Modeling and Assessing Energy System Resilience Against Extreme Weather Events

Madeline Macmillan

Advisor: Morgan Bazilian, Colorado School of Mines
Co-Advisor: Caitlin Murphy, National Renewable Energy Laboratory

A thesis proposal for the Colorado School of Mines Advanced Energy Systems Doctoral Program

ABSTRACT

The frequency and severity of extreme weather events have been rising due to climate change. As a result, weather-related outages and their associated economic consequences have also been increasing in frequency and magnitude. This trend is expected to continue. To mitigate these losses, opportunities to improve energy system resilience must be explored. Current energy system modeling tools lack sufficient capabilities to fully consider severe weather events for investment planning. In this paper, a thesis proposal is introduced. The first two components of the proposed work will identify the major gaps present in resilience research thus far and map existing models to their characteristics lending themselves to applications in resilience assessments. The third portion of research will develop a method to fill an identified data gap by projecting severe weather events using statistical methods and Intergovernmental Panel on Climate Change data. This projection tool will then be integrated into a larger robust decision making process for energy systems, making up the fourth study. In the final study, a framework will be applied to an existing energy model that can better account for extreme weather events to inform planning decisions and the results will be analyzed and compared.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

The latest International Energy Agency (IEA) Net-Zero by 2050 report outlines a roadmap for the global energy sector to achieve net-zero emissions and offers an in-depth analysis of pathways for meeting emissions targets [1]. In addition to accomplishing climate goals, the report highlights that a wider implication of a net-zero energy system is the potential for greater consequences associated with power interruptions, due to increased electrification present in many net-zero pathways. Because the grid is often vulnerable to the effects of severe weather, there is a clear need for energy system stakeholders to mitigate the consequences of climatological threats to critical infrastructure.

Historical data from the U.S. National Oceanic and Atmospheric Administration (NOAA) indicate an upward trend in the frequency and impact of high-impact weather disasters [2], [3]. This trend is visualized in Figure 1.1. These extreme weather events often cause power outages along and adjacent to their tracks [4], [5]. For example, Hurricanes Michael and Florence both occurred in 2018 and resulted in power outages for an estimated 1.7 million people across six southeastern states. That year, customers in affected states experienced an average of 30 hours of power outages [6]. During the California wildfires in 2019, the utilities issued power outages to nearly 500,000 people [7]. A week-long freeze in Texas in February 2021 affected 4.5 million people at its peak [8].

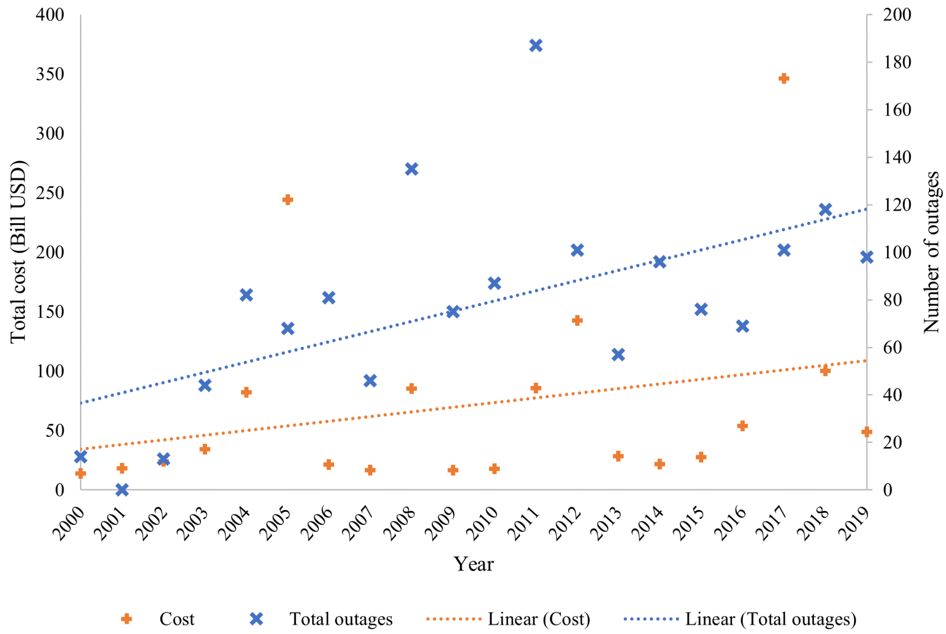

Figure 1.1: Total cost and number of billion-dollar weather events, CPI Adjusted [2]

In addition to costly physical damages from severe weather events, annual outages induce an average of $25 billion in economic damages due to lost economic activity [9]. These economic consequences reflect the country's reliance on the energy system for many industries and critical services, including clean water, communications, education, healthcare services, national security, and production and extraction of essential fuels. The combination of increases in electrification for net-zero pathways, severe weather events, and dependency on the electric grid further indicate that improving the ability of the electric grid to withstand and recover from major weather events could have significant economic and social benefits.

The concept of withstanding disturbances such as hurricanes or wildfires that have the potential to cause power outages has taken many forms in the literature, namely as resilience. Resilience is recognized as an important initiative on the international scale. For example, resilience is included in the Sustainable Development Goals (SDGs) adopted by members of the United Nations: goal 9 emphasizes building resilient infrastructure and goal 11 strives to make cities resilient [10]. The varying and broad definitions of resilience present a challenge when trying to incorporate resilience decision-making into investment and operational models. Specifically, when attempting to represent resilience in energy system tools-—such as energy system optimization models that could be used for long-term investment planning-—the necessary metrics and scenario definitions are unclear [11]–[13].

This thesis proposal proposes several studies to address the research gaps present with integrating resilience against severe weather events in energy system models. Chapter 2 discusses the findings of a literature review. The review covers resilience frameworks, energy system optimization, and the inclusion of resilience in energy system modeling tools. Another review is conducted in Chapter 3 that will develop a mapping of models to their abilities to perform resilience assessments. Chapter 4 proposes a tool to project extreme weather events. In Chapter 5, a novel decision support framework, leveraging extreme weather uncertainty tool from Chapter 4 and robust decision making (RDM), for energy system planning is introduced. Finally, in Chapter 6, the effects of implementing the RDM resilience framework are analyzed. The research proposed is supported by the different Appendices. Appendix D presents a completed study exploring the ability to solve energy system optimization models with open-source solvers. Three themes present throughout the studies in this proposal are tailoring this research to the needs of energy system stakeholders, applying research studies to well-validated models, and making the tools or frameworks developed easily accessible to those who need it. This proposal will contribute to the incorporation of resilience in energy system optimization model decisions, both investment and operational, to minimize the consequences of weather-induced outages.

2 LITERATURE REVIEW

A version of the study below is currently under review at *Renewable and Sustainable Energy Reviews*

2.1 Resilience in the literature

Resilience is a concept that has been explored in several disciplines ranging from youth psychology to ecology [14], [15]. Holling defined resilience in 1973 as "a measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables" [16]. This definition is important as it is the first formal definition of the term in the literature. Resilience is also an important construct for systems, including energy system infrastructure [17]. In this review, qualitative and quantitative definitions of resilience, as it pertains to systems, are summarized and synthesized. The intersection of resilience and renewable energy systems is also explored. This literature review addresses the needs of energy system stakeholders to comprehend resilience as it has evolved conceptually and in application.

2.1.1 Qualitative definitions of resilience

There is significant diversity among qualitative resilience definitions, but some commonalities exist. The collection of reviewed resilience definitions can be found in Appendix A. To sort through the data, a brief analysis was performed to count the number of appearances of each word within the definitions from this literature review. The words with the most number of appearances were those labeled as keywords. Words that do not stand by themselves such as 'a', 'of', 'the', and 'to', were not included in this analysis. The most consistently used terms from the literature review include "ability", "system", "recover", "withstand", and "event". Additionally, Molyneaux et al. analyze the definitions of resilience across a multitude of sectors including ecological resilience, psychological resilience, and risk management resilience [18]. In this review, system diversity, redundancy, efficiency, structure, and organization are identified as important qualities for any system to be considered resilient [18]. These keywords are explored in more detail in this section.

System resilience can be defined in a way that is threat agnostic or threat specific [19]–[23]. This distinction has consequences for how resilience can be improved; resilience can be enhanced in a broad, general sense, or can be designed to counter a particular hazard. A literature review looking at the resilience of transportation infrastructure finds resilience to be dependent on several factors including disturbances experienced by the system in question [21]. For example, a transportation system resilient against a natural disaster such as a hurricane must be able to withstand the physical impacts of the weather event including flooding and obstacles blown into the path. A transportation system resilient against cyber-attacks must be able to withstand threats such as malware and phishing [23]. Each hazard presents unique challenges to the transportation system's resilience. To effectively assess the resilience improvement opportunities of a system, disturbance context is often needed to direct strategies and investments.

Risk managers of technical systems may be familiar with the notion that resilience has been related to the concept of stability [24], [25]. For example, ecological resilience and ecological stability are similar yet distinct: both are related to a system operating in equilibrium, but stability is the ability of a system to return to its known equilibrium state post-disturbance, while resilience allows for multiple equilibrium states. Therefore, the potential for a resilient system to fluctuate between multiple operating states under resilience results in low stability. Inversely, in a complex ecosystem, an abundance of stability is indicative of a lack of resilience, which can lead to system collapse [25]. For a system to be resilient, the structure must strike a balance between flexibility and stability to enable the system to move between several states of equilibrium without going too far off track. Risk managers ought not to be deluded into thinking that stability directly translates to resilience or that an absence of threats or hazards is indicative of resilience. Consequently, a resilient system is one that is proactive against new hazards.

In addition to stakeholders enabling a variety of satisfactory operating states in their systems, it is important to consider other investment (i.e., physical) opportunities available to improve system resilience. In a series of studies, Panteli and Mancarella explore various investment and operational options for improving resilience [26], [27]. The authors identify robustness, redundancy, and responsiveness as dimensions of resilience. For example, [27] tests how investments in robustness, redundancy, and responsiveness improved energy system resilience and found various resilience benefits associated with each attribute tested. For an energy system, robustness can translate to using stronger materials in generation technologies to modify their fragility curves, redundancy can be achieved through parallel generation configurations, and responsiveness can look like a fast response time in the event of an outage. In Luthar et al., more angles of intervention for critical infrastructure resilience are introduced including prevention and learning [17]. Redundancy and robustness from Panteli and Mancarella and prevention and learning from Luthar et al. emphasize survival and avoidance of outages altogether [17], [27]. Additionally, the various dimensions of resilience highlight the importance of considering resilience enhancements for energy systems with respect to both infrastructural and operational pathways. Resilience is a multi-faceted concept. When an energy system can avoid all or most potential interruptions through preventative, educational, and adaptive measures physically and operationally, resilience can be achieved.

Definitions of resilience vary based on the discipline and its associated risks. It is also a characteristic at the intersection of stability and flexibility, therefore requiring a balance of both. A resilient system should be able to withstand disturbances from multiple perspectives, for example, both operationally and physically. Therefore, the authors of this study propose a working definition of resilience for practical applications to energy systems. We argue that an energy system is resilient against acute weather events if it can withstand and recover from them by adapting to different operational and/or infrastructural states of equilibrium. An energy system will remain resilient if the system continues to meet quality standards and customer demand throughout a disturbance. The degree of resilience is determined by the extent to which quality and demand requirements are met and economic consequences associated with power outages are minimized.

2.1.2 Quantitative definitions of resilience

Qualitative definitions identify dimensions as well as the meaning and significance of resilience. However, without actionable and measurable metrics, resilience work would remain purely interpretive. Adding actionable attributes to the qualitative and quantitative definitions of resilience could enable the inclusion of resilience in energy system analyses and application beyond academia. Quantitative frameworks can assess the performance of the qualitative resilience indicators. Therefore, quantitative metrics could guide energy system planning based on the tangible impacts and value of resilience initiatives on resilience dimensions of a system. This is important for energy system stakeholders as they develop a system resilient against uncertain climate threats. Existing literature includes a broad array of resilience metrics, which can be classified by unit of performance or consequence, spatial resolution, temporal scale, and threat. Despite the abundance of metrics in the literature, there is not an accepted, standardized, and validated metric for measuring resilience [28], [29]. We highlight key gaps and important attributes among existing resilience metrics to inform energy system planning and operational decisions.

There are two primary types of resilience metrics: performance-based and attribute-based. Attribute-based metrics compile system properties contributing to resilience such as vulnerability, responsiveness, and adaptability [30]–[32]. These properties (or attributes) are then used to establish a baseline of a system's current resilience, and they can also help assess resilience improvement strategies. Attribute-based resilience metrics are not commonly implemented with energy system modeling efforts and so are not discussed in this paper.

Performance-based metrics are useful in quantitative analyses in energy sector modeling tools. These metrics are evaluated by quantifying performance shortfalls and their resulting consequences, which often accompany disruptions on the energy systems. Generally, these performance shortfalls are characterized by the demand exceeding the supply, as summarized by Equation 2.1:

$$Performanceshortfall = \int_{t_0}^{t_f} C_{pre}(t) - C_{post}(t)\, dt \tag{2.1}$$

The functions C_{pre} and C_{post} are the performance curves with and without a disturbance. The integral over time represents the total loss of functional capacity from the start of the disturbance to after. This functional form is employed in several papers and applications for quantifying the reduction in system performance due to a disturbance [19], [22], [33]. Figure 2.1 provides a visual representation of how the performance losses in Equation 1 are determined with respect to an energy system experiencing a disturbance. With respect to a hypothetical acute weather event, the system function level at t_0 represents the performance of the system prior to any disturbance. The time t_1 is after the event occurs, and the system performance falls due to the impacts of the disruption. Note that causes of performance shortfalls can be attributed to a variety of things—not all of which are deterministic nor independent—and are an important component of performance-based resilience metrics. Between times t_2 and t_3, the natural disaster continues and/or there is a delay in recovering system performance. At t_3 the system begins to recover and regain system performance as restoration strategies are implemented until it has reached t_f. Ultimately, maximizing resilience involves minimizing the area between the purple dashed line and the solid black line, which corresponds to minimizing Equation 2.1.

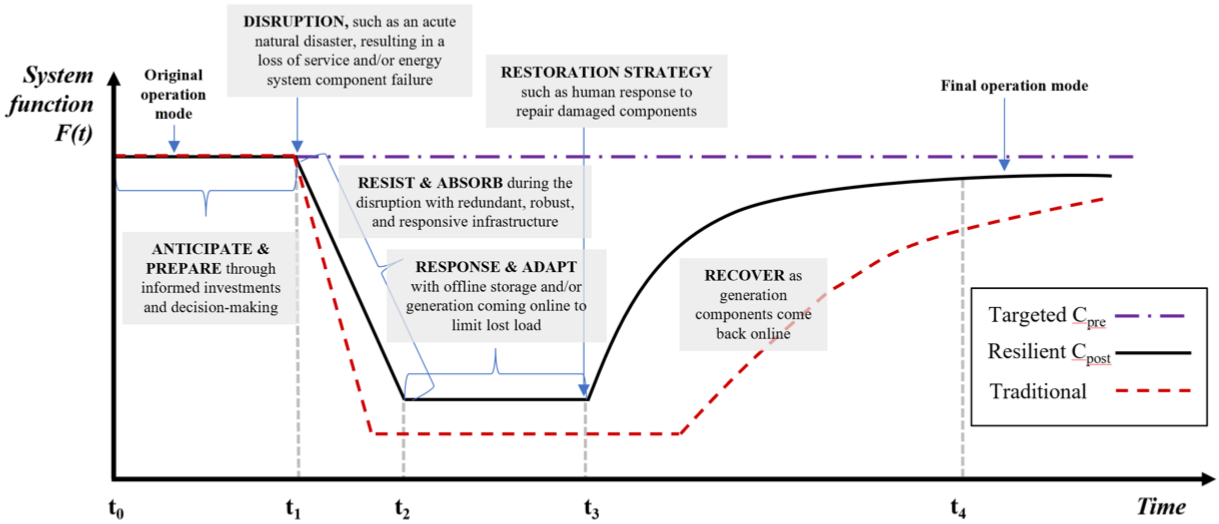

Figure 2.1: A resilient energy system during a disruption, adapted from [34]

There are several shortcomings with recent applications and demonstrations of performance-based resilience metrics. For example, the stochastic nature of both severe weather events and their resulting impacts (including power outages) must be incorporated into energy system planning. Some approaches for incorporating uncertainty in power system models include Monte Carlo simulations and Markov chains, both offering a unique stochastic framework [31], [35], [36]. Applying components of uncertainty into data needed to define parameters that inform energy system planning would also broaden the scope and understanding of the resilience of the system under various scenarios and increase the real-world applicability of the model results.

Interdependencies are also important to consider when implementing performance-based metrics in energy system planning models. Within the power sector, an example of an interdependency is between the electric and natural gas systems where the presence of natural gas and electricity are essential to one another to meet end-user demand and transport fuel to generation facilities [37]–[39]. Sectoral interdependencies remain important when considering the impact of extreme weather events and their accompanying hazards. When intense rain hits, roads can become impassable which limits the transportation of essential fuels and maintenance required to sustain the operations of an energy system. High winds blowing a solar array can disrupt generation, making what was maybe already considered back-up power futile. Omitting sectoral interdependencies in energy system resilience planning can lead to an incomplete understanding of the impacts of outages and can misinform stakeholders and decisionmakers. Therefore, a thorough resilience assessment would incorporate sectoral interdependencies.

Another challenge with implementing performance-based metrics is converting the values into economic consequences to inform decisions about investments and strategies to mitigate the effects of severe weather-induced power outage events. The economic losses associated with outages are often aggregated into a value of lost load (VoLL) metric or indicator [40]–[47]. In the real-world, the VoLL value can vary due to several factors including outage duration, season, time of day, location, and customer type (residential vs. industrial vs. commercial). Equation 2.1 can be adapted to include the appropriate VoLL associated with a weather-induced power outage, as seen in Equation 2.2:

$$\text{Economic consequence from weather - induced performance shortfall} = VoLL \int_{t_0}^{t_f} C_{pre}(t) - C_{post}(t)\, dt \qquad (2.2)$$

In Anderson et al. discussing the economic impact of Superstorm Sandy, the value of the VoLL can range from \$10-300/kWh [33]. In both Anderson et al. and Eskandarpour et al., the adopted VoLL for an extreme event is \$100/kWh [33], [48]. How these values were assigned, however, is not discussed in further detail. Providing more context for a VoLL assignment could enable energy system stakeholders to adapt a study for their own system.

Although the VoLL can be sufficient for short duration outages, its value is (a) often implemented as a static cost-per-load unserved and (b) not well understood for longer-duration outages. In the literature, Ericson et al. take steps to address this through a flexible framework to develop an outage duration-dependent VoLL [49]. This framework reflects both fixed outage costs and costs that vary throughout an outage event (classified in the study as fixed, stock, and flow costs) of any duration. Despite this progress, in many instances, the system-wide VoLL is often underestimated by regulators [44]. To continue to expand the utility of the VoLL to applications in severe weather events, more research is needed into how severe weather events might affect the value and duration-dependence of the metric.

As previously mentioned, our society is interconnected; a downfall in one sector can lead to a downfall in another. Many existing performance-based energy system planning and operation metrics are still restricted by their inability to fully reflect inter- and intra-sector interdependencies, represent uncertainty, and to quantify the economic and social consequences of various resilience events. Recognizing these shortcomings, the quantitative definition of resilience for this paper is adopted from the area under the curve metric introduced in Sepúlveda-Mora and Hegedus [50]. This metric calculates the area under the curve (AUC) of system survival probability, which is defined in Equation 2.3 where N represents the length of the outage being considered.

$$AUC = \sum_{t=1}^{N} P(\text{surviving an outage of} t \text{hours}) * (1 \text{ hour}) \qquad (2.3)$$

This metric is unique because it captures some of the uncertainty present in power outages. It also requires minimal data that would otherwise be needed for metrics involving a VoLL or a composite indicator.

In practice, resilience can range from the capacity to bounce back from an outage to mechanisms of survival during a disruption; the difference being one system is able to avoid the occurrence of an outage altogether, and instead absorb the disturbance. In this paper and based on our previously discuss qualitative definition, we emphasize the prevention and learning dimensions as discussed in Luthar et al. [17]. The metric from Sepúlveda-Mora and Hegedus captures these resilience dimensions by placing priority on the probability of survival [50]. While there is no silver bullet for resilience assessment, of the ideas and metrics available to us, it is important for energy system stakeholders to focus on a notion of energy system resilience that emphasizes the prevention of outages and minimization of system outages and collapse. In this chapter, we have identified a quantitative framework that best matches our qualitative definition of resilience and serves the interests of energy system stakeholders.

2.1.3 Resilience considerations in energy system models

A review of the energy system modeling literature indicates that energy sector models are typically either well established and broadly applied, or they include resilience considerations; only very limited examples exist for models that fall under both categories. Weather-related hazards are evolving, causing a shift in energy system stakeholder concerns; it is increasingly important to assess a system for resilience against multiple outages and potential climate states of the world. Therefore, these stakeholder priorities need to be accounted for in energy system modeling. Current resilience assessments are insufficient at fully capturing the concerns of energy system stakeholders.

On the one hand, several models aim to improve system resilience while representing the consequences of severe weather on energy infrastructure [27], [51]–[59]. However, many of these models lack experience, as they have only been demonstrated on a single test system. On the other hand, Ringkjob et al. provides a large review of energy and electricity system models that have been more widely applied but include little to no resilience considerations [60]. Outside of the review conducted in Ringkjob et al., one example of a popular model with resilience considerations is REopt from the National Renewable Energy Laboratory. REopt employs a value of resilience metric, similar to a VoLL, in post-processing to calculate the potential economic benefits of providing backup generation during grid outages based on the recommended system configurations [61]. REopt is a common tool used in resilience assessments [62]–[66]. Though this example of a resilience metric in an existing model is noteworthy, it is not necessarily useful to all users. The REopt model assumes the user knows the value of resilience for their system. In reality, the numeric value of the VoLL ranges significantly between \$10-\$300/kWh and is highly dependent on numerous factors including the season, time of day, outage duration, geographical location, and customer breakdown [43], [67]. Given these complexities behind a VoLL metric, it is not reasonable to assume the user has calculated the VoLL or that they have all the resources needed to do so. Additionally, the value of resilience is not considered in the actual optimization problem. In other words, the optimization problem determines the necessary distributed energy resource mix with the highest net present value, not accounting for any resilience value. Therefore, the system is not optimized to maximize resilience, but instead treats the value of resilience as a separate stream based on any avoided outages the system would be expected to experience without the model-recommended system amendments. Due to the lack of resilience metrics and the inability to effectively populate energy systems models with power outage and resilience considerations, there exists an opportunity to enhance existing models to consider resilience against natural disasters within their formulation. In summary, existing models do not meet the needs of energy system stakeholders.

Throughout the literature, there is significant variability between definitions and quantifications of resilience. Research to assign a monetary value to the resilience of renewable energy systems has also been met with challenges. With respect to energy system resilience against severe weather events, there are several stakeholders and many reports declaring a need for more work in this field. Given the importance of this work, inconsistencies and limitations in quantifying and representing resilience in energy system optimization planning models highlight an unfulfilled area of research.

2.2 Adapting and enhancing existing models

Due to the identified knowledge gap of the inability to effectively inform energy systems models with outage and resilience considerations, especially within renewable systems, there exists an opportunity to enhance existing models to consider resilience against natural disasters within their formulation. When considering an energy systems optimization planning model that accounts for resilience against extreme weather events, the wheel does not need to be reinvented. Instead, these proposed adaptations and enhancements have the potential to be applied into existing, commonly used energy systems optimization models with base formulations that have already undergone rigorous testing and validation.

2.2.1 Co-optimization and valuing consequences

Like many planning decisions, the economics of a project are a significant deciding factor. Therefore, to enhance the persuasiveness of resilience improvements in an energy system risk assessment, it can be of value to assign a monetary value to resilience. This can help justify the high capital costs of most resilience projects.

