–121]. An alternative approach to a CBA is a cost-effectiveness analysis (CEA) which typically do not include all benefit streams, namely social benefits. Ward et al. [122] discuss some metrics that extend CEA to incorporate equity concerns. Projects that are considering justice and equity concerns will need to ascertain whether to pursue these alternative approaches to CBA or to provide unweighted quantitative CBA results accompanied by qualitative distributional estimates.

5.2. Considering the uncertainties of the future, how will resilience initiatives implemented in a system today continue to contribute to the resilience of the same system in the future?

The frequency and intensity of severe weather are uncertain due to climate change. Further, a system designed to be resilient to a fixed climate may be insufficient to handle increased threats of severe weather. The long-term and complicated relationship between resilience and climate change has been explored in some disciplines, such as bridge performance [123] and coral survivability [124], and more recently explored for energy systems. Di Maio, Tonicello, and Zio [125] analyze future climate change horizons with varying severity in 2040, 2070, and 2100 to flooding impacts. They assess the impacts to an energy system operating under a variety of capabilities i.e., the ability of the system to be islanded or use bidirectional energy conversion, etc. [125]. They find that more integrated systems withstand climate change more effectively [125]. However, they do not conduct economic analysis to determine the costs or benefits of the various systems [125].

None of the models discussed include risk or uncertainty directly as model inputs. However, it is often possible to include uncertainty by running the model multiple times with different input assumptions surrounding the probability and severity of adverse events. This can be done with specific scenarios or with Monte Carlo analysis, where input variables are assigned a probability distribution and each model run samples a value from that distribution [64]. For example, Rose and Lim [126] and He et al. [67] have modelled resilience using IO models. They modelled some sectors remaining operational during an outage and compared those results to a full outage. This concept could be extended to exploring hypothetical future outages under forecasted climate scenarios. This could help policymakers discern which sectors would benefit the most from scarce funds over the long term. The main concern with this type of analysis is that there may be a high degree of error if the current model inputs and assumptions would not represent future conditions. See Brockway et al. [127] for a discussion of the models and techniques used to characterize uncertainty for the electric grid.

5.3. What are inter-sectoral impacts resilience investments might have?

In an increasingly connected world, understanding interactions between various sectors is of growing importance. There are dependencies between the energy, communications, and transportation sectors, to name a few. As a result, it is often of interest to the stakeholders how changes in one sector may affect other sectors [13].

IO and CGE models were designed to estimate inter-sectoral impacts and are good candidates when this type of analysis is needed. The primary consideration is ensuring all desired sectors are included in the model and with sufficient accuracy. For example, transportation is likely to become more dependent on the electrical grid as electric vehicle penetration increases, so the internal model assumptions need to be updated with recent estimates. The U.S. Department of Energy is currently looking at sector coupling challenges expected as more end-uses are electrified. In the case of electrification of transportation, current research is addressing the mutual reliability interdependencies and how mutual reliability can be realized technically.[4]

5.4. What model is most appropriate for a large system? What model is most appropriate for a smaller system?

Resilience projects vary in scope and size. Some models may be better suited to serve larger or smaller projects. The compatibility of a model with the size of the system being analyzed is vital to stakeholders at all levels (local, regional, federal, etc.).

The data collection method employed in Ericson and Lisell [28] can be highly accurate for a single business or campus seeking to determine the benefits of adding resilience. A private business may find this method useful as they would not be concerned with indirect costs or consequences to other sectors. However, this method is less useful for public policy or utility-scale investments as they do not consider indirect costs and are difficult to scale up.

IO and CGE models are best suited for estimating large systems that include multiple sectors of the economy. They are best suited when the estimates of the indirect consequences and costs are large. They are difficult to scale down and are not recommended for small-scale analysis.

Empirical studies typically provide estimates at very-large scales. Therefore, their greatest potential is to estimate the costs at a country or state level as well as any costs that may endure over long periods of time. As these studies require measures of gross product at the national or state level and are not currently suitable for localized outages.

Stated preference surveys can fill a niche for medium-scale projects that utility companies would undertake. They are the most appropriate method to estimate the cost for outages that are more focused on residential customers rather than commercial customers and can easily be scaled up to the number of customers that may be affected. This method cannot estimate indirect or intersectoral costs needed for large and long outages that public projects would address. While the SP literature on long-duration costs is nascent, future studies may help determine how costs scale from short-duration to long-duration.