An important component of valuing economic consequences is the VoLL. As discussed, the VoLL is a commonly used dynamic metric based on several factors, yet has been arbitrarily assigned in past analyses [33], [43], [67]. A VoLL can be used to translate electric service losses into a dollar value that can be incorporated into the optimization problem as a cost variable. A common method for determining the VoLL is through customer surveys [40]. In addition to the phrasing of the questions, the results of these surveys vary by location and customer type. As opposed to conducting surveys that fit each criterion, the existing VoLL survey results could be used to inform the VoLL for other scenarios. By aggregating the data collected thus far, along with accompanying characteristics of the surveys and those being surveyed, machine learning techniques could develop a model to predict the VoLL of a given scenario or system. A similar study develops the Interruption Cost Estimator (ICE) calculator which has been used in other journal articles and by reliability planners [68]–[70]. This calculator employs a "cost per unserved kW" metric to inform its output. These values are based on the state and the customer composition. If more parameters linked to the system could be included, the values used by the ICE calculator that mimic the VoLL could be more accurate. One way to do this could be through improving the spatial resolution considered and increasing it from U.S. states to U.S. counties. An outage in a county with a higher gross domestic product (GDP) and/or higher distributed energy resources deployment (DER), might experience different economic losses than a power outage in a county with a lower GDP and/or lower DERs deployment [71]. It would also be important to implement approaches that uphold environmental justice principles to maintain equal and fair access to services. A VoLL framework that considers socioeconomic and other community factors at a detailed level would enhance the detail of resilience assessments. As a result, consequences would be valued such that each resilience project under review could be fully understood and tailored to the unique characteristics of the serviced area.

While improved VoLL frameworks can populate the objective problem as a cost variable in the constraints, they can also be integrated into the objective function. When the VoLL is included in a cost minimization objective function, the program will minimize the costs incurred from the unmet load. For example, if efficiency or generation capacity is down due to a weather event, the solution must shift to mitigate the unmet load and subsequent costs triggered by the VoLL. This often involves purchasing more efficient or higher capacity (and generally more expensive) system components. For this to come across in the model output, however, the impacts of the weather event on the energy system components must be included in the optimization formulation. Adapted and enhanced from the Oak Ridge National Lab summary of power and energy system vulnerabilities, Table 2.1 summarizes the impacts and associated model augmentations needed to consider the effects of acute weather events on both energy and power systems [72]. With the VoLL in the objective function and the weather event parameters for system components included the formulation, the model could consider the economic value of consequences and resilience when planning for the impacts of extreme weather. This will help energy system stakeholders develop a thorough plan that captures the costs of being weak against extreme weather and the savings of being resilient against extreme weather.

Another advantage of including the value of resilience in the objective function is the possibility of co-optimization of resilience and net-zero goals of an energy system. While the benefits of optimizing for two major issues is enticing, it does introduce some unanswered questions. For example, planning for net-zero goals often results in an increase in renewable deployment. Therefore, as touched on previously, questions arise about the implications renewables have on grid resilience. In practice, Anderson et al. uses REopt to co-optimize for resilience and renewable goals [33]. Though helpful in shedding some light on that relationship, the study falls short in other aspects including an uncertainty framework and parameters for energy system components during the weather event. By continuing to explore the

Risk	Potential Impacts	Model adjustments
Extreme temperatures	• Reduced efficiency • Reduced generation capacity • Reduced transmission capacity • Increase demand	• Adjusted component parameters such as efficiency and capacity active during the weather event • A new demand load active during the weather event
Water scarcity	• Reduced generation capacity • Changes in operations – Especially with coal, natural gas, and nuclear facilities	• Adjusted component parameters such as efficiency and capacity active during the weather event • Updated operational constraints during the weather event
Flooding	• Physical damage • Changes in operations	• Binary variables to indicate generation component availability during the weather event • Updated operational constraints during the weather event
High winds	• High-speed shutoff for wind • Physical damage – Power line damage and/or failure – Debris hitting generation, transmission, and/or distribution equipment	• Binary variables to indicate generation component availability during the weather event
Variable weather conditions	• Variable resource potential for wind and solar • Reduced generation capacity	• Updated VRE generation profiles • Adjusted component parameters such as efficiency and capacity active during the weather event
Wildfires	• Physical damage – Power line damage and/or failure • Reduced transmission capacity	• Binary variables to indicate generation component availability during the weather event • Adjusted component parameters such as efficiency and capacity active during the weather event

Table 2.1: Summary of the potential risks and consequences, and respective model adjustments associated with weather events that could be incorporated into energy sector planning tools' optimization framework

relationship between renewables and resilience, a mapping connecting the renewables to resilience characteristics could be developed. This tool could inform an energy system stakeholder which aspect of their system's resilience would be impacted by increasing PV penetration, for example. This mapping will be possible with greater testing and validation of the interactions between resilience and renewables and will help energy system stakeholders pinpoint the needs of their systems.

Co-optimization and valuing consequences can help to explain several relationships surrounding energy systems and resilience. Notably, they can inform energy system stakeholders navigating extreme weather and an intricate solution space.

2.2.2 Implementing stochastic frameworks

Extreme weather events can be difficult to predict, posing an uncertain risk to energy systems and energy system stakeholders. To improve the capacity to consider energy system resilience against uncertain acute weather events, energy system models such as those in Rinkjob et al. need to incorporate uncertainty frameworks [60]. Some common approaches to modeling the impacts of uncertain extreme weather on energy systems include analytical frameworks such as the Markov approach and simulation techniques such as the Monte Carlo method. These approaches have been shown to improve energy system stakeholders' understanding of the effects of high impact, low probability (HILP) weather events on energy systems [73]–[76]. Employing an uncertainty framework into energy system optimization could allow for the stochastic and time-varying nature of natural disasters to be represented and improve resilient decision making.

To consider uncertainty in energy systems modeling for resilience, several relationships need to be explored. For example, the relationships between climatological threats (such as high wind speeds and severe flooding from a hurricane or extreme temperatures from a heat wave or freeze) and component failure pose threats to a service disruptions, however are not always included in energy system modeling. This particular relationship could be better understood through fragility curves. Fragility curves assign failure probabilities associated with the climatological risks of acute weather events to respective energy system components. Incorporating a range of extreme weather projections into energy system modeling efforts helps to consider uncertainty associated with climate change when planning infrastructure, including the energy system. By considering the relationship between climate and system components, extreme weather can be incorporated into an optimization framework for the energy system. When the uncertainty of extreme weather is captured in energy system modeling, energy system stakeholders can perform a more comprehensive resilience analysis.

Some examples of stochastic frameworks being applied to power and energy system resilience modeling during extreme weather include studies by Panteli and Mancarella, Ahmadi et al., and Zeng et al. [27], [76], [77]. In Panteli and Mancarella, the authors model the influence of HILP weather on the resilience and reliability of a power system [27]. Using Monte Carlo simulations, varying weather conditions and restoration times are used to understand the impacts on outage frequency and duration. A variation of this technique can be incorporated into an existing energy system model. The study in Ahmadi et al. tackles energy system resilience modeling against HILP events as a result of climate change [76]. In this approach, climate change uncertainty is explained to be nonlinear, but for computational tractability, is simplified and applied as a piecewise linear function. In Zeng et al., analytical approaches are used to model the resilience of energy systems during extreme events [77]. The paper develops a function of system states with a transition matrix with a Markov Reward Process (MRP). An MRP is a Markov model with reward structures integrated into the various model states. In this study, the power system experiences a direct loss when it transitions to a state with lower performance due to a disruptive event. Although these are useful examples, they are applied to new models instead of to existing and validated models. As a result, these otherwise valuable frameworks are housed in less accessible and less validated models, making it challenging for utilization by energy system stakeholders. In a more experienced model, the components of Monte Carlo simulations or an MRP approach could be applied to each time step for each relevant energy system component, assuming the component fragility curve data are available, while also making these robust models more accessible to energy system stakeholders. Both methods provide a stochastic framework that can be applied to an existing model; however, the simulation approach requires fewer additions and is more straightforward. As further explored in the following subsection, the data necessary to consider these uncertain relationships is sparse and must come first.

An important uncertainty present in resilience assessments of energy systems is an understanding of how climate change weather events will affect critical infrastructure in the future. It is also of interest to make any frameworks employing uncertainty relationships available to those who would directly benefit from them—namely, energy system stakeholders. As a result, future research efforts to incorporate extreme weather and climate uncertainty in energy system optimization models should be done to validated and accessible models.

2.2.3 Improving data collection and availability

At the core of any robust resilience assessment is quality data with which to populate the inputs; improved data and data collection are essential to a thorough resilience analysis. Energy sector resilience metrics will only be as useful in informing energy system stakeholders and planning as they can be applied and appropriately populated. While better data collection could help improve the understanding of the economic relationships between energy system resilience and other sectors, the cost of acquiring said data might be prohibitive or unjustifiable.

Any efforts to enhance energy system resilience metrics and the associated data collection should target applications that would serve to directly inform the quantification of energy system resilience benefits, planning, and operational decisions with respect to acute weather events. A natural disaster can have a variety of effects on an energy system including energy demand fluctuations, changes in variable renewable energy availability, and damaged system components. Therefore, it would also be of interest to better understand the relationship between natural disasters and changes to the energy system. For example, during a severe winter storm and/or freeze, electric heating consumption is likely to increase, the availability of solar and wind will be dependent on the cloud cover and wind patterns, respectively, and conventional generation may be affected if it may be difficult to transport the fuels [72]. As a result, parameters within an energy system model during an acute natural disaster should be distinct from the "business as usual" parameters. In other words, the data capturing the effects of extreme weather events on energy systems should be included in energy system optimization models. This step would improve the thoroughness of extreme weather considerations for resilience assessments.

A benefit of improved data collection is increased application, validation, and testing of existing resilience metric frameworks. That is to say, when data collection is improved, more data is made available for testing models across various scenarios and disciplines. However, many resilience studies propose their own resilience metric as opposed to adopting an existing (and broad) metric from a previous study [78]–[81]. While this approach has merit, it does not strengthen existing frameworks. Through increasing existing resilience metric applications and testing, instead of routinely developing new metrics, energy system stakeholders could be provided with an enhanced understanding of the validity of existing resilience metrics. Therefore, data collection to populate and test existing resilience frameworks should be a priority.

Many approaches to increase data availability are a significant undertaking. For example, fragility curves would inform the probabilities of infrastructure failure with respect to various climatological threats in the decision-making process within the optimization model. As useful as this may be, it would require a lot of time; several components would need to be tested against several different conditions (wind, rain, etc.). When data collection proves too difficult, time consuming, expensive, or otherwise infeasible, there are alternative ways to populate a model or framework. One method in the literature uses energy system model outputs to inform power system model inputs, or vice versa [82]. Similarly, using outputs from other external models that simulate energy system performance-based metrics can be used as inputs into energy system planning models. This approach combines the advantages and capabilities of the individual models. For energy system resilience planning, this approach could be adapted to accomplish similar goals. For example, a model that simulates fragility curves of an energy system component against varying climatological threats relevant to hurricanes could be used to populate survival probabilities [31]. Economic Input-Output models are an example of a model that can inform energy system models. In [83], a mathematical approach for understanding the interdependencies between a system of systems (SoS) is introduced. System failures that affect other sectors are determined by performance thresholds. By making educated assumptions about the maximum tolerable lost service, a robust space of the various states that can be assumed by the SoS is generated. This space, potentially exhibiting several dimensions, can output performance shortfalls experienced in other sectors based on interruptions in a separate, but connected, sector, such as an outage. The addition of these cascading economic consequences in the objective function of an optimization model can help inform resilient energy system planning decisions. Another approach to informing energy system models without exhausting resources on data collection is through digitalization. From an operations standpoint, machine learning techniques can be employed to detect irregular patterns that may lead to a power outage. This awareness can help the system adapt to the evolving conditions.

Informing energy and power system optimization models with the output of external models is not novel, but specifically doing so for improved resilience planning against acute natural disasters is a relatively nascent space [31], [82]. Data collection can be complicated and unattainable, so leveraging the capabilities of existing models to produce simulated data can help eliminate the need to acquire data while still informing energy system frameworks and stakeholders.

2.3 Contributions

This literature review highlights key gaps in resilience research. These gaps limit the potential of stakeholders to plan energy systems when faced with uncertain extreme weather events. This research :

- Develops a guide to existing resilience definitions, frameworks, and applications for energy system stakeholders
- Highlights key gaps affecting the thoroughness of energy system planning resilience assessments

3 CREATING A GUIDE AROUND EXISTING ENERGY MODELS AND RESILIENCE FOR STAKEHOLDERS

This proposed study will characterize existing models for their applicability and usefulness in resilience assessments.

3.1 Literature review

Power system resilience research has gained momentum as large outages have increasingly impacted the U.S. electrical grid. Resulting service interruptions have spanned from multiple days to weeks. 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. Justifying such investment requires a rigorous understanding of the value of avoiding long-duration power outages.

Natural disasters can cause outages that can last several days or weeks and have implications on a system's resilience. Within the literature reviewed, the term "long-duration outages" is inconsistently defined, often without a clear distinction between short and long duration outages [70], [84], [85]. The cost incurred from long-duration outages are not well documented, particularly how cost varies by location, duration, and scale. This is a key research gap when exploring resilience of the electric grid against long duration outages. Planning power system investments that minimize the damage from outages is difficult when using incomplete modelling.

Resilience is frequently conflated with reliability and mitigation. In power systems reliability is concerned with meeting service standards over a prolonged period of time, whereas power system resilience is the ability of a system to adapt and recover from acute disruptions [86]. Additionally, reliability is dependent on uninterrupted operations with sufficient electricity supply. The core components of resilience are robustness, redundancy, resourcefulness, and rapidity [86]. Mitigation is defined as activities that are implemented before an event and incur a cost regardless of whether a disruption takes place. Two examples of mitigation efforts are hardened transformers and smart meters. Resilience is defined as actions that take place after the event has occurred, and costs can be incurred before or after the event [87]. Resilience can be categorized into three groups; dynamic, inherent, and adaptive [87]. Dynamic resilience takes place by the utility after an outage has occurred and can reduce the duration of the outage. An example of dynamic resilience is quickly dispatching replacement equipment. Inherent resilience describes strategies taken by the customer to reduce the duration of the outage such as purchasing and using a back-up generator. Adaptive resilience is strategies performed by the customer without pre-outage expenses and can be categorized as improvisation during the outage. Adaptive resilience comes in the form of conservation or making up lost production later. The optimal combination of mitigation and resilience efforts would reduce damage from outages in the most cost-effective manner.

Decision-makers are presented with challenging questions when attempting to assess the risks and costs associated with long-duration outages, such as which models are best suited to their needs, what is the uncertainty in the models, and how can they address questions regarding the consequence of potential future problems such as climate change. Resolving these critical stakeholder issues is not straightforward, due to the lack of a clear mapping of which model(s) align against which critical question(s). As a result, stakeholders, who may not always understand the intricacies and distinctions between different candidate model(s), are left without a clear answer. This technology gap between decision-maker needs and the modeling solutions that are currently available was a key motivator for this paper.

Within the United States, many events that threaten the operations of the power grid accompany natural disasters, such as hurricanes in the southeast, freezing temperatures throughout the country and wildfires and earthquakes in the west. Some examples of the consequential outages last from 2 days in North Carolina [88], 2-7 days in Texas [89], 7-51 days in Oregon [90], and nearing 14 days in Louisiana based on the recent Hurricane Ida [91].

In 2018, North Carolina experienced multi-day outages from Hurricane Michael and Hurricane Florence [5]. The outages were within weeks of each other and extended throughout the southeastern region. Approximately 1.7 million customers were affected.

In February 2021, Texas experienced a severe outage following an arctic blast that froze and impacted multiple energy sources. Some of the impacts included frozen wind turbines and ice build-up in natural gas pipelines that prevented fuel delivery to many gas-powered plants. At the peak of the event, about 40% of the state's power generation capacity was affected. The freeze and subsequent outages affected about 4.5 million customers over the course of a week, particularly historically disadvantaged demographics and communities [88], [89]. Additionally, electricity prices in ERCOT temporarily spiked, and the outage is estimated to have cost Texas $80 - $130 billion in direct and indirect economic losses [92].

Louisiana was hit by Hurricane Ida in late August 2021 and was dealing with consequential outages until mid-September. At their peak, the outages affected over 1 million customers. An analysis found that 30,000 utility poles were damaged, double the number damaged during Hurricane Katrina [91]. The power system in the state was particularly damaged due to already aging transmission lines and previous damage sustained from storms the previous year.

Across these events, utility customers in vulnerable socioeconomic classes were hit especially hard [93]. For example, vulnerable communities may be less able to afford measures to avoid a power outage. Although not necessarily intentional, these inequalities are challenging to neutralize [94]. Even though the estimated economic value of lost load to a vulnerable community may be low the social consequences are often high, such as the loss of livelihood in the event of hourly jobs being disrupted. Another issue that arises when discussing these environmental injustices is in determining who pays the costs for resilience improvements. At-risk utility customers may be less able to afford such increases in rates. Striking a balance between environmental equity and reasonable funding plans is difficult, but important.

These events have disrupted utility customers and have also alerted stakeholders of areas of improvement. For example, North Carolina's Climate Risk Assessment and Resilience Plan identifies a need for legislators to develop resiliency metrics to quantify the economic consequences of power outages to better inform power sector infrastructure planning, investments, and operations [88]. For North Carolina, resilience goals and metrics are to ensure no critical infrastructure, especially hospitals, police stations, and fire stations, are left without power for more than 48 hours. Similarly, Oregon's Resilience Plan specifies pressing climatological risks in the state and outlines potential action to improve resilience of infrastructure against natural disasters for the next 50 years. A major earthquake has the potential to cause severe infrastructure damage, death, and major economic consequences [90]. In Oregon, resilience is highly dependent on the status of the critical energy infrastructure hub (CEI Hub) which spans 6 miles along the Willamette River. Several ports, pipelines, substations, and storage facilities are located here [70]. Each region has a range of resilience threats and goals but addressing them requires an understanding of the value of long-duration outages.

3.1.1 Models used to estimate only the direct costs of electrical outages

The direct costs of an electrical outage can be defined as the economic consequences that result from not having access to electricity, typically lost production or consumption. Indirect consequences include the spillover effects from the direct consequences such as supply chain shortages and resulting price changes. They can also include some effects that would mitigate the economics costs such as substitutions in production away from the standard input to one that is more readily available during an outage.

Stated Preference Models

A common method used to estimate the direct costs of electrical outages is customer surveys, typically using stated preference methods. This method has been used in the United States [40], [85], [95]–[101], Europe [102]–[105], developing countries [106], [107], and elsewhere [108]–[110]. Appendix 1 includes a summary table of some of these short-duration estimates. These surveys estimate the costs to residential, commercial, and/or industrial customers. Previous surveys have generally only included questions surrounding short-duration outages (<24 hours) because of concerns that respondents lack sufficient prior experience with long-duration outages to provide accurate responses. Results on short-duration outages cannot be confidently extrapolated to long-duration outages as studies have established that cost estimations of outages as a function of duration are nonlinear and concave i.e., total costs increase with duration, but costs per hour decrease with duration [111]. In addition, these survey-based methods do not account for indirect costs that typically increase with duration. There are two major types of stated preference surveys, contingent valuation (CV) and discrete choice experiments (DCEs). Contingent valuation presents a scenario that includes a benefit (such as prevention or mitigation of an outage) and an associated cost, and ask the respondent whether they would vote "yes" or "no." Discrete choice experiments present the respondent with several scenarios (usually 3-5) and ask which is their most preferred choice. See Champ et al for more detail on the theory and practice of stated preference surveys [112].

An Electric Power Research Institute (EPRI) report reviewed the differences between the use of these two major types of surveys for studying outage costs and discussed their relative strengths and weaknesses [111]. They proposed that DCEs have greater potential to propose longer duration outages in their scenarios to quantify the value of resilience because DCEs emphasize measuring the value of attributes presented in the survey. This would also allow for estimation of the value of advanced notice and frequency, in addition to duration.

Küfeoğlu and Lehtonen [113] reviewed the academic literature on short-term outage customer interruption costs based on customer surveys, indirect analytical methods, case studies, and power quality events. Sullivan et al. conducted a meta-analysis of studies conducted by utility companies in the United State that estimated the value of service reliability [70]. They obtained separate estimates for residential, small commercial, and medium and large commercial customers. Their results show that willingness to pay (WTP) increases with length of outage-duration for all customers. For residential customers, WTP increases with income 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. Lawrence Berkeley National Laboratory has published a tool that accompanies the publication that allows estimation of outage costs for a variety of location and outage parameters.

The major limitation of stated preference surveys is that they typically only ask respondents about outages that last a short time, typically less than 24 hours. Sullivan's meta-analysis and tool use a maximum outage duration of 16 hours [70]. The cost of long-duration outages cannot be determined by extending the results of short-duration surveys. In addition to standard issues of out of sample prediction, outage costs per hour are expected to decrease with outage duration as agents are able to ameliorate the consequences. Because of this, extending short-duration estimates using a linear function would overestimate long-duration costs. Using a non-linear function to predict long-duration costs also causes issues. Sullivan et al. use a quadratic function in their meta-analysis. While this functional choice fits the data well within 16 hours, it predicts a maximum outage cost at a duration slightly past 16 hours [70]. While the per hour costs are expected to decrease with duration, the total outage cost should not.

An active area of research is understanding how effective these survey methods are in estimating the cost of longer-term outages. In principle, it is simple to pose similar questions with longer outage durations listed. However, survey respondents may have difficulty responding accurately to scenarios they have not experienced previously, introducing hypothetical bias [111].

Baik et al. is the first study to use stated preference survey methods to value long-duration outages [85]. They assess the willingness to pay for resilience to a 10-day power disruption. They use a contingent valuation survey method for residents of the northeastern United States. They find that respondents are willing to pay \$1.7-2.3 per kWh. This is on the low end per kWh of estimates reported across studies in Sullivan et al., but on the high end of total WTP per outage [42]. To determine the potential impacts on WTP, the survey asked whether the respondent has experienced a long-term outage. The survey finds that WTP does not change significantly if the respondent has prior experience with long term outages, an encouraging finding for potential studies in the future.

Another study that uses a stated preference survey to estimate the benefits of community resilience to long-duration outages is Hotaling et al. [114]. They use a discrete choice experiment to estimate WTP for a local microgrid. They vary the services that are connected to the microgrid across the survey respondents to determine the WTP for different services and levels of operation. The greatest difference between this study and Baik et al. is that the microgrid in this survey would power community services, but not the survey takers' homes [85].

Hotaling el al. find 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.

Bottom-up Models

Ericson and Lisell have developed a novel framework to estimate the direct losses to commercial and industrial customers [49]. The framework highlights the unrealistic nature of a single price for an outage due to variability in the magnitude, timing, location, and duration of an outages. They develop a method that can be adapted to a wide range of these factors. This method focuses on the outage cost to an individual customer rather than to a community or region.

Within this framework, the total cost associated with an outage is split into three categories. The first category is fixed costs which are independent of the outage duration such as shutdown and startup costs. The second category is flow costs. These are the costs associated with a lack of power that increase with duration. Examples include lost business revenue, fuel for back-up systems, and pain from disabled medical equipment. The final category is the stock costs, which are costs that are affected by duration, but are incurred once per outage and not continually increasing. Examples are food spoilage or vandalism due to loss of power. If the outage is short enough, the food would not spoil and the stock cost would not be incurred. When the duration is long enough, the cost will be incurred, but will not continue to increase with duration, it will only spoil once. In addition to deriving the functional forms of these various costs, the method is applied to two case studies—a manufacturing plant and a fire station.

The structure of this framework allows it to be applied to both short and long duration outages. The model defines which costs will be incurred a single time per outage, and those that will increase as duration increases. Although this framework is relatively flexible, greater development is needed to adequately consider various customer types and to improve data availability. The main limitation of this method that a high level of detail is required for each customer, so aggregating many customers to the sector level for large scale policy analysis may be prohibitive.

3.1.2 Models used to estimate the direct and indirect costs of electrical outages

The indirect costs of electrical outages are defined as the spillover effects of disruptions in the supply chain or transportation networks, and other changes in economic activity such as price increases that results from shortages. This section discusses some of the models that have been used to estimate the indirect damages in addition to the direct damages. The damage is typically measured as a change to gross product at the spatial level being measured (i.e., gross domestic product, gross state product etc.).

Larsen et al. 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 important conversation in these research fields [87].

The most common type of models that ares used to estimate indirect costs are regional economic models. Their use in modeling electricity disruptions is reviewed in [115] and [116]. These 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.

Input-Output Models

Input-Output (IO) models are the simplest type of macroeconomic model used to estimate indirect economic losses. These models use coefficient matrices to capture interdependencies across sectors of the economy. To study electrical outages or natural disasters they commonly assume that sector(s) of the economy become inoperable, and this prevents 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. The major shortcoming to IO models is that the coefficients in the matrix are fixed, so any adaptive behavior or other resilience measures put into place 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.

Rose et al. is an example of using an IO model to estimate the economic impact of a long-duration electrical outage [117]. They examine the 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 reallocation of scarce electricity to the sectors with the largest bottleneck and find that the losses can be dramatically lowered to 12.5% in week zero and 0.58% overall.

Rose and Lim use a different IO model to estimate the economic impact to businesses in Los Angeles from the Northridge earthquake [118]. This is one of the first papers to incorporate resilience measures within an IO model analysis. The model is not able to directly incorporate resilience measures, but the model can be run under assumptions of various resilience measures (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 the resilience measures incorporating production shifting, time of day adjustments, and electricity importance adjustments.

The city of New York commissioned a study following hurricane Sandy that sought to assess the costs of future electrical outages, and how the costs would change under different climate change scenarios [119]. This model bridges some of the gap between Integrated Assessment Models (IAM) that are commonly used to assess the long-term costs of climate change and the IO and computable general equilibrium (CGE) models that are commonly used to assess singular disaster events. This study assesses 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 [111]. They study the resilience benefits of installing a microgrid for one neighborhood in Nassau County that includes about 3,000 residential buildings and 535 commercial and service buildings. Their analysis considers the possibility of 100% economic activity loss, in comparison 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 on the order of $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 3 days during a 5-day outage). However, they do not include any analysis where the microgrid is not able to satisfy 100% of the baseline power needs.

He et al. use an IO model to estimate economic losses due to several different levels of hypothetical electrical outages in China [120]. They use sectoral data from China's economy to model cross-sector interdependencies. They assume that there is an initial shock to production in the energy supply sector, and then model the reduction in output in other sectors. Their model includes forty-two 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 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 REAcct tool that uses IO modelling to estimate economic losses from natural disasters [121]–[123]. The tool uses GIS information to provide results that are spatially appropriate 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 (BEA) [71]. The tool can be used for many types of disasters, and a grid outage can be modelled as a disruption to power plant(s). The tool is useful for decision making within federal agencies, but it has not been widely adopted by other authors within the peer-reviewed literature.

Computable General Equilibrium Models

Computable general equilibrium (CGE) models are another class of models used to estimate indirect losses. CGE models use a framework of demand and supply equations in various markets that are simultaneously in equilibrium. Because CGE models use supply and demand relationships, they can account for behavioral effects such as price changes and substitution among inputs, so it has been argued that CGE models provide more accurate estimates of long-run losses from disasters than IO models. The primary limitation of CGE models is that they are typically more complex, expensive, and computationally demanding than IO models. In addition, CGE models 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 [115]. Another critique of CGE models is that they require a large number of input parameters whose values must be assumed. If the inputs assumptions are incorrect or measured with high uncertainty, the model outputs will not be reliable [124].

Rose et al use a CGE model to study an outage in Los Angeles County caused by a hypothetical terrorist attack [125]. They examine indirect effects that increase costs and resilience measures that can reduce them. The resilience measures they look at include 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%.

Outside the United States, Hu et al. have looked at the costs of snowstorms in China in 2008 [126]. They model the economic losses from a snowstorm with 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. claim that the difference between the two models represent the benefits of resilience. However, this would only represent the adaptive resilience, and this method is not useful for estimating the benefits of dynamic resilience such as grid or infrastructure improvements [126].

Sue Wing and Rose have developed an analytical general equilibrium model to examine economic losses of long-duration power outages, and how resilience measures could reduce losses [127]. The model is simpler than the computable models, using only two sectors. However, the analytical tractability clarifies the mechanisms involved and highlights the importance that mitigation investment and substitutability can play in reducing the 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 within survey-based research.

A recent paper by Baik et al. outlines a hybrid approach to estimating the value of resilient power systems and the costs of outages, both long and short term [128]. 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 any indirect costs. They propose that CGE models 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 commercial and residential 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.

Other models

Macroeconometric models such as structural vector autoregression (VARs) 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 provides an example of this type of analysis, looking at the costs of a terrorist attack in New Jersey [129].

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, then the effects could potentially persist for years. This may be an important 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 firm relocation in addition to traditional measures of economic loss.

An area that has been studied more extensively than long-term electrical outages is the economic losses from natural disasters. The losses due to a natural disasters are typically more extensive than loss of electrical power, including damage to capital and infrastructure. However, a significant portion of economic damage during a disaster is the reduction in economic activity that occurs, 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 [130]. The topic of lost economic activity from natural disasters has been reviewed by Botzen et al. [131].

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 (MRIA) models are a recent advancement in IO modelling that can include spatial substitution effects and dynamic changes across regions. Adaptive regional economics models allow for price changes and sector-specific supply constraints to be included in the model [132], helping to bridge the gap between CGE and IO models.

The second type of model innovation that could be transferred from the natural disaster literature is the use of empirical models (i.e. [133]). 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 [134] 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 because they use GDP as the dependent variable, which is not typically measured on the smaller 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 have begun to explore the use of datasets that measure economic output at a finer spatial scale and incorporate geography into their estimates [135]. These techniques could provide richer estimates of costs and help to understand which locations would benefit the most from resilience infrastructure.

A major advantage of empirical models is that they identify causal estimates from actual outages rather than using simulation. Empirical studies could be used to validate results from IO and CGE models and determine which input assumptions are the most accurate. There are two main limitations to empirical models for estimating the cost of electrical outages. The first is that it is not possible to disentangle the costs specific to the electrical outage from other tangential disaster costs. The second limitation is that because this type of analysis requires data on actual events, it is not possible to simulate changes based on resilience measures or other policy responses.

The direct findings and summaries of these models are summarized in Table 3.1.2.

Model Type	Description	Short Duration vs Long Duration
Stated Preference	Survey-based method. Estimates direct costs only. Only method that can estimate "soft" costs to residential customers.	Duration determined within the survey questions. Large literature on short-duration outages. Small literature on long-duration outages due to concerns of hypothetical bias.
Bottom-up	Focuses on a single customer. Accounting based method that can categorize costs as fixed, flow, or stock. Direct costs only	Categorization of costs allows for costs to be calculated as a function of any duration.
Input-Output (IO)	Simulation based method that estimates costs across industries. Cannot include input substitution or price changes. Resilience measures incorporated by changing inputs to the model such as which industries are operational. Measures upper bound on costs.	Well suited for long-duration outages that affect multiple industries. Can vary the outage duration within the model.
Computable General Equilibrium (CGE)	Simulation based method that can estimate costs across industries. Can incorporate adaptive behavior such as price changes or input substitution. Resilience measures incorporated through supply and demand relationships within the model. Measures lower-bound on costs.	Well suited for long-duration outages that affect multiple industries. Can vary the outage duration within the model.
Empirical	Empirical based method that estimates costs using data from actual outages. Requires data on gross product at the spatial and temporal scale of the outage. Estimates total economic losses, but doe	Only suitable for long-duration. Only method that can estimate potential long-term costs.

Table 3.1: Summary of the models used to estimate costs of long-duration outages.

3.2 Proposed methodologies

When stakeholders such as utility owners and operators, policy makers, and regulators ask resilience-related questions, they need a guide for how they can begin to get answers. For modeling-based questions, these answers may be unclear. There is often a disconnect between the knowledge needed to ask stakeholder questions and the knowledge needed to execute on the answers. This study will produce a clear map from stakeholder questions to appropriate model(s). Models will be classified based on their capabilities with respect to resilience assessments. Some of the stakeholder concerns and questions proposed include:

- Does this model account for energy and environmental justice?
- Are the impacts of electric vehicles considered in this model?
- Does this model consider uncertainty?
- Is this model more suitable for larger or smaller energy systems?
- Does this model consider interdependencies across sectors?

3.3 Contributions

This literature review of models has the potential to develop a helpful guide for energy system stakeholders. The guide would direct energy system stakeholder to the best model(s) for their energy system concerns and characteristics. The proposed research:

- Develops a guide to understanding the benefits and shortcomings of the various models available for resilience analyses
- Creates a mapping between models and their capabilities for resilience assessment

4 EXTREME WEATHER UNCERTAINTY

As explored in Chapter 2, there are several barriers to obtaining high quality and complete data with which to populate energy system models. This is especially a concern when dealing with energy systems faced with uncertain extreme weather. This proposed study will create a tool to project heat waves that can be used to develop future energy loads for various future climate states of the world.

4.1 Literature review

Considering the anticipated increase in severe weather events, it is important to consider the effects of climate change in building energy modeling analyses. In the literature, many current typical weather data projects have failed at considering the effects of changing climate on buildings [136], [137]. The studies that have considered climate change in synthetic weather data projections are not intended to be used in building performance simulation. Thus, there is a need to produce consistent weather inputs that consider the effects of climate change for building energy modeling.

To explore the effects of considering uncertain climate on energy system resilience planning, heat waves will be the first severe weather event explored. Quantifying heat wave intensity is an active area of research [138]. Although more complex methods may be desirable according to Bowles [139], the method in this proposed study will focus on primarily on dry bulb temperature [140]. Concerning resilience studies to extreme heat or cold, existing papers have explored a loss of productivity due to power outages correlated to extreme heat conditions [141], thermal comfort and survivability issues [142], [143], changes in peak load, and energy consumption [144]. Similarly, this tool will be able to inform an energy system of uncertain climate, quantify thermal comfort, and quantify changes in energy consumption.

4.2 Proposed methodologies

This potential study proposes a model to produce stochastic, temporally-resolved weather patterns that follow IPCC climate projections. The tool, which will be called the Multi-scenario Extreme Weather Simulator (MEWS) tool, will project severe weather into the future. While the exact equations for this proposed model are in both proprietary and developmental stages, some of the relationships defined in Li et al. will guide this model [140]. The projections will be calculated using a combination of historical daily summaries and hourly normals from NOAA, IPCC SSP cases, and typical meteorological year data [145], [146]. The process will characterize historical statistics of heat waves and extrapolate increasing frequency and severity as defined by IPCC scenarios. The primary relationships needed to be quantified for this tool will be the functional forms of extreme temperature events, the classification of extreme temperature events, the frequency of extreme temperature events, the severity of extreme temperature events, and the anticipated increases in the frequency and severity of extreme temperature events as they relate to various IPCC scenarios. MEWS will be validated to show that the results statistically center on regional climate model results over a broad range of climate locations. The output of MEWS will be used with EnergyPlus and OpenStudio to develop energy load profiles for several future climate states of the world.

4.3 Contributions

This proposed study:

- Develops an open-source weather projection tool based on statistical methods informed by IPCC scenarios to project extreme weather in future climate scenarios for any U.S. latitude and longitude pair
- Considers climate change in synthetic weather data projections and is intended for building performance simulation and energy modeling uses

5 DEVELOPING ENERGY SYSTEM PLANNING FRAMEWORK WITH ROBUST DECISION MAKING

Considering the three main gaps in efforts to enhance energy system resilience modeling identified in Chapter 2 coupled with the qualitative and quantitative definitions of resilience, the need for a new framework for resilience assessment is evident. The main modeling gaps are insufficient data, inclusion of a stochastic framework, and valuing the consequences of extreme weather, all with an emphasis on accessible and validated models for energy system stakeholders. All the gaps are important, so our proposed approach touches on all of them. Combining all the above augmentations into one model, however, may be computationally expensive. Instead, it is worth exploring the opportunities to combine numerous existing models, leveraging their individual capabilities to develop a robust resilience assessment framework for energy systems and their stakeholders.

When planning an energy system, there are several factors and uncertainties to consider. Often times, the relationships between the forces of long-term changes, namely climate change, are not agreed upon. In order to address this deep uncertainty, a sufficient uncertainty framework is needed. Tools supporting these needs are known as Decision Making under Deep Uncertainty (DMDU) methods. DMDU methods include Robust Decision Making (RDM), Dynamic Adaptive Planning (DAP), Dynamic Adaptive Policy Pathways (DAPP), Info-Gap Theory (IG), and Engineering Options Analysis (EOA) [147]. To understand the uses of these methods, an initial review is conducted in the following section.

5.1 Literature Review

Robust decision making (RDM) is a framework that makes decisions in the face of several unknown variables. Instead of attempting to predict the unknown with imperfect forecasts, RDM leans into the unknown by testing several potential scenarios. RDM is used to go beyond a single optimal solution, and instead test the vulnerabilities of several solutions to achieve the best result based on threshold criteria of the stakeholders [148]. The RDM framework consists of several iterative steps and the flexibility to consider full ranges of uncertainties [149].

Dynamic Adaptive Planning (DAP) is a method of dealing with deep uncertainty that embraces the idea that the world will change over time. As a result, DAP produces system strategies that work *with* the changing world [150]. For a given project employing DAP, several uncertainties are monitored throughout the project's lifetime [150]. At various points, the basic policy of the project has the potential to be adjusted based on the development of the uncertain vulnerabilities [150]. The possible adjustments in DAP are defensive actions, corrective actions, capitalizing actions, and reassessment [150]. The adjustments based on uncertain vulnerabilities continue until a trigger event is reached at some point in the future that concludes the policy [150].

Dynamic Adaptive Policy Pathways (DAPP) combines DAP with Adaption Pathways (AP) [151]. DAPP emphasizes system objectives, constraints, and uncertainties when dealing with vulnerabilities. Similar to DAP, when an action meets a tipping point, the pathway is adjusted as needed [151]. In DAPP, when the pathway needs adjustments, it is done in a way that limits terminal pathways, keeping them open and functional for as long as possible [151]. Another important component of DAPP is continuous monitoring of the system policy, the world, and the interactions between the system policy and the world [151].

Info-Gap (IG) Decision Theory is a DMDU method that decides between robustness and opportuneness [152]. Robustness is achieved by a strategy that performs sufficiently over a wide range of possible scenarios [152]. Opportuneness is when a strategy windfalls, or is identified due to its potential to take advantage of best case scenarios [152]. The ultimate decision faced by stakeholders employing IG Decision Theory is met with the innovation dilemma in which the decisionmaker must choose between an option that is acknowledged to perform better than another, but with much greater uncertainty [152].

Finally, Engineering Options Analysis (EOA) assigns value to the flexibility and management of engineered systems and compares these values across different strategy options [153]. The metrics presented are average expectations, extreme possibilities, and capital expenses [153]. EOA sets up an engineered system to be flexible and responsive to opportunities and threats, as needed [153]. Generally, an EOA will output a recommended first action from which the system will be poised to respond in such a way that continues to maximize the chances of success [153]. Applications of uncertainty frameworks has spanned several disciplines, however, as discussed in Section 2, applications for resilience assessments and planning in validated energy system models is a nascent space.

5.2 Proposed methodologies

Based on the above review, there are several DMDU methods to consider, but this research plan proposes adapting an RDM framework to energy system planning for resilience assessment against natural disasters. Applying this approach to resilient energy system planning will analyze the performance of multiple system configurations under various uncertain climate states of the world based on energy system stakeholder specified criteria, addressing many of the gaps discussed throughout Section 2.

The RDM framework consists of several iterative steps. As discussed throughout this proposal, existing models on their own do not meet energy system stakeholder needs. As a result, each step within the RDM process would incorporate a model tailored to (a) utilizing knowledge gained from the previous step and its corresponding model(s), (b) executing the responsibilities of its assigned task, and (c) informing the next step and its model(s). This approach results in models being populated by the outputs of other models, instead of needing to collect new data. It would also enable several scenarios to be tested under several uncertain extreme weather events, introducing a robust stochastic framework into the decision making process. Given a common theme of this paper, the authors suggest that the RDM framework be applied to an accessible (user-friendly and affordable) model that includes renewable and net-zero considerations, too. Based on the previous review, REopt stands out as a promising model candidate. The details of this framework are outlined below, adapted from in-depth books and papers covering general RDM by Kalra et al. and Marchau et al. [154], [155]. These phases are repeated until criteria threshold are met.

According to the methods developed in Kalra et al. and Marchau et al., the primary steps of RDM are as follows: 1) decision structuring, 2) strategy generation and evaluation, 3) vulnerability assessment, 4) tradeoff analysis, and 5) develop new strategies [154], [155]. A visual representation of this proposed RDM framework applied to an energy system is summarized in Figure 5.1 and throughout the following subsections.

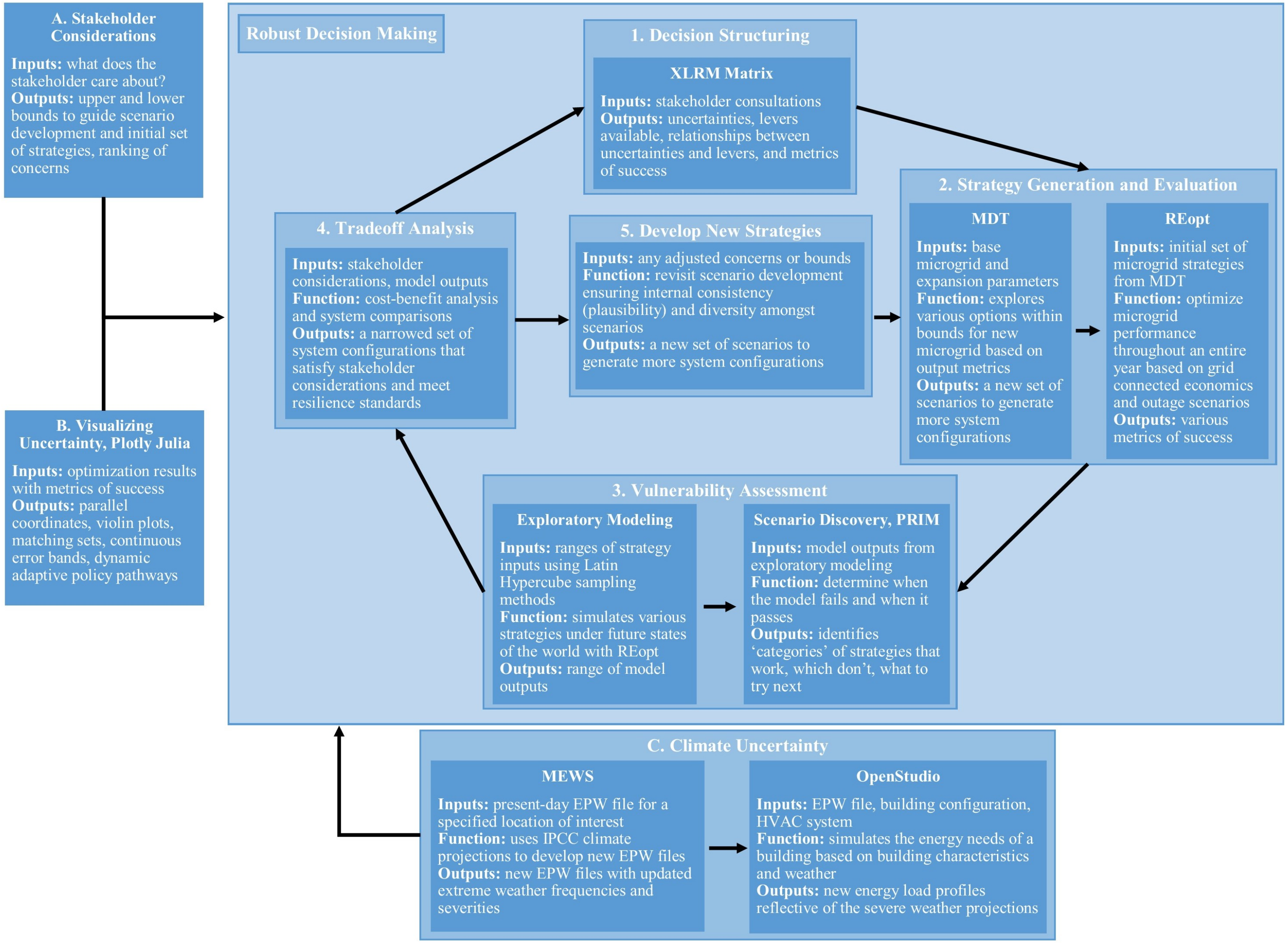

Figure 5.1: Process flow diagram

5.2.1 Decision structuring

The decision structuring phase will compile a list of stakeholder considerations, ideally directly from the stakeholder. This information will inform key decisions in the remainder of the framework. Some of the key data pieces include system uncertainties, levers, relationships between uncertainties and levers (models), and metrics of success. Based on the review from this paper, a metric of success that may be of interest is the identified quantitative framework for resilience, Equation 2.3. The information collected will vary based on the system, the environment of the system, and the stakeholder. For this project, an XLRM would be an appropriate approach. The actual values in an XLRM matrix will vary based on the system and the stakeholder. An example XLRM matrix for robust resilient energy system planning can be found in Figure 5.2.

Uncertainties (X)	Levers Available (L)

• **Natural Threats** (Earthquakes, Land/Mud slides, Tsunamis, Volcano eruptions or ash falls, Flooding, Hurricane force winds, Severe winter storm, and/or Wildfires)
• **Human-caused Threats** (Cyber attacks)
• **Technological Threats** (Power and/or Cyber system infrastructure failures)
• **Energy Sector Transition** (Power generation & storage system costs and energy carrier costs)
• **Mission Changes** (Base or installation mission that impact infrastructure and power demand)
	MDT
	• Microgrid Power Generation & Storage System Options and Sizes
	• Microgrid typology, distribution lines, switches, transformers
	REopt
	• Power Generation & Storage System Options and Sizes
	• Systems Locations
	    • spatial (on or near base, for example accounting for transmission losses)
	    • infrastructure (roof vs land)

Relationships between uncertainties and levers (R)	**Metrics of success (M)**
• Sandia's Microgrid Design Toolkit (MDT) • NREL's REopt Model • Cornell's Rhodium or BORG DMDU tools (https://reed.cee.cornell.edu/software/)	• Mission Availability/Assurance % (Total operable time [hrs] / total operable + inoperable time [hrs]) [*MDT*] • NPV ($) [REopt] • GHG Emissions (ton CO2eq) [REopt] • Outage Survivability [*REopt]*

Figure 5.2: XLRM Matrix, populated for an energy system

5.2.2 Strategy generation and evaluation

For strategy generation and evaluation, energy system models will create initial energy system designs and a pareto front. In this step, models REopt and the Microgrid Design Toolkit will generate initial designs and initial optimization results. An initial evaluation of the outputs will eliminate strategies that are known to not be of interest or not meet metrics of success. These initial results will direct the next phase of RDM.

5.2.3 Vulnerability assessment

Based on the outputs from strategy generation and evaluation results, exploratory modeling and scenario discovery will perform vulnerability assessments. Together, these components will explore a wide range of system strategies and their viability with respect to key resilience criteria, as specified in the decision structuring phase.

The model used in strategy generation and evaluation will have capabilities for vulnerability assessments built-in or is open-source and can accommodate the necessary formulation augmentations. For example, the model needs to enable the user to establish an array of uncertainties and uncertainty distributions from which to generate scenarios. The uncertainties accepted will include a significant portion of the inputs including outage start time, outage duration, and energy demand. With these new inputs, the model will iterate through a specified number of scenarios, each of which drawing randomly from the probability distributions of each uncertainty. Each scenario will be optimized. Given the criteria, REopt is a good candidate once again as it is open-source. Once the necessary augmentations have been made, the model can optimize several different scenarios by randomly drawing from a defined range of inputs. An example of the REopt inputs are previewed in Appendix B.