5.5. How might an increase in the adoption of electric vehicles affect the resilience of and the ability to model a system?

There has been a sharp increase in the adoption of electric vehicles (EVs) around the world, and forecasts anticipate this trend continuing [128,129]. As these vehicles become increasingly common, it is useful to understand their role in energy resilience and the capabilities of models to consider these changes.

The increased adoption of EVs creates a unique situation regarding resilience to power outages. With appropriate bi-directional electricity infrastructure in place, EVs can partially be used as reserve capacity to offset the outage costs for short-duration outages. Critical appliances can be powered for a short time using the vehicle's battery. Some studies have analyzed the benefits and support provided to energy systems in the event of an outage [130–134]. However, the inability to charge EVs during long-duration outages has the potential to significantly increase societal costs due to major disruptions to the transportation network, especially if long-haul commercial freight is converted to EVs.

A few studies have examined the potential consequences of being

[4] U.S. Department of Energy, Office of Electricity, initiated research with Pacific Northwest National Laboratory to explore the mutual interdependencies between electricity and transportation sectors.

unable to charge EVs during a natural disaster [135,136]. These focus primarily on the physical constraints rather than the economic costs. Future research on outage costs should incorporate transportation network costs and EVs' impacts. Studies that use IO and CGE models should look to update the sectors and industries by adding transportation networks as a new sector to the model or by updating the cross-industry coefficients and supply-demand equations to reflect a transportation network with higher dependence on the grid. Stated preference surveys could incorporate questions about transportation network costs such as in Collins et al. [137].

6. Conclusions

This paper has reviewed some of the models used to estimate the costs of electrical outages and outlined which models are suited for stakeholder questions. We highlight some of the strengths and weaknesses of several models. Some of the limitations of this review is that the focus in on resilience more than reliability, the conclusions may not generalize to setting other than electrical outages, and that quantitative estimates were not systematically presented for meta-analysis.

We reviewed stated preference survey methods, IO, CGE, empirical, and other macroeconomic models. More SP surveys with questions on long-duration outages will help estimate longer-duration outage costs. However, these types of studies cannot account for indirect "spillover" costs. Beyond surveys, some economic models may lend themselves to estimating these outage values independently or by improving the extrapolation from short-duration surveys. IO models, CGE models, and commercial and industrial surveys all have strengths for calculating values of long-duration outages, and each has its respective limitations. Future work can explore how to leverage the strengths of recent modeling advancements to overcome some of the limitations. For example, IO models do not capture adaptive behavior, CGE models assume unrealistic market conditions, and survey methods do not capture indirect effects.

A relatively nascent area of research is implementing empirical models to estimate power outage losses. Further investigating this potential application of empirical models can offer an alternative to valuing resilience that has the potential to corroborate the simulation-based models. Recent research has begun to explore the use of these models to estimate the distributional consequences and equity concerns of outages. Improved outage value estimation methods can help improve our understanding of the resilience values of a system, allowing for more informed spending on resilience.

Some recommendations for future research are:

- Standardizing the units of measurement. Different Studies report values per kWh, per event, or as added to a monthly bill. Monthly WTP can be difficult to compare to total economic losses from regional models. Reporting estimates by duration and per kWh would allow for better meta-analyses, increasing reliability and accuracy of estimates.
- Standardization and generalization of estimates for long-duration outages. Most of the studies reviewed analyze a single event and do not include how their results would generalize to a different location or a different incident. Resilience planning could be dramatically improved if estimates could be transferred to new projects under consideration without requiring an original study.
- Incorporating distributional and regional differences in the estimates for regional economic models (IO and CGE) to capture environmental justice and equity concerns. This will allow policymakers to make decisions on resilience projects that incorporate information on distributional consequences.
- Estimates from IO and CGE models need to be validated by empirical estimates. The simulation-based IO and CGE models have not been compared to estimates from empirical methods or case studies of economic damages to determine the accuracy of their estimates or the validity of their input assumptions.
- Similarly, the estimates from stated preference surveys need to be validated by estimates from revealed preference methods. Stated preference studies that estimate the cost of long-duration outages compare their estimates to short-duration stated preference studies to establish reliability. However, neither short-duration nor long-duration cost estimates have been validated by comparison to revealed preference techniques. This type of validation has been done for other research domains that use stated preference techniques and has provided greater confidence that the stated preference estimates do not suffer major hypothetical bias [138–140].