The process of selecting potential scenarios is often in the hands of the stakeholders, modelers, or the model itself. Regardless, the scope of the selected scenarios often falls short of sufficient diversity and representing probabilistic concerns. To solve this issue, scenario discovery is proposed. Scenario discovery, or sub-group discovery, employs systematic and analytical methods to assess the model outputs of the scenarios considered thus far, and suggests other relevant and potentially viable strategies to test. Based on the flexibility of the Patient Rule Induction Method (PRIM) sub-group discovery algorithm when compared to Classification and Regression Trees (CART), PRIM will be used in this step to search for potential strategies that will result in improved criteria of interest [156]. To be compatible with REopt, PRIM will be written in Julia. An outline of the PRIM algorithm is presented in more detail in Appendix C. Based on a batch of initial optimization model inputs and corresponding outputs collected in strategy generation and evaluation, the PRIM algorithm will search for new input combinations that improve key metrics such as a decreased life cycle cost, decreased lost load, and increased area under the curve of system survival probability (Equation 2.3). This phase will highlight new scenarios to explore, the viable scenarios explored thus far, and eliminate candidate scenarios, all based on the threshold criteria and stakeholder-specified metrics of success.

5.2.4 Tradeoff analysis

Trade-off analysis will identify the best strategies based on the set of viable ones identified during vulnerability assessment. This will be done through a cost-benefit analyss, a decoupled net-present value, and/or other similar calculation [98]. Additionally, the degree of resilience (calculated by Equation 2.3) of the energy system will be explored and compared across potential strategies.

5.2.5 Develop new strategies

Based on the results of the tradeoff analysis, new strategies will be identified and explored as needed, keeping in mind the importance of plausibility and diversity in a robust process. These phases will continue in an iterative process as necessary until stakeholder preferences have been met or are within a certain threshold. Through the continuation of this process, the proposed system will be tested from multiple perspectives to ensure resilience.

5.2.6 Additional components

In addition to the primary phases described above, a few additional components are required. The three additional components are stakeholder feedback, climate uncertainty, and visualization of uncertainty.

The first component address is stakeholder feedback. In addition to initial stakeholder considerations, it is also important to maintain relations with stakeholders throughout the decision-making process. This will work to ensure the assessment is tailored to the needs and specifications of the system for the entire framework.

Climate uncertainty is another major shortcoming of current energy system resilience assessments. As discussed in Chapter 2 and Chapter 4, severe weather events are increasing. However, by what magnitude they're increasing is not known with certainty. When planning energy systems to be resilient against acute natural disasters, it is important to test the system under multiple potential future climate states of the world to account for this uncertainty. Climate uncertainty (in the form of MEWS from Chapter 4) will be integrated into this framework with the output being used to develop different energy loads based on anticipated changes in demand during severe weather projected into the future. These energy load profiles will then be an uncertainty available in the RDM process when developing scenarios for REopt.

Finally, a complete understanding of the uncertainties considered throughout this framework is important to making decisions. Therefore, visualizing deep uncertainty will inform the stakeholders as they make pivotal decisions regarding system configurations for energy system resilience against acute weather. Considering the numerous uncertainty inputs in this framework, translation into a visual aid will help stakeholders understand the caveats included in each strategy based on the variables considered. Additionally, this component will be incorporated into several phases of the framework.

The RDM framework has a lot of puzzle pieces that, when put together, will have the potential to elevate resilience assessments for energy systems against acute weather events, or potentially other disturbances. As emphasized throughout this entire proposal, a successful RDM framework will be one that is accessible and useful to energy system stakeholders as they plan for an uncertain climate future. This proposed framework has potential but requires implementation and validation.

5.3 Contributions

This proposed study:

- Develops a novel decision-making under deep uncertainty framework for energy system planning for resilience against extreme weather
- Writes an open-source subgroup discovery algorithm written in an otherwise unavailable language

6 APPLYING RDM FRAMEWORK TO AN ENERGY SYSTEM

This proposed study will apply the RDM framework for energy systems, introduced in Section 5, to a real system. The goal will be to understand the impacts of the RDM framework on the resilience of the proposed strategy.

6.1 Proposed methodologies

Once the process outlined in Chapter 5 is operating as expected, the next step will be to apply the framework to a sample case. When selecting the appropriate case study, it is important the stakeholders are available to collaborate and provide feedback. The case study will be a military base in the ASHRAE climate zone 7A. The modelers and energy system stakeholders will work together to establish a seamless workflow and communication structure to ensure the results satisfy the stated preferences. The results of this process will be compared to those of the original, non-RDM process. A successful project will result in an understanding of the effects of RDM on energy system planning for resilience against severe weather.

6.2 Contributions

This proposed study:

- Develops a real-world application of a novel framework for energy system resilience planning
- Performs an analysis to understand the impacts of RDM on energy system planning decisions
- Conducts a comparison between different energy system resilience assessments to understand trade-offs

7 CONCLUSIONS AND FUTURE WORK

There is a clear need to improve resilience of energy infrastructure against severe weather events. This thesis proposal address several gaps present in the literature. Gaps and modeling needs to improve resilience considerations are discussed in Chapter 2. A novel mapping of current models and their resilience assessment capabilities is proposed in Chapter 3. Chapter 4 proposes a novel weather projection tool that considers climate change impacts and is designed for building performance simulation and modeling. The research proposed in Chapter 5 will introduce a novel tool to energy system planning and resilience assessment under deep uncertainty against severe weather events associated with climate change. Finally, the research in Chapter 6 will apply the new tools to an energy system to understand the benefits and shortcomings of a robust energy system planning tool for resilience against severe weather. All of the proposed work will be done with stakeholder needs in mind. Additionally, enhancements will be performed on well-validated and accessible models only–any stakeholder who needs to conduct a resilience assessment against severe weather on their energy system will be able to do so.

To complete this thesis, I plan to:

- Submit a paper on the work described in Chapter 3 to *Energy Economics* by October 2022.
- Develop the tool described in Chapter 4, backed by statistical methods and basic physical equations, by October 2022.
- Complete the development of the RDM framework for energy system resilience by December 2022.
- Submit a paper on the work described in Chapter 4 to *Energy and Buildings* by January 2023.
- Perform a qualitative analysis of the RDM framework applied to an energy system by December 2022 and submit a paper to *Environmental Science & Technology* by April 2023.

BIBLIOGRAPHY

[1] *Net Zero by 2050 – Analysis*. IEA. URL: https://www.iea.org/reports/net-zero-by-2050 (visited on 05/25/2021).

[2] Adam B. Smith and NOAA National Centers For Environmental Information. *U.S. Billion-dollar Weather and Climate Disasters, 1980 - present (NCEI Accession 0209268)*. type: dataset. 2020. DOI: 10.25921/STKW-7W73. URL: https://accession.nodc.noaa.gov/0209268 (visited on 05/01/2020).

[3] *Hurricanes Like Laura Are More Likely Because Of Climate Change*. NPR.org. URL: https://www.npr.org/sections/hurricane-laura-live-updates/2020/08/27/906633395/hurricanes-like-laura-are-more-likely-because-of-climate-change (visited on 08/28/2020).

[4] *Hurricane Matthew caused millions of customers to go without power - Today in Energy - U.S. Energy Information Administration (EIA)*. URL: https://www.eia.gov/todayinenergy/detail.php?id=28372 (visited on 07/07/2020).

[5] *Hurricane Michael caused 1.7 million electricity outages in the Southeast United States - Today in Energy - U.S. Energy Information Administration (EIA)*. URL: https://www.eia.gov/todayinenergy/detail.php?id=37332 (visited on 05/01/2020).

[6] *U.S. customers experienced an average of nearly six hours of power interruptions in 2018 - Today in Energy - U.S. Energy Information Administration (EIA)*. URL: https://www.eia.gov/todayinenergy/detail.php?id=43915 (visited on 06/22/2020).

[7] Emma Newburger. *'There are lives at stake': PG&E criticized over blackouts to prevent California wildfires*. CNBC. Section: Environment. Oct. 23, 2019. URL: https://www.cnbc.com/2019/10/23/pge-rebuked-over-imposing-blackouts-in-california-to-reduce-fire-risk.html (visited on 05/25/2021).

[8] Jeffrey Ball February 19 and 2021 97. *The Texas Blackout Is the Story of a Disaster Foretold*. Texas Monthly. Feb. 19, 2021. URL: https://www.texasmonthly.com/news-politics/texas-blackout-preventable/ (visited on 05/25/2021).

[9] Elnaz Kabir, Seth D. Guikema, and Steven M. Quiring. "Predicting Thunderstorm-Induced Power Outages to Support Utility Restoration". In: *IEEE Transactions on Power Systems* 34.6 (Nov. 2019). Conference Name: IEEE Transactions on Power Systems, pp. 4370–4381. ISSN: 1558-0679. DOI: 10.1109/TPWRS.2019.2914214.

[10] *Transforming our world: the 2030 Agenda for Sustainable Development .:. Sustainable Development Knowledge Platform*. URL: https://sustainabledevelopment.un.org/post2015/transformingourworld (visited on 05/21/2020).

[11] Linas Martišauskas, Juozas Augutis, and Ričardas Krikštolaitis. "Methodology for energy security assessment considering energy system resilience to disruptions". In: *Energy Strategy Reviews* 22 (Nov. 1, 2018), pp. 106–118. ISSN: 2211-467X. DOI: 10.1016/j.esr.2018.08.007. URL: http://www.sciencedirect.com/science/article/pii/S2211467X18300750 (visited on 05/29/2020).

[12] I. F. Abdin, Y. -P. Fang, and E. Zio. "A modeling and optimization framework for power systems design with operational flexibility and resilience against extreme heat waves and drought events". In: *Renewable and Sustainable Energy Reviews* 112 (Sept. 1, 2019), pp. 706–719. ISSN: 1364-0321. DOI: 10.1016/j.rser.2019.06.006. URL: http://www.sciencedirect.com/science/article/pii/S1364032119303971 (visited on 06/22/2020).

[13] Yi-Ping Fang and Enrico Zio. "An adaptive robust framework for the optimization of the resilience of interdependent infrastructures under natural hazards". In: *European Journal of Operational Research* 276.3 (Aug. 1, 2019), pp. 1119–1136. ISSN: 0377-2217. DOI: 10.1016/j.ejor.2019.01.052. URL: http://www.sciencedirect.com/science/article/pii/S0377221719300876 (visited on 05/22/2020).

[14] Staci M. Zolkoski and Lyndal M. Bullock. "Resilience in children and youth: A review". In: *Children and Youth Services Review* 34.12 (Dec. 1, 2012), pp. 2295–2303. ISSN: 0190-7409. DOI: 10.1016/j.childyouth.2012.08.009. URL: http://www.sciencedirect.com/science/article/pii/S0190740912003337 (visited on 05/01/2020).

[15] *Resilience and Stability of Ecological Systems | Annual Review of Ecology, Evolution, and Systematics*. URL: https://www.annualreviews.org/doi/abs/10.1146/annurev.es.04.110173.000245 (visited on 05/08/2020).

[16] C S Holling. "Resilience and Stability of Ecological Systems". In: *Annual Review of Ecology and Systematics* 4.1 (1973). _eprint: https://doi.org/10.1146/annurev.es.04.110173.000245, pp. 1–23. DOI: 10.1146/annurev.es.04.110173.000245. URL: https://doi.org/10.1146/annurev.es.04.110173.000245 (visited on 05/01/2020).

[17] Suniya S. Luthar, Dante Cicchetti, and Bronwyn Becker. "The Construct of Resilience: A Critical Evaluation and Guidelines for Future Work". In: *Child development* 71.3 (2000), pp. 543–562. ISSN: 0009-3920. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1885202/ (visited on 06/22/2022).

[18] Lynette Molyneaux, Colin Brown, Liam Wagner, et al. "Measuring resilience in energy systems: Insights from a range of disciplines". In: *Renewable and Sustainable Energy Reviews* 59 (June 1, 2016), pp. 1068–1079. ISSN: 1364-0321. DOI: 10.1016/j.rser.2016.01.063. URL: http://www.sciencedirect.com/science/article/pii/S1364032116000939 (visited on 05/01/2020).

[19] Yi Qiang, Qingxu Huang, and Jinwen Xu. "Observing community resilience from space: Using nighttime lights to model economic disturbance and recovery pattern in natural disaster". In: *Sustainable Cities and Society* 57 (June 1, 2020), p. 102115. ISSN: 2210-6707. DOI: 10.1016/j.scs.2020.102115. URL: http://www.sciencedirect.com/science/article/pii/S2210670720301025 (visited on 05/01/2020).

[20] Judith Johnson, Maria Panagioti, Jennifer Bass, et al. "Resilience to emotional distress in response to failure, error or mistakes: A systematic review". In: *Clinical Psychology Review* 52 (Mar. 1, 2017), pp. 19–42. ISSN: 0272-7358. DOI: 10.1016/j.cpr.2016.11.007. URL: http://www.sciencedirect.com/science/article/pii/S0272735816302902 (visited on 05/01/2020).

[21] Derek Freckleton, Kevin Heaslip, William Louisell, et al. "Evaluation of Resiliency of Transportation Networks after Disasters:" in: *Transportation Research Record* (Jan. 1, 2012). Publisher: SAGE PublicationsSage CA: Los Angeles, CA. DOI: 10.3141/2284-13. URL: https://journals.sagepub.com/doi/10.3141/2284-13 (visited on 05/22/2020).

[22] Gabriela Quitana, María Molinos-Senante, and Alondra Chamorro. "Resilience of critical infrastructure to natural hazards: A review focused on drinking water systems". In: *International Journal of Disaster Risk Reduction* 48 (Sept. 1, 2020), p. 101575. ISSN: 2212-4209. DOI: 10.1016/j.ijdrr.2020.101575. URL: http://www.sciencedirect.com/science/article/pii/S2212420919313342 (visited on 05/01/2020).

[23] Mikhail Buinevich and Andrei Vladyko. "Forecasting Issues of Wireless Communication Networks' Cyber Resilience for An Intelligent Transportation System: An Overview of Cyber Attacks". In: *Information* 10.1 (Jan. 2019). Number: 1 Publisher: Multidisciplinary Digital Publishing Institute, p. 27. DOI: 10.3390/info10010027. URL: https://www.mdpi.com/2078-2489/10/1/27 (visited on 02/12/2021).

[24] David D. Woods. "Four concepts for resilience and the implications for the future of resilience engineering". In: *Reliability Engineering & System Safety*. Special Issue on Resilience Engineering 141 (Sept. 1, 2015), pp. 5–9. ISSN: 0951-8320. DOI: 10.1016/j.ress.2015.03.018. URL: http://www.sciencedirect.com/science/article/pii/S0951832015000848 (visited on 09/03/2020).

[25] Caleb P. Roberts, Dirac Twidwell, David G. Angeler, et al. "How do ecological resilience metrics relate to community stability and collapse?" In: *Ecological Indicators* 107 (Dec. 1, 2019), p. 105552. ISSN: 1470-160X. DOI: 10.1016/j.ecolind.2019.105552. URL: http://www.sciencedirect.com/science/article/pii/S1470160X19305436 (visited on 10/24/2020).

[26] Mathaios Panteli and Pierluigi Mancarella. "Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies". In: *Electric Power Systems Research* 127 (Oct. 1, 2015), pp. 259–270. ISSN: 0378-7796. DOI: 10.1016/j.epsr.2015.06.012. URL: http://www.sciencedirect.com/science/article/pii/S037877961500187X (visited on 09/03/2020).

[27] M. Panteli and P. Mancarella. "Modeling and Evaluating the Resilience of Critical Electrical Power Infrastructure to Extreme Weather Events". In: *IEEE Systems Journal* 11.3 (Sept. 2017). Conference Name: IEEE Systems Journal, pp. 1733–1742. ISSN: 1937-9234. DOI: 10.1109/JSYST.2015.2389272.

[28] Department of Energy. *Valuation of Energy Security for the United States, Report to Congress*. Article. Conference Name: United States. Department of Energy Publisher: United States. Department of Energy. Jan. 1, 2017. URL: https://www.hsdl.org/?abstract&did= (visited on 12/15/2020).

[29] *A comparative overview of resilience measurement frameworks: analysing indicators and approaches*. ODI. URL: https://www.odi.org/publications/9632-comparative-overview-resilience-measurement-frameworks-analysing-indicators-and-approaches (visited on 12/15/2020).

[30] Kathryn M. Connor and Jonathan R. T. Davidson. "Development of a new resilience scale: The Connor-Davidson Resilience Scale (CD-RISC)". In: *Depression and Anxiety* 18.2 (2003). _eprint: https://onlinelibrary.wiley.com/doi/pc pp. 76–82. ISSN: 1520-6394. DOI: 10.1002/da.10113. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/da.10113 (visited on 08/12/2020).

[31] M. Panteli, C. Pickering, S. Wilkinson, et al. "Power System Resilience to Extreme Weather: Fragility Modeling, Probabilistic Impact Assessment, and Adaptation Measures". In: *IEEE Transactions on Power Systems* 32.5 (Sept. 2017). Conference Name: IEEE Transactions on Power Systems, pp. 3747–3757. ISSN: 1558-0679. DOI: 10.1109/TPWRS.2016.2641463.

[32] E. Vugrin, A. Castillo, and C. Silva-Monroy. *Resilience Metrics for the Electric Power System: A Performance-Based Approach (Technical Report No*. Issues SAND2017-1493, 2017. 49 pp. URL: http://prod.sandia.gov/techlib/access-control.cgi/2017/171493.pdf.

[33] Kate Anderson, Nicholas Laws, Spencer Marr, et al. "Quantifying and Monetizing Renewable Energy Resiliency". In: *Sustainability* 10.4 (Mar. 23, 2018), p. 933. ISSN: 2071-1050. DOI: 10.3390/su10040933. URL: http://www.mdpi.com/2071-1050/10/4/933 (visited on 05/01/2020).

[34] Zhaohong Bie, Yanling Lin, Gengfeng Li, et al. "Battling the Extreme: A Study on the Power System Resilience". In: *Proceedings of the IEEE* 105.7 (July 2017). Conference Name: Proceedings of the IEEE, pp. 1253–1266. ISSN: 1558-2256. DOI: 10.1109/JPROC.2017.2679040.

[35] C. Wang, P. Ju, S. Lei, et al. "Markov Decision Process-Based Resilience Enhancement for Distribution Systems: An Approximate Dynamic Programming Approach". In: *IEEE Transactions on Smart Grid* 11.3 (May 2020). Conference Name: IEEE Transactions on Smart Grid, pp. 2498–2510. ISSN: 1949-3061. DOI: 10.1109/TSG.2019.2956740.

[36] Xiaoyang Bai, Liang Liang, and Xueqin Zhu. "Improved Markov-chain-based ultra-short-term PV forecasting method for enhancing power system resilience". In: *The Journal of Engineering* n/a (n/a). _eprint: https://ietresearch.onlinelibra ISSN: 2051-3305. DOI: https://doi.org/10.1049/tje2.12015. URL: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/tje2.12015 (visited on 03/19/2021).

[37] Federal Energy Regulatory Commission. *Report on the FERC-NERC-Regional Entity Joint Review of Restoration and Recovery Plans, Recommended Study: Blackstart Resources Availability*. 2018.

[38] Engineering National Academies of Sciences. *Enhancing the Resilience of the Nation's Electricity System*. July 20, 2017. ISBN: 978-0-309-46307-2. DOI: 10.17226/24836. URL: https://www.nap.edu/catalog/24836/enhancing-the-resilience-of-the-nations-electricity-system (visited on 12/15/2020).

[39] *January 2014 Polar Vortex Review*. URL: https://www.nerc.com/pa/rrm/Pages/January-2014-Polar-Vortex-Review.aspx (visited on 12/15/2020).

[40] L. Lawton, M. Sullivan, Van Liere, et al. *A framework and review of customer outage costs: Integration and analysis of electric utility outage cost surveys (LBNL-54365)*. Lawrence Berkeley National Lab, 2003.

[41] W. Rickerson, J. Gillis, and M. Bulkeley. *The Value of Resilience for Distributed Energy Resources: An Overview of Current Analytical Practices*. Microgrid Knowledge, 2019.

[42] M. Sullivan, J. Schellenberg, and M. Blundell. *Updated Value of Service Reliability Estimates for Electric Utility Customers in the United States*. 2015.

[43] Thomas Schröder and Wilhelm Kuckshinrichs. "Value of Lost Load: An Efficient Economic Indicator for Power Supply Security? A Literature Review". In: *Frontiers in Energy Research* 3 (2015). Publisher: Frontiers. ISSN: 2296-598X. DOI: 10.3389/fenrg.2015.00055. URL: https://www.frontiersin.org/articles/10.3389/fenrg.2015.00055/full (visited on 05/29/2020).

[44] Eimear Leahy and Richard S. J. Tol. "An estimate of the value of lost load for Ireland". In: *Energy Policy* 39.3 (Mar. 1, 2011), pp. 1514–1520. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2010.12.025. URL: http://www.sciencedirect.com/science/article/pii/S0301421510009250 (visited on 05/01/2020).

[45] Abhishek Shivakumar, Manuel Welsch, Constantinos Taliotis, et al. "Valuing blackouts and lost leisure: Estimating electricity interruption costs for households across the European Union". In: *Energy Research & Social Science* 34 (Dec. 1, 2017), pp. 39–48. ISSN: 2214-6296. DOI: 10.1016/j.erss.2017.05.010. URL: http://www.sciencedirect.com/science/article/pii/S2214629617301184 (visited on 05/01/2020).

[46] Aaron J. Praktiknjo. "Stated preferences based estimation of power interruption costs in private households: An example from Germany". In: *Energy* 76 (Nov. 1, 2014), pp. 82–90. ISSN: 0360-5442. DOI: 10.1016/j.energy.2014.03.089. URL: http://www.sciencedirect.com/science/article/pii/S0360544214003533 (visited on 05/01/2020).

[47] Sinan Küfeoğlu and Matti Lehtonen. "Interruption costs of service sector electricity customers, a hybrid approach". In: *International Journal of Electrical Power & Energy Systems* 64 (Jan. 1, 2015), pp. 588–595. ISSN: 0142-0615. DOI: 10.1016/j.ijepes.2014.07.046. URL: https://www.sciencedirect.com/science/article/pii/S0142061514004815 (visited on 03/29/2021).

[48] Rozhin Eskandarpour, Amin Khodaei, A. Paaso, et al. "Artificial Intelligence Assisted Power Grid Hardening in Response to Extreme Weather Events". In: *arXiv:1810.02866 [cs, eess]* (Oct. 5, 2018). arXiv: 1810.02866. URL: http://arxiv.org/abs/1810.02866 (visited on 06/17/2021).

[49] S. Ericson and L. Lisell. "A flexible framework for modeling customer damage functions for power outages." In: *NREL* 11.1 (2018).

[50] Sergio B. Sepúlveda-Mora and Steven Hegedus. "Resilience analysis of renewable microgrids for commercial buildings with different usage patterns and weather conditions". In: *Renewable Energy* 192 (June 1, 2022), pp. 731–744. ISSN: 0960-1481. DOI: 10.1016/j.renene.2022.04.090. URL: https://www.sciencedirect.com/science/article/pii/S0960148122005584 (visited on 05/24/2022).

[51] G. Fu, S. Wilkinson, R. J. Dawson, et al. "Integrated Approach to Assess the Resilience of Future Electricity Infrastructure Networks to Climate Hazards". In: *IEEE Systems Journal* 12.4 (Dec. 2018). Conference Name: IEEE Systems Journal, pp. 3169–3180. ISSN: 1937-9234. DOI: 10.1109/JSYST.2017.2700791.

[52] J. Arteaga and H. Zareipour. "A Price-Maker/Price-Taker Model for the Operation of Battery Storage Systems in Electricity Markets". In: *IEEE Transactions on Smart Grid* 10.6 (Nov. 2019). Conference Name: IEEE Transactions on Smart Grid, pp. 6912–6920. ISSN: 1949-3061. DOI: 10.1109/TSG.2019.2913818.

[53] R. Billinton and K. E. Bollinger. "Transmission System Reliability Evaluation Using Markov Processes". In: *IEEE Transactions on Power Apparatus and Systems* PAS-87.2 (Feb. 1968). Conference Name: IEEE Transactions on Power Apparatus and Systems, pp. 538–547. ISSN: 0018-9510. DOI: 10.1109/TPAS.1968.292051.

[54] P. Wang and R. Billinton. "Reliability Cost/Worth Assessment of Distribution Systems Incorporating Time Varying Weather Conditions and Restoration Resources". In: *IEEE Power Engineering Review* 21.11 (Nov. 2001). Conference Name: IEEE Power Engineering Review, pp. 63–63. ISSN: 1558-1705. DOI: 10.1109/MPER.2001.4311187.

[55] Stephanie E. Chang and Masanobu Shinozuka. "Measuring Improvements in the Disaster Resilience of Communities". In: *Earthquake Spectra* 20.3 (Aug. 1, 2004). Publisher: SAGE Publications Ltd STM, pp. 739–755. ISSN: 8755-2930. DOI: 10.1193/1.1775796. URL: https://doi.org/10.1193/1.1775796 (visited on 04/02/2021).

[56] Min Ouyang, Leonardo Dueñas-Osorio, and Xing Min. "A three-stage resilience analysis framework for urban infrastructure systems". In: *Structural Safety* 36-37 (May 1, 2012), pp. 23–31. ISSN: 0167-4730. DOI: 10.1016/j.strusafe.2011.12.004. URL: https://www.sciencedirect.com/science/article/pii/S0167473011000956 (visited on 04/02/2021).

[57] Francesco Cadini, Gian Luca Agliardi, and Enrico Zio. "A modeling and simulation framework for the reliability/availability assessment of a power transmission grid subject to cascading failures under extreme weather conditions". In: *Applied Energy* 185 (Jan. 1, 2017), pp. 267–279. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2016.10.086. URL: https://www.sciencedirect.com/science/article/pii/S030626191631529X (visited on 04/02/2021).

[58] G. Li, P. Zhang, P. B. Luh, et al. "Risk Analysis for Distribution Systems in the Northeast U.S. Under Wind Storms". In: *IEEE Transactions on Power Systems* 29.2 (Mar. 2014). Conference Name: IEEE Transactions on Power Systems, pp. 889–898. ISSN: 1558-0679. DOI: 10.1109/TPWRS.2013.2286171.

[59] Roberto Rocchetta, Enrico Zio, and Edoardo Patelli. "A power-flow emulator approach for resilience assessment of repairable power grids subject to weather-induced failures and data deficiency". In: *Applied Energy* 210 (Jan. 15, 2018), pp. 339–350. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2017.10.126. URL: https://www.sciencedirect.com/science/article/pii/S0306261917315738 (visited on 04/02/2021).

[60] Hans-Kristian Ringkjøb, Peter M. Haugan, and Ida Marie Solbrekke. "A review of modelling tools for energy and electricity systems with large shares of variable renewables". In: *Renewable and Sustainable Energy Reviews* 96 (Nov. 1, 2018), pp. 440–459. ISSN: 1364-0321. DOI: 10.1016/j.rser.2018.08.002. URL: http://www.sciencedirect.com/science/article/pii/S1364032118305690 (visited on 05/28/2020).

[61] Emma Elgqvist. "REopt Lite Web Tool: Capabilities and Features". In: (), p. 30.

[62] Nicholas D. Laws, Kate Anderson, Nicholas A. DiOrio, et al. "Impacts of valuing resilience on cost-optimal PV and storage systems for commercial buildings". In: *Renewable Energy* 127 (Nov. 1, 2018), pp. 896–909. ISSN: 0960-1481. DOI: 10.1016/j.renene.2018.05.011. URL: https://www.sciencedirect.com/science/article/pii/S0960148118305305 (visited on 07/30/2021).

[63] Alexis Lagrange, Miguel de Simón-Martín, Alberto González-Martínez, et al. "Sustainable microgrids with energy storage as a means to increase power resilience in critical facilities: An application to a hospital". In: *International Journal of Electrical Power & Energy Systems* 119 (July 1, 2020), p. 105865. ISSN: 0142-0615. DOI: 10.1016/j.ijepes.2020.105865. URL: https://www.sciencedirect.com/science/article/pii/S0142061519330595 (visited on 05/24/2022).

[64] Katherine H. Anderson, Nicholas A. DiOrio, Dylan S. Cutler, et al. "Increasing Resiliency Through Renewable Energy Microgrids". In: *International Journal of Energy Sector Management* 2.2 (Aug. 1, 2017). Institution: National Renewable Energy Lab. (NREL), Golden, CO (United States) Number: NREL/JA-7A40-69034 Publisher: Emerald Publishing Ltd. ISSN: 1750-6220. URL: https://www.osti.gov/pages/biblio/1389210-increasing-resiliency-through-renewable-energy-microgrids (visited on 05/24/2022).

[65] Travis Simpkins, Kate Anderson, Dylan Cutler, et al. "Optimal sizing of a solar-plus-storage system for utility bill savings and resiliency benefits". In: *2016 IEEE Power Energy Society Innovative Smart Grid Technologies Conference (ISGT)*. 2016 IEEE Power Energy Society Innovative Smart Grid Technologies Conference (ISGT). ISSN: 2472-8152. Sept. 2016, pp. 1–6. DOI: 10.1109/ISGT.2016.7781237.

[66] Enrique Rosales-Asensio, Miguel de Simón-Martín, David Borge-Diez, et al. "Microgrids with energy storage systems as a means to increase power resilience: An application to office buildings". In: *Energy* 172 (Apr. 1, 2019), pp. 1005–1015. ISSN: 0360-5442. DOI: 10.1016/j.energy.2019.02.043. URL: https://www.sciencedirect.com/science/article/pii/S0360544219302324 (visited on 05/24/2022).

[67] Michael Stadler, Gonçalo Cardoso, Salman Mashayekh, et al. "Value streams in microgrids: A literature review". In: *Applied Energy* 162 (Jan. 15, 2016), pp. 980–989. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2015.10.081. URL: http://www.sciencedirect.com/science/article/pii/S0306261915013082 (visited on 05/29/2020).

[68] Amanda J. Harker Steele, J. Wesley Burnett, and John C. Bergstrom. "The impact of variable renewable energy resources on power system reliability". In: *Energy Policy* 151 (Apr. 1, 2021), p. 111947. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2020.111947. URL: https://www.sciencedirect.com/science/article/pii/S0301421520306583 (visited on 09/07/2021).

[69] *Power Outages in NOLA: The Problem, Implications, Solutions, and Moving Forward*. Alliance for Affordable Energy. URL: http://www.all4energy.org/2/post/2019/06/power-outages-in-nola-the-problem-implications-solutions-and-moving-forward.html (visited on 09/07/2021).

[70] Michael Sullivan, Matthew Mercurio, and Josh Schellenberg. *Estimated Value of Service Reliability for Electric Utility Customers in the United States*. Pages: 130. 2009.

[71] *U.S. Bureau of Economic Analysis (BEA)*. URL: https://www.bea.gov/ (visited on 10/01/2021).

[72] Melissa (ORCID:0000000233190846) Dumas, Binita (ORCID:0000000161265369) Kc, and Colin I. Cunliff. *Extreme Weather and Climate Vulnerabilities of the Electric Grid: A Summary of Environmental Sensitivity Quantification Methods*. ORNL/TM-2019/1252. Oak Ridge National Lab. (ORNL), Oak Ridge, TN (United States), Aug. 1, 2019. DOI: 10.2172/1558514. URL: https://www.osti.gov/biblio/1558514 (visited on 06/18/2021).

[73] Xiufeng Yue, Steve Pye, Joseph DeCarolis, et al. "A review of approaches to uncertainty assessment in energy system optimization models". In: *Energy Strategy Reviews* 21 (Aug. 1, 2018), pp. 204–217. ISSN: 2211-467X. DOI: 10.1016/j.esr.2018.06.003. URL: http://www.sciencedirect.com/science/article/pii/S2211467X18300543 (visited on 05/01/2020).

[74] Qianzhi Zhang, Zhaoyu Wang, Shanshan Ma, et al. "Stochastic pre-event preparation for enhancing resilience of distribution systems". In: *Renewable and Sustainable Energy Reviews* 152 (Dec. 1, 2021), p. 111636. ISSN: 1364-0321. DOI: 10.1016/j.rser.2021.111636. URL: https://www.sciencedirect.com/science/article/pii/S1364032121009114 (visited on 10/04/2021).

[75] Sebastián Espinoza, Mathaios Panteli, Pierluigi Mancarella, et al. "Multi-phase assessment and adaptation of power systems resilience to natural hazards". In: *Electric Power Systems Research* 136 (July 1, 2016), pp. 352–361. ISSN: 0378-7796. DOI: 10.1016/j.epsr.2016.03.019. URL: http://www.sciencedirect.com/science/article/pii/S0378779616300669 (visited on 05/01/2020).

[76] Somayeh Ahmadi, Amir Hossein Fakehi Khorasani, Ali Vakili, et al. "Developing an innovating optimization framework for enhancing the long-term energy system resilience against climate change disruptive events". In: *Energy Strategy Reviews* 40 (Mar. 1, 2022), p. 100820. ISSN: 2211-467X. DOI: 10.1016/j.esr.2022.100820. URL: https://www.sciencedirect.com/science/article/pii/S2211467X22000207 (visited on 06/30/2022).

[77] Zhiguo Zeng, Yi-Ping Fang, Qingqing Zhai, et al. "A Markov reward process-based framework for resilience analysis of multistate energy systems under the threat of extreme events". In: *Reliability Engineering & System Safety* 209 (May 1, 2021), p. 107443. ISSN: 0951-8320. DOI: 10.1016/j.ress.2021.107443. URL: https://www.sciencedirect.com/science/article/pii/S0951832021000041 (visited on 04/02/2021).

[78] B. Cai, M. Xie, Y. Liu, et al. "Availability-based engineering resilience metric and its corresponding evaluation methodology". In: *Reliability Engineering & System Safety* 172 (2017).

[79] Susan L. Cutter, Christopher G. Burton, and Christopher T. Emrich. "Disaster Resilience Indicators for Benchmarking Baseline Conditions". In: *Journal of Homeland Security and Emergency Management* 7.1 (Aug. 4, 2010). Publisher: De Gruyter Section: Journal of Homeland Security and Emergency Management. ISSN: 10.2202/1547-7355.1732. DOI: 10.2202/1547-7355.1732. URL: https://www.degruyter.com/view/journals/jhsem/7/1/article-jhsem.2010.7.1.1732.xml.xml (visited on 05/01/2020).

[80] Y. -P. Fang, N. Pedroni, and E. Zio. "Resilience-Based Component Importance Measures for Critical Infrastructure Network Systems". In: *IEEE Transactions on Reliability* 65.2 (2016).

[81] D. Henry, Emmanuel Ramirez-Marquez, and J. "Generic metrics and quantitative approaches for system resilience as a function of time". In: *Reliability Engineering & System Safety* 99 (2011).

[82] A. R. de Queiroz, D. Mulcahy, A. Sankarasubramanian, et al. "Repurposing an energy system optimization model for seasonal power generation planning". In: *Energy* 181 (Aug. 15, 2019), pp. 1321–1330. ISSN: 0360-5442. DOI: 10.1016/j.energy.2019.05.126. URL: https://www.sciencedirect.com/science/article/pii/S0360544219310084 (visited on 04/15/2021).

[83] Angelo Alessandri and Roberto Filippini. "Evaluation of Resilience of Interconnected Systems Based on Stability Analysis". In: *Critical Information Infrastructures Security*. Ed. by Bernhard M. Hämmerli, Nils Kalstad Svendsen, and Javier Lopez. Lecture Notes in Computer Science. Berlin, Heidelberg: Springer, 2013, pp. 180–190. ISBN: 978-3-642-41485-5. DOI: 10.1007/978-3-642-41485-5_16.

[84] Richard J Campbell. "Weather-Related Power Outages and Electric System Resiliency". In: (), p. 18.

[85] Sunhee Baik, Alex Davis, Jun Park, et al. "Estimating what US residential customers are willing to pay for resilience to large electricity outages of long duration". In: *Nature Energy* 5 (Mar. 1, 2020), pp. 250–258. DOI: 10.1038/s41560-020-0581-1.

[86] Eklas Hossain, Shidhartho Roy, Naeem Mohammad, et al. "Metrics and enhancement strategies for grid resilience and reliability during natural disasters". In: *Applied Energy* 290 (May 15, 2021), p. 116709. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2021.116709. URL: https://www.sciencedirect.com/science/article/pii/S0306261921002294 (visited on 07/13/2022).

[87] P. H. Larsen, A. H. Sanstad, K. H. LaCommare, et al. *Frontiers in the Economics of Widespread*. Long-Duration Power Interruptions: Proceedings from an Expert Workshop, 2019.

[88] *NC DEQ: NC Climate Risk Assessment and Resilience Plan*. URL: https://deq.nc.gov/energy-climate/climate-change/nc-climate-change-interagency-council/climate-change-clean-energy-17 (visited on 01/19/2021).

[89] *How long will my power be out? Here's what you need to know about Texas' outages*. Dallas News. Section: Weather. Feb. 16, 2021. URL: https://www.dallasnews.com/news/weather/2021/02/15/how-long-will-my-power-be-out-heres-what-you-need-to-know-about-texas-rotating-outages/ (visited on 07/13/2022).

[90] *State of Oregon: Oregon Resiliency Report -*. URL: https://www.oregon.gov/gov/policy/orr/pages/index.aspx (visited on 02/12/2021).

[91] *Hurricane Michael caused 1.7 million electricity outages in the Southeast United States*. URL: https://www.eia.gov/todayinenergy/detail.php?id=37332 (visited on 07/13/2022).

[92] *Cost of Texas' 2021 Deep Freeze Justifies Weatherization*. URL: https://www.dallasfed.org:443/research/economics/2021/0415 (visited on 06/07/2021).

[93] *Texas Blackouts Hit Minority Neighborhoods Especially Hard - The New York Times*. URL: https://www.nytimes.com/2021/02/16/climate/texas-blackout-storm-minorities.html (visited on 06/07/2021).

[94] Alexandra Villarreal. "Winter storm amplifies power grid inequalities for disadvantaged Texans". In: *The Guardian* (Feb. 17, 2021). ISSN: 0261-3077. URL: https://www.theguardian.com/us-news/2021/feb/17/texas-winter-storm-power-outages (visited on 07/14/2022).

[95] Sunhee Baik, Alexander L. Davis, and M. Granger Morgan. "Assessing the Cost of Large-Scale Power Outages to Residential Customers". In: *Risk Analysis* 38.2 (2018). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/risa.12842, pp. 283–296. ISSN: 1539-6924. DOI: 10.1111/risa.12842. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/risa.12842 (visited on 07/14/2022).

[96] David F. Layton and Klaus Moeltner. "The Cost of Power Outages to Heterogeneous Households". In: *Applications of Simulation Methods in Environmental and Resource Economics*. Ed. by Riccardo Scarpa and Anna Alberini. The Economics of Non-Market Goods and Resources. Dordrecht: Springer Netherlands, 2005, pp. 35–54. ISBN: 978-1-4020-3684-2. DOI: 10.1007/1-4020-3684-1_3. URL: https://doi.org/10.1007/1-4020-3684-1_3 (visited on 07/14/2022).

[97] A.A. Chowdhury, T.C. Mielnik, L.E. Lawion, et al. "Reliability worth assessment in electric power delivery systems". In: *IEEE Power Engineering Society General Meeting, 2004*. IEEE Power Engineering Society General Meeting, 2004. June 2004, 654–660 Vol.1. DOI: 10.1109/PES.2004.1372892.

[98] S. A. Yin, R. F. Chang, and C. N. Lu. "Reliability Worth Assessment of High-Tech Industry". In: *IEEE Power Engineering Review* 22.11 (Nov. 2002). Conference Name: IEEE Power Engineering Review, pp. 56–56. ISSN: 1558-1705. DOI: 10.1109/MPER.2002.4311818.

[99] M.J. Sullivan, B. Noland Suddeth, T. Vardell, et al. "Interruption costs, customer satisfaction and expectations for service reliability". In: *IEEE Transactions on Power Systems* 11.2 (May 1996). Conference Name: IEEE Transactions on Power Systems, pp. 989–995. ISSN: 1558-0679. DOI: 10.1109/59.496185.

[100] S. Burns and G. Gross. "Value of service reliability". In: *IEEE Transactions on Power Systems* 5.3 (Aug. 1990). Conference Name: IEEE Transactions on Power Systems, pp. 825–834. ISSN: 1558-0679. DOI: 10.1109/59.65911.

[101] Raymond S. Hartman, Michael J. Doane, and Chi-Keung Woo. "Consumer Rationality and the Status Quo". In: *The Quarterly Journal of Economics* 106.1 (1991). Publisher: Oxford University Press, pp. 141–162. ISSN: 0033-5533. DOI: 10.2307/2937910. URL: https://www.jstor.org/stable/2937910 (visited on 07/14/2022).

[102] Fredrik Carlsson and Peter Martinsson. "Does it matter when a power outage occurs? — A choice experiment study on the willingness to pay to avoid power outages". In: *Energy Economics* 30.3 (May 1, 2008), pp. 1232–1245. ISSN: 0140-9883. DOI: 10.1016/j.eneco.2007.04.001. URL: https://www.sciencedirect.com/science/article/pii/S0140988307000618 (visited on 07/14/2022).

[103] Guido Pepermans. "The value of continuous power supply for Flemish households". In: *Energy Policy*. Clean Cooking Fuels and Technologies in Developing Economies 39.12 (Dec. 1, 2011), pp. 7853–7864. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2011.09.032. URL: https://www.sciencedirect.com/science/article/pii/S030142151100721X (visited on 07/14/2022).

[104] Markus Bliem. "Economic Valuation of Electrical Service Reliability in Austria - A Choice Experiment Approach". In: *IHSK WORKING PAPER* (Apr. 1, 2009).

[105] Karyn Morrissey, Andrew Plater, and Mary Dean. "The cost of electric power outages in the residential sector: A willingness to pay approach". In: *Applied Energy* 212 (Feb. 15, 2018), pp. 141–150. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2017.12.007. URL: https://www.sciencedirect.com/science/article/pii/S0306261917317208 (visited on 07/14/2022).

[106] Sabah Abdullah and Petr Mariel. "Choice experiment study on the willingness to pay to improve electricity services". In: *Energy Policy* 38.8 (Aug. 1, 2010), pp. 4570–4581. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2010.04.012. URL: https://www.sciencedirect.com/science/article/pii/S0301421510002855 (visited on 07/14/2022).

[107] Tarik Hubana and Nerman Ljevo. "Willingness to Pay for Reliable Electricity: A Contingent Valuation Study in Bosnia and Herzegovina". In: *Advanced Technologies, Systems, and Applications IV -Proceedings of the International Symposium on Innovative and Interdisciplinary Applications of Advanced Technologies (IAT 2019)*. International Symposium on Innovative and Interdisciplinary Applications of Advanced Technologies. Springer, Cham, 2020, pp. 107–116. DOI: 10.1007/978-3-030-24986-1_8. URL: https://link.springer.com/chapter/10.1007/978-3-030-24986-1_8 (visited on 07/14/2022).

[108] David Hensher, Nina Shore, and Kenneth Train. "Willingness to pay for residential electricity supply quality and reliability". In: *Applied Energy* 115 (Feb. 1, 2014), pp. 280–292. DOI: 10.1016/j.apenergy.2013.11.007.

[109] Asher A. Blass, Saul Lach, and Charles F. Manski. "Using Elicited Choice Probabilities to Estimate Random Utility Models: Preferences for Electricity Reliability*". In: *International Economic Review* 51.2 (2010). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-2354.2010.00586.x, pp. 421–440. ISSN: 1468-2354. DOI: 10.1111/j.1468-2354.2010.00586.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-2354.2010.00586.x (visited on 07/14/2022).

[110] Francisco Javier Amador, Rosa Marina González, and Francisco Javier Ramos-Real. "Supplier choice and WTP for electricity attributes in an emerging market: The role of perceived past experience, environmental concern and energy saving behavior". In: *Energy Economics* 40 (Nov. 1, 2013), pp. 953–966. ISSN: 0140-9883. DOI: 10.1016/j.eneco.2013.06.007. URL: https://www.sciencedirect.com/science/article/pii/S0140988313001205 (visited on 07/14/2022).

[111] *Electric Power System Resiliency: Challenges and Opportunities*. URL: https://www.epri.com/research/products/000000003002007376 (visited on 07/14/2022).

[112] Patricia A. Champ, Kevin J. Boyle, and Thomas C. Brown, eds. *A Primer on Nonmarket Valuation*. 2nd ed. 2017 edition. Dordrecht: Springer, Feb. 17, 2017. 513 pp. ISBN: 978-94-007-7103-1.

[113] Sinan Küfeoğlu and Matti Lehtonen. "A review on the theory of electric power reliability worth and customer interruption costs assessment techniques". In: *2016 13th International Conference on the European Energy Market (EEM)*. 2016 13th International Conference on the European Energy Market (EEM). ISSN: 2165-4093. June 2016, pp. 1–6. DOI: 10.1109/EEM.2016.7521239.

[114] Chelsea Hotaling, Stephen Bird, and Martin D. Heintzelman. "Willingness to pay for microgrids to enhance community resilience". In: *Energy Policy* 154 (July 1, 2021), p. 112248. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2021.112248. URL: https://www.sciencedirect.com/science/article/pii/S0301421521001178 (visited on 07/14/2022).

[115] A. Sanstad. *Regional Economic Modeling of Electricity Supply Disruptions: A Review and Recommendations for Research*. 2016.

[116] *Measuring the Value of Electric System Resiliency: A Review of Outage Cost Surveys and Natural Disaster Impact Study Methods*. URL: https://www.epri.com/research/products/000000003002009670 (visited on 07/14/2022).

[117] A. Rose, J. Benavides, S. E. Chang, et al. "The Regional Economic Impact of an Earthquake: Direct and Indirect Effects of Electricity Lifeline Disruptions". In: *Journal of Regional Science* 37.3 (1997).

[118] Adam Rose and Dongsoon Lim. "Business interruption losses from natural hazards: conceptual and methodological issues in the case of the Northridge earthquake". In: *Global Environmental Change Part B: Environmental Hazards* 4.1 (Mar. 1, 2002), pp. 1–14. ISSN: 1464-2867. DOI: 10.1016/S1464-2867(02)00012-8. URL: https://www.sciencedirect.com/science/article/pii/S1464286702000128 (visited on 07/14/2022).

[119] *New York City, ConEd Storm Hardening and Resiliency Collaborative | Adaptation Clearinghouse*. URL: https://www.adaptationclearinghouse.org/resources/new-york-city-coned-storm-hardening-and-resiliency-collaborative.html (visited on 07/14/2022).

[120] Peijun He, Tsan Sheng Ng, and Bin Su. "Energy-economic recovery resilience with Input-Output linear programming models". In: *Energy Economics* 68 (Oct. 1, 2017), pp. 177–191. ISSN: 0140-9883. DOI: 10.1016/j.eneco.2017.10.005. URL: https://www.sciencedirect.com/science/article/pii/S0140988317303432 (visited on 07/14/2022).

[121] Vanessa N. Vargas and Mark A. Ehlen. "REAcct: a scenario analysis tool for rapidly estimating economic impacts of major natural and man-made hazards". In: (2013). ISSN: 2194-5403. URL: https://pubag.nal.usda.gov/catalog/73433 (visited on 07/14/2022).

[122] Mark Andrew Ehlen, Vanessa N. Vargas, Verne William Loose, et al. *Regional Economic Accounting (REAcct). A software tool for rapidly approximating economic impacts*. SAND2009-6552. Sandia National Lab. (SNL-NM), Albuquerque, NM (United States), July 1, 2011. DOI: 10.2172/1204083. URL: https://www.osti.gov/biblio/1204083 (visited on 07/14/2022).