Answering these questions and obtaining more estimates of long-duration outage costs will serve many stakeholders, such as states that have developed resilience plans for their electrical grids. Better informed planning and reduced outage costs can be achieved through improved resilience valuation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Appendix A

Table A1 includes estimates from various studies that have estimated the cost of short-duration electricity outages that were used to construct the map in Section 3.4. These estimates show that the value varies significantly by customer type, duration, and location. Results are reported in the original currency measured. A comparison of these WTP estimates should consider variation in exchange rates and country-specific inflation over time. Several studies report more estimates than what is listed in this table. Many studies report the variation in WTP across demographic attributes of the survey respondents.

Table A1
Summary of estimates for short-duration outages.

Author	Year	Country	Outage duration	Customer type	Survey type	Value
Carlsson and Martinsson [38]	2008	Sweden	4 h	Residential	DCE	8.53–28.40 SEK
Abdullah and Mariel [41]	2010	Kenya	3 h	Residential	DCE	62 Ksh
Ozbafli and Jenkins [141]	2016	North Cyprus	1 h	Residential	DCE	£0.06–0.28
Pepermans [39]	2011	Belgium	1 h	Residential	DCE	€26.40–39
Accent [142]	2008	UK	1 h	Residential	DCE	£4.20
Hensher et al. [43]	2014	Australia	8 h	Residential	DCE	$AU60
Bliem [40]	2009	Austria	4 h	Residential	DCE	16 %
Amador et al. [45]	2013	Canary Isles	1 h	Residential	DCE	4.2 % (£1.99 per month)
Blass et al. [44]	2010	Israel	1 min reduction in 1 hour outage	Residential	DCE	$0.42
Morrissey et al. [29]	2018	UK	1 h	Residential	DCE	£1.57–31.37
Hubana and Ljevo [42]	2019	Bosnia and Herzegovina	1 h	Residential and business	CV	$1.81 (residential)-$63.20 (business)
Baik et al. [6]	2020	USA	10 days	Residential	CV	$1.7–2.3/kWh for critical private demand, $19–26/day for communities
Baik, Davis, and Morgan [30]	2018	USA	24 h	Residential	CV	$0.35–0.51/kWh for non-critical demands, $0.75–1.2kWh-1.2/kWh for critical demands on average. Ranges vary by the level of information about the outage.
Layton and Moeltner [31]	2005	USA	Momentary - 24 h	Residential	CV	$2.06–5.34/kWh
Chowdhury et al. [32]	2004	USA	1 h	Residential, commercial, industrial, and government	CV	$0.53 (res), $37.52 (commercial), $23.41 (industrial), $21.20 (non-profit/government) per kWh
Lawton et al. [33]	2003	USA	Momentary - 12 h	Residential, commercial, and industrial	CV	WTP/WTA: $6.9–7.14/$10.52–12.49 (residential, per event). See images 8 and 9 for commercial and industrial
Yin et al. [34]	2003	USA	Momentary - 24 h	Industrial	CV	$5.25 (momentary)–$682 (8 h)
Sullivan et al. [35]	1996	USA	Momentary - 4 h	Residential, commercial, and industrial	CV	$5.38–10.10/kWh (system-wide), $2.07/kWh (residential), $45.82/kWh (commercial), $7.61/kWh (industrial)
Burns and Gross [36]	1990	USA	Not specified	Residential, commercial, agricultural, and industrial	CV	$4.05/kWh (res), $39.69/kWh (commercial), $6.78/kWh (industrial), $3.53/kWh (agriculture)
Hartman, Doane, and Woo [37]	1991	USA	Momentary-12 h	Residential	CV	$0.16–38.03
Woo et al. [143]	2014	Hong Kong	15 min–1 h	Residential	CV	HK$90–350
Kim et al. [144]	2015	S. Korea	2 h rolling blackout	Residential	CV	KRW3900 (sudden), KRW3100 (announced) per month
Amoah et al. [145]	2019	Ghana	24-hour service. Baseline not specified.	Residential	CV	GHS 67 per month
Abrate et al. [146]	2016	Italy	1 min-6 h	Residential	DCE	€25.37/kWh
Oseni [147]	2017	Nigeria	Reduce incidences to half present level (72 h/ week)	Residential	CV	$0.15–0.41/kWh
Broberg et al. [148]	2021	Sweden	5 30-minute blackouts per month	Residential	CV	SEK3,000–4200

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