[123] Vanessa N. Vargas, Bern Caudill Dealy, Braeton James Smith, et al. *The Regional Economic Accounting Tool: Updates and Extensions*. SAND2015-2549C. Sandia National Lab. (SNL-NM), Albuquerque, NM (United States), Apr. 1, 2015. URL: https://www.osti.gov/biblio/1247108-regional-economic-accounting-tool-updates-extensions (visited on 07/14/2022).

[124] P. Romer. *The Trouble with Macroeconomics*. 2016. URL: https://www.semanticscholar.org/paper/The-Trouble-with-Macroeconomics-Romer/6edc098c372a59184851a517bcbd42859f820c82 (visited on 07/14/2022).

[125] Adam Rose, Gbadebo Oladosu, and Shu-Yi Liao. "Business interruption impacts of a terrorist attack on the electric power system of Los Angeles: customer resilience to a total blackout". In: *Risk Analysis: An Official Publication of the Society for Risk Analysis* 27.3 (June 2007), pp. 513–531. ISSN: 0272-4332. DOI: 10.1111/j.1539-6924.2007.00912.x.

[126] Aijun Hu, Wei Xie, Ning Li, et al. "Analyzing regional economic impact and resilience: A case study on electricity outages caused by the 2008 snowstorms in southern China". In: *Natural Hazards* 70 (Jan. 1, 2014). DOI: 10.1007/s11069-013-0858-9.

[127] Ian Sue Wing and Adam Z. Rose. "Economic consequence analysis of electric power infrastructure disruptions: General equilibrium approaches". In: *Energy Economics* 89 (June 1, 2020), p. 104756. ISSN: 0140-9883. DOI: 10.1016/j.eneco.2020.104756. URL: https://www.sciencedirect.com/science/article/pii/S0140988320300955 (visited on 07/14/2022).

[128] Sunhee Baik, Alan H. Sanstad, Nichole Hanus, et al. "A hybrid approach to estimating the economic value of power system resilience". In: *The Electricity Journal* 34.8 (Oct. 1, 2021), p. 107013. ISSN: 1040-6190. DOI: 10.1016/j.tej.2021.107013. URL: https://www.sciencedirect.com/science/article/pii/S1040619021001044 (visited on 07/14/2022).

[129] Michael Greenberg, Nancy Mantell, Michael Lahr, et al. "Short and intermediate economic impacts of a terrorist-initiated loss of electric power: Case study of New Jersey". In: *Energy Policy* 35.1 (Jan. 1, 2007), pp. 722–733. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2006.01.017. URL: https://www.sciencedirect.com/science/article/pii/S0301421506000668 (visited on 07/14/2022).

[130] Steve Liesman. *Sandy's Economic Cost: Up to $50 Billion and Counting*. Section: Economy. Oct. 31, 2012. URL: https://www.cnbc.com/id/49622885 (visited on 07/14/2022).

[131] W. J. Wouter Botzen, Olivier Deschenes, and Mark Sanders. "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies". In: *Review of Environmental Economics and Policy* 13.2 (July 1, 2019). Publisher: The University of Chicago Press, pp. 167–188. ISSN: 1750-6816. DOI: 10.1093/reep/rez004. URL: https://www.journals.uchicago.edu/doi/10.1093/reep/rez004 (visited on 06/20/2021).

[132] Stéphane Hallegatte. "An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina". In: *Risk Analysis: An Official Publication of the Society for Risk Analysis* 28.3 (June 2008), pp. 779–799. ISSN: 1539-6924. DOI: 10.1111/j.1539-6924.2008.01046.x.

[133] Gabriel Felbermayr and Jasmin Gröschl. "Naturally negative: The growth effects of natural disasters". In: *Journal of Development Economics*. Special Issue: Imbalances in Economic Development 111 (Nov. 1, 2014), pp. 92–106. ISSN: 0304-3878. DOI: 10.1016/j.jdeveco.2014.07.004. URL: https://www.sciencedirect.com/science/article/pii/S0304387814000820 (visited on 07/14/2022).

[134] Sara Lazzaroni and Peter A. G. van Bergeijk. "Natural disasters' impact, factors of resilience and development: A meta-analysis of the macroeconomic literature". In: *Ecological Economics* 107 (Nov. 1, 2014), pp. 333–346. ISSN: 0921-8009. DOI: 10.1016/j.ecolecon.2014.08.015. URL: https://www.sciencedirect.com/science/article/pii/S0921800914002705 (visited on 07/14/2022).

[135] Roberta Capello. *Regional Economics*. 2nd ed. London: Routledge, Nov. 24, 2015. 378 pp. ISBN: 978-1-315-72007-4. DOI: 10.4324/9781315720074.

[136] Chun Yin Siu and Zaiyi Liao. "Is building energy simulation based on TMY representative: A comparative simulation study on doe reference buildings in Toronto with typical year and historical year type weather files". In: *Energy and Buildings* 211 (Mar. 15, 2020), p. 109760. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2020.109760. URL: https://www.sciencedirect.com/science/article/pii/S0378778819325733 (visited on 07/14/2022).

[137] Hamed Yassaghi, Nariman Mostafavi, and Simi Hoque. "Evaluation of current and future hourly weather data intended for building designs: A Philadelphia case study". In: *Energy and Buildings* 199 (Sept. 15, 2019), pp. 491–511. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2019.07.016. URL: https://www.sciencedirect.com/science/article/pii/S0378778819305584 (visited on 07/14/2022).

[138] Omid Mazdiyasni, Mojtaba Sadegh, Felicia Chiang, et al. "Heat wave Intensity Duration Frequency Curve: A Multivariate Approach for Hazard and Attribution Analysis". In: *Scientific Reports* 9.1 (Oct. 1, 2019). Number: 1 Publisher: Nature Publishing Group, p. 14117. ISSN: 2045-2322. DOI: `10.1038/s41598-019-50643-w`. URL: `https://www.nature.com/articles/s41598-019-50643-w` (visited on 07/13/2022).

[139] Erik Henry Bowles. "Classifying heat waves in the United States". In: (2009). Accepted: 2009-04-15T13:57:22Z Publisher: Kansas State University. URL: `https://krex.k-state.edu/dspace/handle/2097/1324` (visited on 07/14/2022).

[140] Xin Li, Guoyu Ren, Suyan Wang, et al. "Change in the heatwave statistical characteristics over China during the climate warming slowdown". In: *Atmospheric Research* 247 (Jan. 1, 2021), p. 105152. ISSN: 0169-8095. DOI: `10.1016/j.atmosres.2020.105152`. URL: `https://www.sciencedirect.com/science/article/pii/S0169809520310887` (visited on 07/13/2022).

[141] Paul Mathew, Lino Sanchez, Sang Hoon Lee, et al. "Assessing the Energy Resilience of Office Buildings: Development and Testing of a Simplified Metric for Real Estate Stakeholders". In: *Buildings* 11.3 (Mar. 2021). Number: 3 Publisher: Multidisciplinary Digital Publishing Institute, p. 96. ISSN: 2075-5309. DOI: `10.3390/buildings11030096`. URL: `https://www.mdpi.com/2075-5309/11/3/96` (visited on 07/13/2022).

[142] R. Rahif, D. Amaripadath, and S. Attia. "Review on Time-Integrated Overheating Evaluation Methods for Residential Buildings in Temperate Climates of Europe". In: *Energy and Buildings* 252 (Dec. 1, 2021), p. 111463. ISSN: 0378-7788. DOI: `10.1016/j.enbuild.2021.111463`. URL: `https://www.sciencedirect.com/science/article/pii/S0378778821007477` (visited on 07/13/2022).

[143] Kaiyu Sun, Michael Specian, and Tianzhen Hong. "Nexus of thermal resilience and energy efficiency in buildings: A case study of a nursing home". In: *Building and Environment* 177 (June 15, 2020), p. 106842. ISSN: 0360-1323. DOI: `10.1016/j.buildenv.2020.106842`. URL: `https://www.sciencedirect.com/science/article/pii/S0360132320302018` (visited on 07/13/2022).

[144] Daniel L. Villa. "Institutional heat wave analysis by building energy modeling fleet and meter data". In: *Energy and Buildings* 237 (Apr. 15, 2021), p. 110774. ISSN: 0378-7788. DOI: `10.1016/j.enbuild.2021.110774`. URL: `https://www.sciencedirect.com/science/article/pii/S037877882100058X` (visited on 07/13/2022).

[145] Valérie Masson-Delmotte, Panmao Zhai, Anna Pirani, et al., eds. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, 2021.

[146] *Search | Climate Data Online (CDO) | National Climatic Data Center (NCDC)*. URL: `https://www.ncdc.noaa.gov/cdo-web/search?datasetid=GHCND` (visited on 07/13/2022).

[147] Muriel C. Bonjean Stanton and Katy Roelich. "Decision making under deep uncertainties: A review of the applicability of methods in practice". In: *Technological Forecasting and Social Change* 171 (Oct. 1, 2021), p. 120939. ISSN: 0040-1625. DOI: `10.1016/j.techfore.2021.120939`. URL: `https://www.sciencedirect.com/science/article/pii/S0040162521003711` (visited on 07/12/2022).

[148] 1776 Main Street Santa Monica and California 90401-3208. *Robust Decision Making*. URL: `https://www.rand.org/topics/robust-decision-making.html` (visited on 07/01/2022).

[149] Robert Lempert, Steven Popper, and Steven Bankes. "Robust Decision Making: Coping with Uncertainty". In: *Futurist* 44 (Jan. 1, 2010), pp. 47–48.

[150] J. W. G. M. van der Pas, W. E. Walker, V. A. W. J. Marchau, et al. "Operationalizing adaptive policymaking". In: *Futures* 52 (Aug. 1, 2013), pp. 12–26. ISSN: 0016-3287. DOI: `10.1016/j.futures.2013.06.004`. URL: `https://www.sciencedirect.com/science/article/pii/S0016328713000888` (visited on 07/13/2022).

[151] Marjolijn Haasnoot, Jan H. Kwakkel, Warren E. Walker, et al. "Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world". In: *Global Environmental Change* 23.2 (Apr. 1, 2013), pp. 485–498. ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2012.12.006. URL: https://www.sciencedirect.com/science/article/pii/S095937801200146X (visited on 07/13/2022).

[152] Yakov Ben-Haim. *Info-Gap Economics, An Operational Introduction*. Pages: 245. Jan. 1, 2010. 1 p. ISBN: 978-1-349-30991-7. DOI: 10.1057/9780230277328.

[153] Richard de Neufville, Kim Smet, Michel-Alexandre Cardin, et al. "Engineering Options Analysis (EOA): Applications". In: *Decision Making under Deep Uncertainty: From Theory to Practice*. Ed. by Vincent A. W. J. Marchau, Warren E. Walker, Pieter J. T. M. Bloemen, et al. Cham: Springer International Publishing, 2019, pp. 223–252. ISBN: 978-3-030-05252-2. DOI: 10.1007/978-3-030-05252-2_11. URL: https://doi.org/10.1007/978-3-030-05252-2_11 (visited on 07/13/2022).

[154] Nidhi Kalra, Stephane Hallegatte, Robert Lempert, et al. *Agreeing on Robust Decisions : New Processes for Decision Making under Deep Uncertainty*. Accepted: 2014-06-25T21:59:54Z. Washington, DC: World Bank, June 2014. DOI: 10.1596/1813-9450-6906. URL: https://openknowledge.worldbank.org/handle/10986/18772 (visited on 07/08/2022).

[155] Vincent A. W. J. Marchau, Warren E. Walker, Pieter J. T. M. Bloemen, et al., eds. *Decision Making under Deep Uncertainty: From Theory to Practice*. Cham: Springer International Publishing, 2019. ISBN: 978-3-030-05251-5 978-3-030-05252-2. DOI: 10.1007/978-3-030-05252-2. URL: http://link.springer.com/10.1007/978-3-030-05252-2 (visited on 04/21/2022).

[156] Ameen Abu-Hanna, Barry Nannings, Dave Dongelmans, et al. "PRIM versus CART in subgroup discovery: When patience is harmful". In: *Journal of Biomedical Informatics* 43.5 (Oct. 1, 2010), pp. 701–708. ISSN: 1532-0464. DOI: 10.1016/j.jbi.2010.05.009. URL: https://www.sciencedirect.com/science/article/pii/S1532046410000675 (visited on 02/21/2022).

[157] Carl Folke. "Resilience: The emergence of a perspective for social–ecological systems analyses". In: *Global Environmental Change*. Resilience, Vulnerability, and Adaptation: A Cross-Cutting Theme of the International Human Dimensions Programme on Global Environmental Change 16.3 (Aug. 1, 2006), pp. 253–267. ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2006.04.002. URL: http://www.sciencedirect.com/science/article/pii/S0959378006000379 (visited on 09/03/2020).

[158] Leah McMillan Polonenko, Mohamed A. Hamouda, and Mohamed M. Mohamed. "Essential components of institutional and social indicators in assessing the sustainability and resilience of urban water systems: Challenges and opportunities". In: *Science of The Total Environment* 708 (Mar. 15, 2020), p. 135159. ISSN: 0048-9697. DOI: 10.1016/j.scitotenv.2019.135159. URL: http://www.sciencedirect.com/science/article/pii/S0048969719351514 (visited on 10/24/2020).

[159] Sidney Dekker and Erik Hollnagel. "Resilience Engineering: New directions for measuring and maintaining safety in complex systems". In: (May 22, 2020).

[160] Jongseong Ryu, Thomas M. Leschine, Jungho Nam, et al. "A resilience-based approach for comparing expert preferences across two large-scale coastal management programs". In: *Journal of Environmental Management* 92.1 (Jan. 1, 2011), pp. 92–101. ISSN: 0301-4797. DOI: 10.1016/j.jenvman.2010.08.020. URL: http://www.sciencedirect.com/science/article/pii/S0301479710002689 (visited on 08/11/2020).

[161] Yao Hu. "The Modeling, Analysis and Control of Resilient Manufacturing Enterprises". In: *Theses and Dissertations–Electrical and Computer Engineering* (Jan. 1, 2013). URL: https://uknowledge.uky.edu/ece_etds/15.

[162] *Presidential Policy Directive – Critical Infrastructure Security and Resilience*. whitehouse.gov. Library Catalog: obamawhitehouse.archives.gov. Feb. 12, 2013. URL: https://obamawhitehouse.archives.gov/the-press-office/2013/02/12/presidential-policy-directive-critical-infrastructure-security-and-resil (visited on 05/21/2020).

[163] Virendra Proag. "The Concept of Vulnerability and Resilience". In: *Procedia Economics and Finance*. 4th International Conference on Building Resilience, Incorporating the 3rd Annual Conference of the ANDROID Disaster Resilience Network, 8th – 11th September 2014, Salford Quays, United Kingdom 18 (Jan. 1, 2014), pp. 369–376. ISSN: 2212-5671. DOI: 10.1016/S2212-5671(14)00952-6. URL: http://www.sciencedirect.com/science/article/pii/S2212567114009526 (visited on 05/08/2020).

[164] *AR5 Synthesis Report: Climate Change 2014 — IPCC*. Library Catalog: www.ipcc.ch. URL: https://www.ipcc.ch/report/ar5/syr/ (visited on 05/22/2020).

[165] *Conceptual Framework for Developing Resilience Metrics for the Electricity, Oil, and Gas Sectors in the United States (September 2015)*. Energy.gov. URL: https://www.energy.gov/oe/downloads/conceptual-framework-developing-resilience-metrics-electricity-oil-and-gas-sectors (visited on 09/03/2020).

[166] Sara Meerow, Joshua P. Newell, and Melissa Stults. "Defining urban resilience: A review". In: *Landscape and Urban Planning* 147 (Mar. 1, 2016). Publisher: Elsevier, pp. 38–49. ISSN: 0169-2046. DOI: 10.1016/j.landurbplan.2015.11.011. URL: https://asu.pure.elsevier.com/en/publications/defining-urban-resilience-a-review (visited on 09/03/2020).

[167] Michael C. W. Kintner-Meyer, Juliet S. Homer, Patrick J. Balducci, et al. *Valuation of Electric Power System Services and Technologies*. PNNL-25633. Pacific Northwest National Lab. (PNNL), Richland, WA (United States), Aug. 1, 2017. DOI: 10.2172/1393762. URL: https://www.osti.gov/biblio/1393762 (visited on 09/03/2020).

[168] Min Ouyang. "A mathematical framework to optimize resilience of interdependent critical infrastructure systems under spatially localized attacks". In: *European Journal of Operational Research* 262.3 (Nov. 1, 2017), pp. 1072–1084. ISSN: 0377-2217. DOI: 10.1016/j.ejor.2017.04.022. URL: http://www.sciencedirect.com/science/article/pii/S0377221717303557 (visited on 05/22/2020).

[169] Salim Moslehi and T. Agami Reddy. "Sustainability of integrated energy systems: A performance-based resilience assessment methodology". In: *Applied Energy* 228 (Oct. 15, 2018), pp. 487–498. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2018.06.075. URL: http://www.sciencedirect.com/science/article/pii/S0306261918309401 (visited on 01/20/2021).

[170] *Resilience Roadmap*. URL: https://www.nrel.gov/resilience-planning-roadmap/ (visited on 08/11/2020).

[171] Jian Zhou, Stamatis Tsianikas, Dunbar P. Birnie, et al. "Economic and resilience benefit analysis of incorporating battery storage to photovoltaic array generation". In: *Renewable Energy* 135 (May 1, 2019), pp. 652–662. ISSN: 0960-1481. DOI: 10.1016/j.renene.2018.12.013. URL: http://www.sciencedirect.com/science/article/pii/S0960148118314459 (visited on 10/24/2020).

[172] *Grid Modernization: Metrics Analysis (GMLC1.1) Resilience | Grid Modernization Lab Consortium*. URL: https://gmlc.doe.gov/resources/grid-modernization-metrics-analysis-gmlc1.1-resilience (visited on 06/24/2020).

[173] *Solving the Climate Crisis: The Congressional Action Plan for a Clean Energy Economy and a Healthy and Just America*. Select Committee on Climate Crisis. June 29, 2020. URL: https://climatecrisis.house.gov/report (visited on 08/13/2020).

[174] Maedeh Mahzarnia, Mohsen Moghaddam, Payam Teimourzadeh Baboli, et al. "A Review of the Measures to Enhance Power Systems Resilience". In: *IEEE Systems Journal* PP (Jan. 29, 2020), pp. 1–12. DOI: 10.1109/JSYST.2020.2965993.

[175] Yacov Y. Haimes. "On the Definition of Resilience in Systems". In: *Risk Analysis* 29.4 (2009). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1539-6924.2009.01216.x, pp. 498–501. ISSN: 1539-6924. DOI: 10.1111/j.1539-6924.2009.01216.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1539-6924.2009.01216.x (visited on 08/12/2020).

[176] *A resilience assessment framework for infrastructure and economic systems: Quantitative and qualitative resilience analysis of petrochemical supply chains to a hurricane - Vugrin - 2011 - Process Safety Progress - Wiley Online Library*. URL: https://aiche.onlinelibrary.wiley.com/doi/full/10.1002/prs.10437?casa_token=ASlLnO33pCUAAAAA%3AF2jNq4mHC1erL97BybxLNOwqTKuXUb6761mBOmA (visited on 05/28/2020).

[177] Robert Neches. *Engineered Resilient Systems (ERS) S&T Priority Description and Roadmap*. Section: Technical Reports. OFFICE OF THE DEPUTY ASSISTANT SECRETARY OF DEFENSE FOR SYSTEMS ENGINEERING WASHINGTON DC, Nov. 8, 2011. URL: https://apps.dtic.mil/sti/citations/ADA554841 (visited on 08/13/2020).

[178] Simon R. Goerger, Azad M. Madni, and Owen J. Eslinger. "Engineered Resilient Systems: A DoD Perspective". In: *Procedia Computer Science*. 2014 Conference on Systems Engineering Research 28 (Jan. 1, 2014), pp. 865–872. ISSN: 1877-0509. DOI: 10.1016/j.procs.2014.03.103. URL: http://www.sciencedirect.com/science/article/pii/S1877050914001665 (visited on 10/24/2020).

[179] Francesco Gracceva and Peter Zeniewski. "A systemic approach to assessing energy security in a low-carbon EU energy system". In: *Applied Energy* 123 (June 15, 2014), pp. 335–348. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2013.12.018. URL: http://www.sciencedirect.com/science/article/pii/S0306261913010179 (visited on 01/20/2021).

[180] Reza Arghandeh, Alexandra von Meier, Laura Mehrmanesh, et al. "On the definition of cyber-physical resilience in power systems". In: *Renewable and Sustainable Energy Reviews* 58 (May 1, 2016), pp. 1060–1069. ISSN: 1364-0321. DOI: 10.1016/j.rser.2015.12.193. URL: http://www.sciencedirect.com/science/article/pii/S1364032115015762 (visited on 05/01/2020).

[181] James Glynn, Alessandro Chiodi, and Brian Ó Gallachóir. "Energy security assessment methods: Quantifying the security co-benefits of decarbonising the Irish Energy System". In: *Energy Strategy Reviews* 15 (Mar. 1, 2017), pp. 72–88. ISSN: 2211-467X. DOI: 10.1016/j.esr.2016.11.005. URL: http://www.sciencedirect.com/science/article/pii/S2211467X16300621 (visited on 08/13/2020).

[182] Dimitris N. Trakas and Nikos D. Hatziargyriou. "Optimal Distribution System Operation for Enhancing Resilience Against Wildfires". In: *IEEE Transactions on Power Systems* 33.2 (Mar. 2018). Conference Name: IEEE Transactions on Power Systems, pp. 2260–2271. ISSN: 1558-0679. DOI: 10.1109/TPWRS.2017.2733224.

[183] John Renne, Brian Wolshon, Pamela Murray-Tuite, et al. "Emergence of resilience as a framework for state Departments of Transportation (DOTs) in the United States". In: *Transportation Research Part D: Transport and Environment* 82 (May 1, 2020), p. 102178. ISSN: 1361-9209. DOI: 10.1016/j.trd.2019.11.007. URL: http://www.sciencedirect.com/science/article/pii/S1361920918309519 (visited on 08/12/2020).

[184] Qi Tong, Ming Yang, and Altyngul Zinetullina. "A Dynamic Bayesian Network-based approach to Resilience Assessment of Engineered Systems". In: *Journal of Loss Prevention in the Process Industries* 65 (May 1, 2020), p. 104152. ISSN: 0950-4230. DOI: 10.1016/j.jlp.2020.104152. URL: http://www.sciencedirect.com/science/article/pii/S0950423020302813 (visited on 08/11/2020).

[185] Kathryn A. Foster. *A Case Study Approachto Understanding Regional Resilience*. undefined. 2006. URL: /paper/A-Case-Study-Approachto-Understanding-Regional-Foster/28fa17bc5d7e86777662336 (visited on 08/11/2020).

[186] Asad Asadzadeh, Theo Kötter, and Esfandiar Zebardast. "An augmented approach for measurement of disaster resilience using connective factor analysis and analytic network process (F'ANP) model". In: *International Journal of Disaster Risk Reduction* 14 (Dec. 1, 2015), pp. 504–518. ISSN: 2212-4209. DOI: 10.1016/j.ijdrr.2015.10.002. URL: http://www.sciencedirect.com/science/article/pii/S2212420915301023 (visited on 05/22/2020).

[187] Oluwateniola Ladipo, Georg Reichard, Andrew McCoy, et al. "Attributes and metrics for comparative quantification of disaster resilience across diverse performance mandates and standards of building". In: *Journal of Building Engineering* 21 (Jan. 1, 2019), pp. 446–454. ISSN: 2352-7102. DOI: 10.1016/j.jobe.2018.11.007. URL: http://www.sciencedirect.com/science/article/pii/S2352710218310386 (visited on 05/22/2020).

[188] C. Chethika Abenayake, Yoshiki Mikami, Yoko Matsuda, et al. "Ecosystem services-based composite indicator for assessing community resilience to floods". In: *Environmental Development* 27 (Sept. 1, 2018), pp. 34–46. ISSN: 2211-4645. DOI: 10.1016/j.envdev.2018.08.002. URL: http://www.sciencedirect.com/science/article/pii/S2211464517301057 (visited on 05/08/2020).

[189] Ann S. Masten and Jenifer L. Powell. "A resilience framework for research, policy, and practice". In: *Resilience and vulnerability: Adaptation in the context of childhood adversities*. New York, NY, US: Cambridge University Press, 2003, pp. 1–25. ISBN: 978-0-521-80701-2 978-0-521-00161-8. DOI: 10.1017/CBO9780511615788.003.

[190] James Gerhart, Sean O'Mahony, Ira Abrams, et al. "A pilot test of a mindfulness-based communication training to enhance resilience in palliative care professionals". In: *Journal of Contextual Behavioral Science* 5.2 (Apr. 1, 2016), pp. 89–96. ISSN: 2212-1447. DOI: 10.1016/j.jcbs.2016.04.003. URL: http://www.sciencedirect.com/science/article/pii/S2212144716300187 (visited on 08/11/2020).

[191] Erik Hollnagel. *Safety-II in Practice: Developing the Resilience Potentials*. Google-Books-ID: _AkqDwAAQBAJ. Taylor & Francis, July 14, 2017. 145 pp. ISBN: 978-1-351-78076-6.

[192] Susan Yoon, Rebecca Dillard, Fei Pei, et al. "Defining resilience in maltreated children from the practitioners' perspectives: A qualitative study". In: *Child Abuse & Neglect* 106 (Aug. 1, 2020), p. 104516. ISSN: 0145-2134. DOI: 10.1016/j.chiabu.2020.104516. URL: http://www.sciencedirect.com/science/article/pii/S014521342030171X (visited on 08/12/2020).

[193] *PRIM/prim at master · Project-Platypus/PRIM*. GitHub. URL: https://github.com/Project-Platypus/PRIM (visited on 07/14/2022).

[194] Jerome H. Friedman and Nicholas I. Fisher. "Bump hunting in high-dimensional data". In: *Statistics and Computing* 9.2 (Apr. 1, 1999), pp. 123–143. ISSN: 1573-1375. DOI: 10.1023/A:1008894516817. URL: https://doi.org/10.1023/A:1008894516817 (visited on 07/14/2022).

A DEFINITIONS OF RESILIENCE

Discipline	Year	Definition
General/other resilience	1973	“a measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables” [16]
	2006	“the capacity of the system to absorb disturbance and re-organize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks” [157], [158]
	2008	the ability “to adjust its functioning prior to, during, or following changes and disturbances, so that it can continue to perform as required after a disruption or a major mishap, and in the presence of continuous stresses” [159]
	2011	“the capacity to absorb shocks while maintaining system functions” and “the capacity for renewal, re-organization and development, should the system collapse” [160]
	2012	“the ability to absorb shocks and still retain function” [18]
	2013	“the ability to withstand [a] disruption and operate smoothly in a volatile environment” [161]
	2013	“the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions, resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents” [162]
	2014	“the direct strength of structures or institutions when placed under pressure” and the “ability of systems to absorb and recover from the impact of disruptive events without fundamental changes in function or structure” [163]
	2014	“the capacity of social, economic and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganizing in ways that maintain their essential function, identity and structure, while also maintaining the capacity for adaptation, learning, and transformation” [164]
	2015	“the rebound from trauma and return to equilibrium, synonym for robustness, opposite of brittleness, network architectures that can sustain the ability to adapt to future surprises as conditions evolve” [24]
	2015	“the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions... [including] deliberate attacks, accidents, or naturally occurring threats or incidents” [165]
	2016	“the ability of an urban system-and all its constituent socio-ecological and socio-technical networks across temporal and spatial scales-to maintain or rapidly return to desired functions in the face of a disturbance, to adapt to change, and to quickly transform systems that limit current or future adaptive capacity” [166]

	2016	“withstand and recover quickly from extreme external events such as natural disasters, maintain system operations during an extreme external disruption, return the system to normal operation following a disruption” [167]
	2017	“the capability of a system to withstand internal/external stresses and recover from them” [168]
	2018	“the ability of the system to meet as much of its intended functionalities as possible when interrupted by either external or internal disruptions” [169]
	2019	“the ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions through adaptable and holistic planning and technical solutions” [170]
	2019	“the ability of a system to withstand or quickly return to normal condition after the occurrence of an event that disrupts its state” [171]
	2020	“the ability of an individual or a system to adapt to and recover from external shocks or stresses” [19]
	2020	“the ability to prepare for an adapt to changing conditions and withstand and recover rapidly from disruptions, including the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents” [172]
	2020	“the capability to anticipate, prepare for, respond to, and recover from significant multi-hazard threats with minimum damage to social well-being, health, and the environment” [173]
	2020	“the ability of a system to predict a rare disastrous event, withstand or absorb it, to adapt to its consequences, and quickly recover its performance to an acceptable level after facing such an event” [174]
Critical infrastructure and system resilience	2009	“the ability of systems to withstand a major disruption within acceptable degradation parameters and to recover with a suitable time and reasonable costs and risks” [175]
	2011	“given the occurrence of a particular disruptive event, the resilience of a system to that event is the ability to reduce efficiently both the magnitude and duration of the deviation from targeted system performance levels” [176]
	2011	“trusted and effective out of the box in a wide range of contexts, easily adapted to many others through reconfiguration or replacement, with graceful and detectable degradation of function” [177], [178]
	2012	“the ability for a transportation network to absorb disruptive events gracefully and return itself to a level of service equal to or greater than the predisruption level of service within a reasonable time frame” [21]
	2013	“the ability to resist to internal drift and cascading failures, and recover back to the initial operation state” [83]
	2014	An energy system that “can source alternative modes of production or consumption in response to sudden and transient shocks…the ability of the system to tolerate and absorb change” [179]
	2015	“the ability of a power system to withstand extraordinary and high impact-low probability events such as due to extreme weather, rapidly recover from such disruptive events, and absorb lessons for adapting its operation and structure to prevent or mitigate the impact of similar events in the future” [26]
	2016	“the ability of a power system to withstand the initial shock, rapidly recover from the disruptive event, and apply adaptation measures for mitigating the impact of similar events in the future” [75]

	2016	a "system's ability to maintain continuous electricity flow to customers given a certain load prioritization scheme, [respond] to cyber-physical disturbances in real-time or semi real-time, avoiding interruptions of critical services, [alter] its structure, loads and resources in an agile way" [180]
	2017	"the absence of, protection from, or adaptability to threats that are caused by or have impact on the [system]" [181]
	2018	the "ability [of the system] to withstand extraordinary and high-impact, low-probability events that may have never been experienced before, rapidly recover from such disruptive events, and adapt its operation and structure to prevent or mitigate the impact of similar events in the future" [182]
	2018	"preventing power disruption and restoring electricity supply as quickly as possible when an outage does occur, while mitigating the consequences of the outage" [33]
	2020	"[the ability] to ensure. . . systems are able to withstand extreme weather events resulting from climate change, terrorism, cyber-attacks and again infrastructure" [183]
	2020	the infrastructure's behavior and level of service during a disruptive event and subsequent recovery process measured in terms of robustness, redundancy, adaptability, reliability, rapidity, and resourcefulness [22]
	2020	"a power system [that] can recover itself using minimum human interventions as quickly as possible" [174]
	2020	"the probability of a systems functionality state sustaining a high state or restoring to a high state from a low state during and after the occurrence of disruptions in the operation of a system within a specific time" [184]
Disaster resilience	2006	"the ability of a region to anticipate, prepare for, respond to and recover from a disturbance" [185]
	2015	"the ability of a system, community or society to resist, mitigate, respond and recover from the effects of a hazard/shock in an efficient way and timely manner" [186]
	2019	"functionality prior to, before, and after a natural hazard event, as well as the time it takes to recover functionality" [187]
Community resilience	2018	"the ability of a socio-ecological system to survive the disturbances, reorganize into a desirable functional system, and anticipate trajectories and strengthen adaptive capacity to floods" [188]
	2020	"the ability to absorb/resist/withstand disturbance and the ability to respond/recover/restore the acceptable level of functioning and structure" [19]
Psychological and healthcare resilience	2003	"the personal qualities that enable one to thrive in the face of adversity" [30]
	2003	"patterns of positive adaptation in the context of significant risk or adversity" [189]
	2016	"mindfully disengaging from aversive traumatic events to replenish depleted resources such as arrest and social support, and limit exposure to further trauma" [190]
	2018	"the ability to sustain everyday operations under anticipated and unanticipated conditions" [191]

	2020	"surviving, thriving, [persevering] reconciling and integrating traumatic experiences into healthy identity development, and advocating for self [following adversity]" [192]

B RDM-REopt

Included in this section is an overview of what a REopt user will need to input for an RDM-REopt run, once the RDM framework has been applied. The example shown is with the escalation percent of the electricity cost, outage start time, and the PV sizing as uncertainties. The uncertainties will also be accompanied by their distribution types, as well as the standard deviations and means to form the distributions. The input `Nscenarios` will be the number of scenarios optimized. The more scenarios, the more robust the assessment.

```
using RDMREopt
using Distributions
using Test
using Xpress

@testset "threaded_scenarios" begin
    u1 = Uncertainty(
        name="Financial.elec_cost_escalation_pct",
        distribution=Uniform(-0.01, 0.03)
        )

    u2 = Uncertainty(
        name="ElectricUtility.outage_start_timesteps",
        distribution=Uniform(1, 8000),
        is_integer=true,
        is_vector=true
         )

     u3 = Uncertainty(
        name="PV.size_kw", distribution=Normal(500, 50)
        )

    uncertainties = [u1, u2, u3]

     metrics = [
        "Financial.lcc",
        "PV.lcoe_per_kwh",
        "probability_of_survival_10_time_steps"
        ]

    scenarios = Scenarios(
        "base_scenario.json",
        uncertainties,
```

```
        metrics;
        Nscenarios=10,
        Nparallel=6
        );

    rs, outage_sim_results = RDMREopt.run_threaded_scenarios(scenarios, Xpress.Optimizer;
    remove_series=true);
    df = dicts_to_dataframe(rs)
    save_dataframe_as_csv(df, "results.csv")
    save_opt_and_outage_sim_results_as_json("results.json", rs, outage_sim_results)
end

@testset "serial_scenarios" begin
    u1 = Uncertainty(
        name="Financial.elec_cost_escalation_pct",
        distribution=Uniform(-0.01, 0.03)
        )

    u2 = Uncertainty(
        name="ElectricLoad.annual_kwh",
        distribution=Normal(2_849_901, 100_000)
        )

    u3 = Uncertainty(
        name="PV.size_kw",
        distribution=Normal(500, 50)
        )

    uncertainties = [u1, u2, u3]

    metrics = [
        "Financial.lcc",
        "PV.lcoe_per_kwh",
        "probability_of_survival"
        ]

    scenarios = Scenarios(
        "base_scenario.json",
        uncertainties,
        metrics;
        Nscenarios=2,
        Nparallel=6
        );

    results, outage_sim_results =
    RDMREopt.run_serial_scenarios(scenarios, Xpress.Optimizer;
    remove_series=true);

    df = dicts_to_dataframe(results)
```

```
    save_dataframe_as_csv(df, "results.csv")
end
```

C PRIM

The Patient Rule Induction Method (PRIM) is a sub-group discovery algorithm. Given high-dimensional data, PRIM searches for sub-regions of the input space that result in the mean of dimensions of the output space being improved compared to the average over the entire input domain. To identify these sub-groups, there are two primary components to PRIM: pasting and peeling. In this appendix, the math behind PRIM is described. PRIM will be written and tested in Julia. To validate the code, examples from Project Platypus will be used [193]. All of this math is derived from Friedman and Fisher [194].

C.1 PRIM variables and parameters

There are a few important variables and parameters when working with PRIM. The first variable is B which covers **all** of the data. The next two variables are b and b^* which are derived from B. The variable b is a sub-box of B and b^* is the sub-box of B chosen to be removed from B. The parameters B, b, and b^* are updated as PRIM iterates. This is explained in the following section.

An important parameter in PRIM is β. Otherwise known as the support, this parameter ensures that the sub-region is not over-fitted. The parameter β_0 is the specific threshold that dictates when iterations stop. The other two parameters are the peeling and pasting parameters, α_{peel} and α_{paste}, respectively. These values determine the rate at which data will be removed from or added back to the overall data. Typically, values for α are less than or equal to 0.1.

C.2 Peeling

To identify sub-groups, PRIM seeks to remove input spaces that bring down the target mean. This process of removing data is called peeling. When peeling, a small box, b, is removed from the full data set, B. The sub-box chosen for removal is b^*. The size of the sub-box to be removed from B is determined by the size of the current B and the value of the peeling parameter, α_{peel}. This is depicted in Equation C.1 where N_B is the number of observations in the current box of data and α_{peel} is the peeling fraction.

$$b = \alpha_{peel} N_B \tag{C.1}$$

For each iteration, there are two sub-boxes eligible for removal. One which borders the lower boundaries of B and the other which borders the upper boundaries of B, both of which are on a given input variable, for example j, as depicted in C.2.

$$\begin{aligned} b_{j-} &= \{\mathbf{x} | x_j < x_{j(\alpha)}\} \\ b_{j+} &= \{\mathbf{x} | x_j > x_{j(1-\alpha)}\} \end{aligned} \tag{C.2}$$

The sub-box chosen for removal is based on the candidate boxes from Equation C.2 that results in the largest output mean in the resultant box. At the conclusion of each peeling iteration, the current box is updated in accordance with Equation C.3. The peeling continues until β_B falls below a threshold value of β_0, as described in Equation C.4.

$$B \leftarrow B - b^* \tag{C.3}$$

$$\beta_B = \frac{1}{N} \sum_{N}^{i=1} (x_i \in B) \leq \beta_0 \tag{C.4}$$

C.3 Pasting

When the peeling algorithm is complete, the target mean will be relatively large. However, peels are performed without the knowledge of future peels. Therefore, it is possible that the target mean could be improved further by re-incorporating some of the previously peeled data. This is done through a pasting algorithm that is the inverse of the peeling procedure. Pasting is also iteratively applied, increasing the size of B. When the algorithm reaches the point where the output mean begins to decrease, the pasting stops and the current box becomes the solution.

C.4 Iterations

The pasting and peeling functions of PRIM are repeated until there are no more improvements in the output space. A visual representation of how PRIM operates is in Figure C.1. When the algorithm reaches its final solution, the user will be informed about useful input spaces and potentially new scenarios to test.

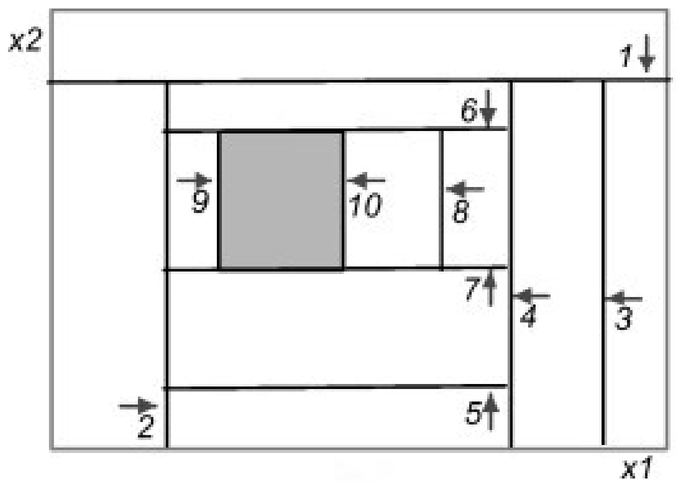

Figure C.1: An example of PRIM identifying a sub-region based on two dimensions [156]

D SOLVING A LARGE ENERGY SYSTEM OPTIMIZATION MODEL USING AN OPEN-SOURCE SOLVER

The following study was published in the EMP-NA 2020 special issue of *Energy Strategy Reviews* in November 2021. This study

D.1 Contributions

Along with the following contributions, this study aligns with the theme throughout this proposal of making energy system modeling accessible to everyone. This study:

- Evaluates the ability of open-source solvers to solve large electricity models
- Summarizes techniques to improve the solvability of open-source energy models
- Analyzes the trade-offs of model detail, solve time, and modeling outcomes

Solving a large energy system optimization model using an open-source solver

Madeline Macmillan[a,b], Kelly Eurek[b], Wesley Cole[b], and Morgan D. Bazilian[a]

[a]Colorado School of Mines, 1500 Illinois St., Golden, CO 80401 USA

[b]National Renewable Energy Laboratory, 15013 Denver West Parkway, Golden, CO 80401 USA

1. Introduction

Energy system models are essential for informing researchers, utility owners, and policy makers. These tools vary by, among other aspects, sectoral coverage, spatial and temporal scales, and application. Until recently, most energy-system models available—even those of which the underlying code was made freely available—required licensing of commercial solvers. In the case of the Network-Enabled Optimization Server (NEOS) server, an open-source server with several solvers available, anyone can access the tool, but only for non-commercial purpose. More recently, a handful of research organizations have developed similar, more accessible tools that provide not just the model code freely, but were also developed to use open-source or open-access solvers [1–3].

The Open-Source Initiative, which aims to promote and protect open-source software, defines open-source software as that which can be developed and distributed by many people in a way that "grants all the rights to use, study, change, and share the software in modified and unmodified form" [4]. The essential component of open-source software is to "enable community development". Within open-source software initiatives, there are efforts focused specifically on energy system modeling. Open energy modeling applies the same principles as open software: "source code that can be studied, changed, and improved as well as freely available energy system data" [5]. Regardless of the application of "open", the idea to provide accessible products and platforms for collaborative development for all remains consistent [6]. In this study, we consider open-source solvers.

There are many advantages to open-source resources and software. Providing access to a tool can increase the sustainability of the project, promote collaboration, and further development of the tool. There are also possible disadvantages, including the possibility of low-quality end-user documentation, the constant evolution of software with no guarantee of cohesiveness across versions, potential security violations, and loss of competitive advantage [6]. Another potential drawback of open-source or open-access software, particularly open-source solvers, are their solving capabilities relative to similar, commercial alternatives.

Optimization solver software is essential to computing solutions for energy system modeling tools. A barrier to entry of some commercial software is the licensing cost, although some commercial solvers are available for free or at low cost to academic communities [7]. Organizations or researchers with limited budgets, however, may not be able to afford commercial solvers. Therefore, it is of interest to identify open-source solvers that can produce robust results. Past efforts have evaluated open-source solvers for linear programming problems. A study from 2008 applies three different solvers for electricity spot market problems [8]. Another study from 2013 applies the same three solvers for a cell suppression problem [9]. The fastest solver is different for each study due to the inherent difference in the problem structures.

In this paper, we compare the capability of open-source and commercial linear programming solvers to compute solutions for a large-scale energy model. We evaluate solver performance when applied to problem instances of the Regional Energy Deployment System (ReEDS) model developed by the National Renewable Energy Laboratory (NREL) [10]. First, we introduction the ReEDS model (Section 2). We then compare the merits of several open-source linear programming solvers to select a candidate to apply to ReEDS and explore methods for improving the solvability and speed of ReEDS (Section 3). Next, we summarize the performance of an open-source solver applied to several reduced-form versions of ReEDS and examine the model outputs (Section 4). Finally, we propose next steps for future research (Section 5).

2. Model Background

As previously mentioned, "open-source" is a form of software available for development and distribution by any interested party. Although ReEDS is available for distribution through an NREL form, users are not permitted to redistribute to third parties [11]. To access the ReEDS repository, follow the link in SI-1. The usage of ReEDS also requires paid licenses such as General Algebraic Modeling System (GAMS). This means that although ReEDS does not fit the definition of "open-source" it does have a level of openness.

The ReEDS model is a long-term planning model for the electric power sector. Given assumptions about future conditions (e.g., technology costs and performance, fuel prices, policy), the model determines the least-cost mix of generation, transmission, and storage resources necessary to meet physical constraints and policy requirements. The model is populated by several parameters within including annual capital expenditures, levelized costs of energy, and capacity factors, many of which are housed within the Annual Technology Baseline [12]. The model was first developed for the conterminous United States but has since been extended to Canada, Mexico, and India [13]–[15]. The core of ReEDS is a linear program (LP) that minimizes the net present value of electric power sector costs subject to a suite of constraints governing the investment and operation of supply-side resources on a substate resolution. The constraints include balancing supply and demand for electricity, meeting reliability requirements for planning and operating reserves, abiding by physical operational constraints, transmission flows, and compliance with state and federal policies.

ReEDS is typically solved myopically with limited foresight about future conditions to inform investment decisions. As the model steps forward in time, new information about the future is revealed, and new decisions are made. In this sequential solve procedure, investments made in prior years affect decisions in future years.

ReEDS has a modular structure. Information is passed between modules to optimize or calculate various outcomes of the long-term planning process. A sequential ReEDS model solve begins with a supply module being provided inputs from previous model years. The solution and outputs are passed to a variable renewable energy and storage module to calculate the capacity values and curtailment rates of variable renewable generation technologies and storage technologies using hourly chronological data. These values are then given to the supply module to solve the next model year. This process continues until the end of the time horizon is reached (which is typically 2050) [10].

Another characteristic of ReEDS is how it treats historical years differently than present and future years. For example, new investments are limited to the exogenous capacity prescriptions in the years 2010-2018. Endogenous investments and endogenous retirements are enabled in 2020 and 2024, respectively. These years are updated as current years become historical years. Because historical plants are tracked separately from new plants, this results in an increase in the number of generation and storage resources within the model results and increases the size of the model A-matrix (number of rows, columns, and nonzeros). The ReEDS model has been used by various researchers for a variety of research questions [16]–[20]. Therefore, ReEDS is a valuable starting point to understand the ability of open-source solvers to solve the linear program.

3. Methods

3.1 Evaluation of linear programing solvers for ReEDS

With a basic understanding of the ReEDS model, we began looking at different linear programming solvers to identify the best one to test. From literature, we compiled a list of candidate open-source solvers for ReEDS, identified available linear program solution algorithms with each solver, classified the solvers' compatibility with ReEDS, and examined their solve time performance for standardized model instances from benchmark studies. Based on these criteria, we selected one candidate open-source solver to test on ReEDS.

The ReEDS linear program is written in the GAMS mathematical programming software and is typically solved using the CPLEX commercial solver, applying the interior point method plus crossover to obtain a basic feasible solution. Therefore, candidate open-source solvers for ReEDS should be compatible with GAMS and should contain the interior point method.

In one 2020 study of energy system optimization model performance, Scholz et al. (2021) note that the interior point method usually outperforms both the primal and dual simplex methods for solving large-scale LPs of the electricity system [21]. Based on the experience of practitioners at NREL, the interior point method is faster than the simplex method for solving common ReEDS instances [22]. Klotz and Newman offer insights into the potential performance of these two methods based on the A-matrix characteristics of a difficult linear program problem instance [23].

For this study, we considered the following solvers as potential lower-cost alternatives to CPLEX for the ReEDS model:

- **Brook, Drud, and Meeraus Linear Program solver (BDMLP)** [24] – Linear programming solver managed by GAMS. The solver is not open source, but it is available with the purchase of a GAMS license. BDMLP has been dropped from the GAMS distribution as of GAMS version 34.
- **COIN-OR Linear Programming (CLP)** [25] – Free, open-source linear programming solver made available through the COIN-OR project. A link between GAMS to CLP is available with the purchase of a GAMS license.
- **GNU Linear Programming Kit (GLPK)** [26] – Free, open-source linear programming package. GLPK is no longer part of the GAMS distribution.
- **Interior Point Optimizer (IPOPT)** [21, 22] – Free, open-source suite of interior point solvers for linear and nonlinear optimization problems available through the COIN-OR project. A link between GAMS and IPOPT is available with the purchase of a GAMS license.
- **LP Solve** [29] – Not commonly used for GAMS models, but examples of links between GAMS and LP Solve exist. There are examples of LP Solve being used for models developed in R programming language.
- **Modular In-core Nonlinear Optimization System (MINOS)** [30] – Commercial software with discounted academic licenses and government licenses. A GAMS/MINOS-Link is not offered to GAMS customers, so an organizations such as a government-based research institution, would have to pay the standard rate for a GAMS/MINOS license.
- **Parallel Interior Points Solver (PIPS)** [31] – Free, open-source suite of parallel optimization solvers developed by Argonne National Laboratory. A PIPS-IPM solver link for GAMS was developed for the BEAM-ME Project [32], but the link is not publicly available.
- **Sequential Object-oriented simPlex (SOPLEX)** [33] – Commercial optimization package for linear programming problems. Free versions are available for noncommercial and academic institutions and links to GAMS are available with the purchase of a GAMS license.

Table 1 summarizes the criteria we used to evaluate the eight solvers listed above for use with ReEDS, but this table can also reflect solver compatibility with other programming platforms dependent on the energy model in question. We gave priority to solvers that: (1) are open-source, (2) include the interior point method—the recommended solution method for ReEDS is interior point with crossover, (3) are compatible with GAMS—the ReEDS formulation is written in GAMS, (4) performed well in past benchmark studies, and (5) are available at low or no cost—software fees are an important factor for organizations with limited budgets. The execution of the ReEDS model requires a fee-based license for GAMS, so the additional cost for a commercial solver like CPLEX increases the cost burden. If all other criteria are met, then we used the benchmark performance as a deciding factor for which solver may exhibit superior performance for ReEDS.

Table 1. Candidate solver options for ReEDS.

Solver	Open Source?	Solver Cost [28–30]	LP Solution Algorithms	Compatibility with GAMS	Performance benchmarks in [34]	Performance benchmarks in [37]
BDMLP	No	Only available through commercial software	• Simplex	Managed by GAMS and available with the GAMS Base Module License	Not included	Not included
CLP	Yes	Free	• Simplex • Interior Point	GAMS solver link available with the GAMS Base Module License	• Successfully solved 180/180 problems • Aggregate solve time 213 times slower than CPLEX	Successfully solved 40/40 problems
GLPK	Yes	Free	• Simplex • Interior Point	No longer part of the GAMS distribution	• Successfully solved 138/180 problems • Aggregate solve time 459 times slower than CPLEX	Successfully solved 36/40 problems
IPOPT	Yes	Free	• Interior Point • (no crossover)	GAMS solver link available with the GAMS Base Module License	Not included	Not included
LP Solve	Yes	Free	• Simplex	Not commonly used for GAMS models and no formal GAMS solver link is available	• Successfully solved 150/180 problems • Aggregate solve time 510 times slower than CPLEX	Not included
MINOS	No	• $936 – academic* and government • $25,000 – commercial**	• Simplex	GAMS solver link does not exist, accessible with a GAMS\MINOS license	• Successfully solved 151/180 problems • Aggregate solve time 613 times slower than CPLEX	Not included
PIPS	Yes	Free	• Simplex • Interior Point	Open-source solver, GAMS solver link is not publicly available.	Not included	Not included
SOPLEX	No	• Free – academic • High – commercial	• Simplex	GAMS solver link: available with the GAMS Base Module License (Academic Only), also accessible with a GAMS/SCIP license	Not included	Successfully solved 36/40 problems

*University-wide license
**Company-wide license

The benchmark performance metrics provide insights into how the solvers compare with each other. A 2013 report from Sandia National Laboratories compares the solvability and solve time of CPLEX and a variety of open-source solvers (CLP, GLPK, LP Solve, MINOS) on a suite of 180 standardized linear programing problem instances of varying sizes (rows, columns, and nonzeros) [34]. The largest problem tested on these solvers has more than 1.9 million rows and more than 0.64 million columns. For reference, this problem is larger than the largest ReEDS problem size after the CPLEX presolve that occurs in the final year of the modeling horizon, in this case the year 2050, which has 0.44 million rows and 0.52 million columns.

The authors find the CLP solver can solve the tested problems faster than any of the other open-source solvers tested, but CPLEX is superior across all test problem instances. Among the open-source solvers tested on the 180 problem instances, CLP was able to solve the most problems out of the open-source solvers tested. Within the Hans Mittleman "Benchmarks for Optimization Software," CLP generally yielded faster solve times compared to other open-source linear program solvers [37]. Finally, a 2006 study found that CLP outperformed GLPK and LP Solve for electricity spot market optimization problems [8]. While the electricity spot market problem does not consider investment decision-making, the problem includes many of the same types of operational variables and constraints as ReEDS.

Based on Table 1, we excluded solvers that:

- Are not open source (BDMLP, PIPS, and SOPLEX)
- Are not free or are not low-cost for nonacademic use (SOPLEX; MINOS)
- Do not use the interior point method (BDMLP; SOPLEX; MINOS; LP Solve)
- Are not directly accessible in GAMS (PIPS; GLPK; LP Solve)
- Are not tested in past benchmark studies (BDMLP; IPOPT; PIPS; SOPLEX).

The CLP solver is the only open-source solver to satisfy all our criteria for use with the ReEDS model and was therefore selected for further characterization. Although IPOPT is not represented in the benchmark studies, it satisfies every other requirement. In an initial test, we found IPOPT produces solutions that are not compatible with the ReEDS sequential-solve algorithmic structure [11]. For example, after solving one model year, IPOPT would include nonzero values for variables not considered in the model. These nonzero values would create issues when solving later model years. This is explained in greater detail in SI-2.

2.2 Improving the solvability of the ReEDS reference case on CLP

We tested CLP on the ReEDS "reference case" for two spatial extents: (1) the Electric Reliability Council of Texas (ERCOT); and (2) the conterminous United States (CONUS). CLP was able to solve the ERCOT model instance but failed to solve the CONUS model instance for the full model planning horizon within the 10,000 seconds (~2 hours 47 minutes), our default solver time limit for this study.

Excessive run time can be indicative of a large problem size that is cumbersome for the solver and/or a problem instance with numerical issues [23]. Numerical issues, such as inaccuracies from round off errors that occur with floating point calculations (ex. a poorly scaled A-matrix with coefficients that have a large difference in their orders of magnitude), will hinder the performance of any solver, but more so for free solvers that have less sophisticated algorithms to abate these numerical issues. Although CLP could theoretically solve a ReEDS model instance given sufficient time, it is not time efficient. It is also important to consider the impact the CPLEX presolve algorithms might have on model tractability when compared to those of CLP and how that may affect the solve time of the model [32].

By reducing the problem size or simplifying the model formulation of linear programs, solve time can be reduced [21]. Klotz and Newman as well as Scholz et al. offer guidelines for improving the solve times of linear programs [15, 17]. Some of these guidelines are specific to CPLEX, while others are solver agnostic.

We identify several methods to improve the solvability of a large model on open-source solvers (Table 2). The following sections will provide more details on each technique employed for the ReEDS model in this study.

Table 2. Techniques to improve solvability of large models on open-source solvers.

Category	Technique	ReEDS examples from this study
Reducing numerical issues in the A-matrix	Round matrix coefficients	Round emission rates
	Scale matrix coefficients	Scale emissions variables
Reducing the size of the A-matrix	Remove variables and constraints for: (a) low-impact features (b) advanced features	(a) Exclude variables and constraints for technologies that are unlikely to be deployed in a reference case
		(b) Do not allow endogenous retirements as a decision variable
	Reduce the model dimensions	Reduce the spatial extent of the model to ERCOT Reduce the number of investment periods

2.4 Improving the A-matrix

To identify possible areas for avoiding numerical issues, we inspect the A-matrix, b-vector, and c-vector through a mathematical programming system (MPS) file. All of these values are accessible through solver output. As a standardized format for storing linear programming problems, MPS files include the coefficients we aim to stabilize. MPS files are also organized by variable and constraint for easy classification of unstable constraints or areas for improvement. A sample of our MPS file can be found in SI-3.

2.4.1 Round matrix coefficients

The first method attempted to improve the stability of the A-matrix was to round specific coefficients. Many of the coefficients, regardless of their scaling, had excessive and unrealistic precision (e.g., 40.0000001). Rounding should be performed with caution and should only be applied to input data. To reduce this source of instability, the ReEDS model code was edited to round the coefficients more effectively. An example of when this might be necessary and useful is when a 100-MW photovoltaic system with a capacity factor of 0.00005 produces 0.003 megawatt-hours of energy in an hour. In such a situation, it would be reasonable to round the capacity factor to zero and assume the PV system does not produce any energy during the period in question.

2.4.2 Scale matrix coefficients

The second method for improving stability was to adjust the scaling factors. Throughout the ReEDS formulation, there are instances of poorly scaled A-matrix coefficients. By improving the scaling of the A-matrix coefficients and moving them closer to unity, solve time can be reduced. The best practice is for the maximum difference between the smallest and largest coefficient orders of magnitude to be 12 (e.g., 1e-6 to 1e+6), but with smaller spreads resulting in better scaling [23]. By inspecting the matrix, we can round coefficients to reduce instances of very small coefficients, adjust scaling factors, and remove variables and/or constraints causing numerical issues while keeping in mind the impact on the solution.

There are a few options for scaling the coefficients in the A-matrix. The first is indicating scaling preferences within the solver options. For this study, both solvers with GAMS compatibility had a unique set of options [33]. Alternatively, manual scaling was possible with user-defined scaling factors. In this study, we adjusted the ReEDS scaling factor applied to emissions constraints because we identified them as a source of the poor scaling within the A-matrix. The ReEDS emissions constraints are responsible for maintaining emissions levels within the required emission limits. In the original problem formulation, the parameter is in units of megatons across the three pollutants considered in the model (CO_2, SO_x, and NO_x). Because power sector CO_2 emissions were orders of magnitude larger than SO_x and NO_x emissions, poor scaling ensued. To test whether scaling of the A-matrix coefficients might improve model tractability and solver solve time, we conducted a run where the emission scaling parameter was adjusted to be specific to each pollutant type [40].

2.5 Remove variables and constraints

The third method explored for improving solver performance was removing select sets of variables and constraints. Problematic variables and constraints, such as those with numerical issues, can be identified by filtering the MPS file, as necessary. We determined which variables and constraints to remove by (1) excluding features that may not have a strong impact on the solution, (2) excluding advanced features, and (3) reducing the model dimensionality. Within ReEDS, many of the relevant variables and constraints were those dictating emissions policies. These constraints, among a few others, were removed to understand if and how these changes would affect the solve time. A complete list of the various model features turned off throughout this study is shown in Table 3.

Table 3. Sample list of model features that can be turned off in ReEDS.

Model Feature	Category	Description
RGGI (Regional Greenhouse Gas Initiative)	Emissions (EMIS)	Limit total CO_2 emission for states participating in RGGI
AB-32/SB-32 (Assembly Bill 32 and Senate Bill 32)	Emissions (EMIS)	California CO_2 cap and trade program
CSAPR (Cross State Air Pollution Rule)	Emissions (EMIS)	SOx/NOx emission caps for specific states
Endogenous retirements	Capital stock (CAP)	Endogenous decision for model plants to be retired prior to the end of their maximum lifetime
Capacity refurbishments	Capital stock (CAP)	Endogenous decision to refurbish a technology after the end of its lifetime
Carbon capture and storage	Technology (TECH)	Represent CCS technology options for coal and natural gas
State renewable portfolio standards (RPSs)	State RPS (RPS)	Enforce state-level RPSs, including constraints for renewable energy credit (REC) creation and REC trading
Operating reserves	Operating reserves (OR)	Balance the supply and demand for operating reserves and limit which technologies can provide reserves

Model dimensionality is typically categorized by space, time, and the technologies represented. Across space, the number of regions is defined based on the spatial extent and the size of the regions. The spatial dimension can be reduced by limiting an analysis to a small number of regions and/or by clustering regions into larger groups [41]. For this study, we tested a scenario focused on the ERCOT interconnection, which represents about 5% of the total number of regions in the full U.S. ReEDS model.

In the time domain, models include both operation time periods (e.g., time slices) and investment time periods (e.g., years). Models need sufficient operational time periods to capture, for example, seasonal and diurnal patterns for load and renewable resource profiles. For investment time periods, some analyses focus on the year-to-year pathway from today to the future, whereas others focus on the system design for a single future year. For this study, we test a scenario with investment decisions made once in each decade versus the default of 2-year investment periods through 2030 and 5-year investment period thereafter.

With respect to technologies, models can track generation capacity as individual generators or clusters of generators. Clusters are typically defined based on the location, age, and performance of the generators. For this study we did not adjust the default assumptions of the technology representation.

2.6 Establishing a baseline for solve time

Before testing the above methods, we established baseline solve times for both CPLEX (the default solver used by NREL [10]) and CLP. All runs were performed on an Intel(R) Xeon(R) Gold 5120 machine with CPU speeds of 2.20GHz along with 14 Cores, 28 Logical Processors, and 768 GB of memory [42].

The default, U.S. reference case for ReEDS Version 2020, was used for the baseline [22]. Figure 1 reports the baseline solve times for the two solvers. Table 4 summarizes the problem size before and after the CPLEX presolve. CPLEX employs a presolve that reduces the original size of the model. This is shown in the GAMS log as “reduced LP size”. The CLP output in the GAMS log was not available by default but was applied and did impact the size of the LP.

The recorded problem size was the same regardless of the solver used, so the values reported are from CPLEX output. Figure 2 reports the model size as it increases throughout the solution time. Figure 1, shows that the full ReEDS model can be solved by CPLEX, but after the year 2022, the solver CLP times out after the default timeout of 10,000 seconds spent on one model year. Figure 2 visualizes the problem size after presolve and highlights how the ReEDS problem size increases throughout the model horizon. The baseline values in Figure 2. are the same for both the commercial and open-source solver and were used throughout the study to characterize the various methods employed to improve tractability and solve time.

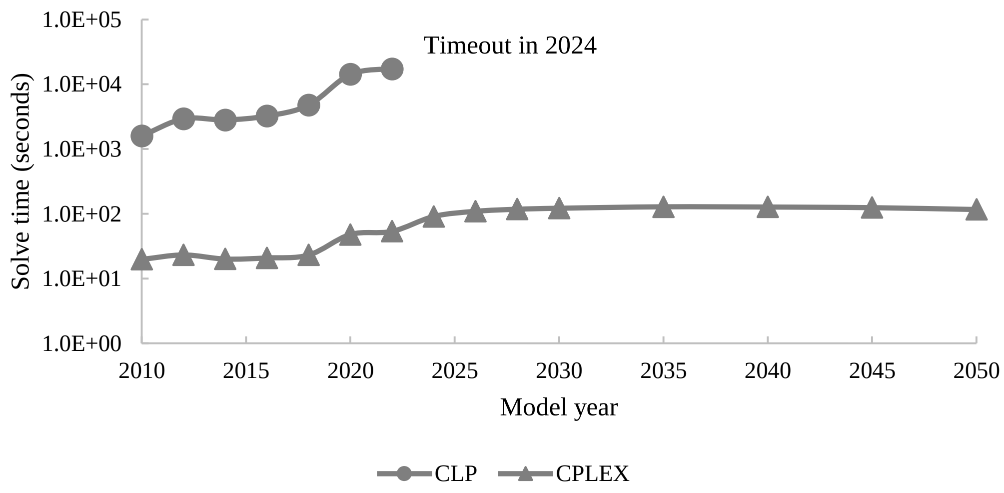

Figure 1.

Table 4. Baseline problem size in 2050.

ReEDS Model Instance	Rows	Columns	Nonzeros
U.S. (2050) – CPLEX	3.0 million	4.5 million	23.3 million
U.S. (2050) – after CPLEX presolve	0.44 million	0.52 million	2.4 million

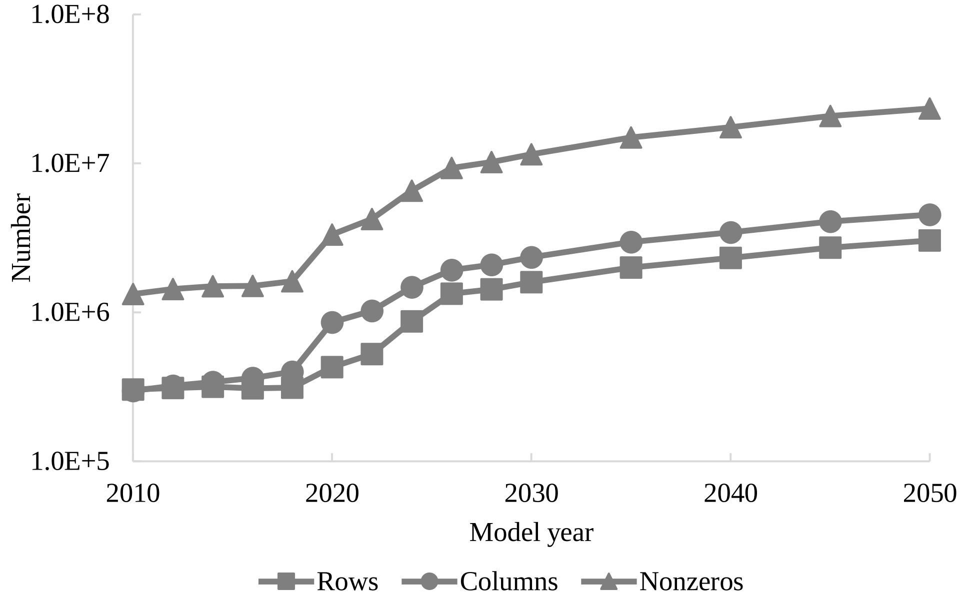

Figure 2.

3 Results and Discussion

Table 5Figure 5 summarizes the suite of ReEDS scenarios that we attempted to solve using CLP. These scenarios are modified versions of the default formulation of the ReEDS model using strategies described in Section 2, including rounding parameters, scaling parameters, removing variables and constraints, and reducing the model dimensions.

Table 5. Summary of the ReEDS scenarios attempted using the CLP solver.

Scenario Name	**Technique**	**Description**	**Impact on 2010 solve time relative to CLP – BASE***	**Percent change in objective value****
BASE	N/A	Default U.S. model	Timeout in 2024	N/A
Emit_rate	Rounding parameters	Set the rounding of the emissions rate parameter to four decimal points	No solve time improvement through 2022 Timeout in 2024	N/A
Emit_scale	Scaling parameters	Scale the emissions variables and constraints using a scaling parameter that is specific to the pollutant type	No solve time improvement through 2022 Timeout in 2024	N/A
EMIS	Removing variables and constraints	Turn off all constraints associated with emissions	Approximately the same problem size as BASE No solve time improvement through 2022 Timeout in 2024	N/A
RPS OR	Removing variables and constraints	Turn off state RPS requirements and operating reserve requirements	20x reduction in solve time through 2022 Solves through 2050	- 0.44%

CAP TECH RPS OR	Removing variables and constraints	Turn off constraints for capital stock such as endogenous retirements, technologies, state RPSs, and operating reserves	20x reduction in solve time through 2022 Solves through 2050	+ 0.73%
ALL	Removing variables and constraints	Turn off all model features indicated in Table 3	27x reduction in solve time through 2022 Solves through 2050	+ 0.56%
ERCOT	Reducing the model dimensions	Reduce the spatial extent to the ERCOT system	30x reduction in solve time Solves through 2050	0%
DECADES	Reducing the model dimensions	Original U.S. model solved only for 2010, 2020, 2030, 2040, and 2050	Limited solve time improvement Solves through 2020	N/A

*Because several runs did not run to completion, one model year was selected for comparison.

**The percent change in the total system objective cost from CPLEX – BASE in the year 2050

3.1 Exploring the solvability of ReEDS using CLP

Figure 3 summarizes the solve times associated with different scenarios using CLP. To compare the performance of CLP versus CPLEX, we include the solve times for BASE, ERCOT, and DECADES using CPLEX.

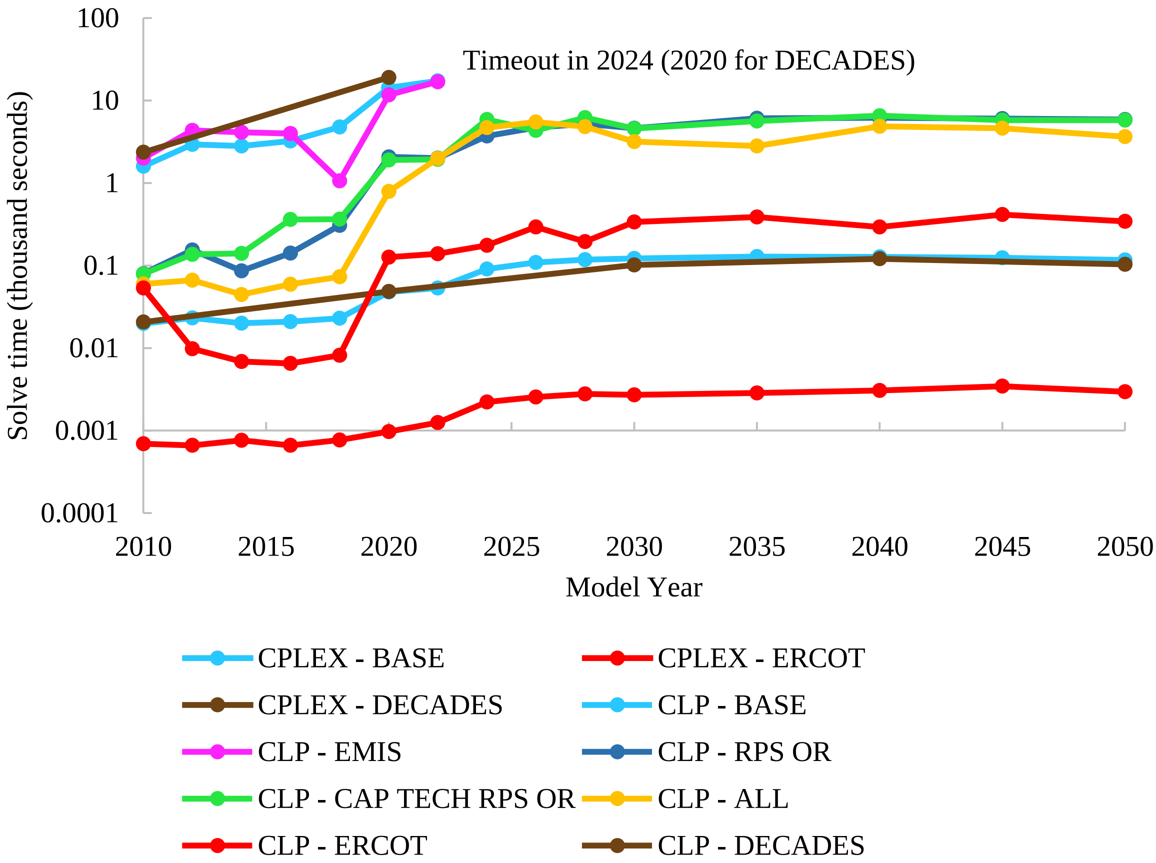

Figure 3.

Figure 3 shows that the removal of emissions constraints alone is not sufficient to enable CLP to solve additional model years within the cutoff time. The two scenarios with parameter modifications—Emit_rate and Emit_scale—were omitted from Figure 3, because the modifications made to the model for these scenarios did not change the outcome relative to BASE. CLP was able to solve all model years (to 2050) for scenarios that removed combinations of variables and constraints, including emissions policies, capital stocks, RPS policies, reliability and carbon capture and storage (CAP TECH RPS OR, RPS OR, and ALL). The RPS OR scenario was solved by CLP for all model years with the fewest number of constraints turned off. This is important to note because fewer constraints turned off means fewer changes to the formulation, potentially resulting in the most comparable solutions to the BASE model. The implications of turning off these constraints on the ReEDS solution are explored in Section 3.2. The ALL scenario was solved by CLP for all model years with the fastest cumulative run time relative to other scenarios with variables and constraints removed. Although solve times for ReEDS scenarios using CLP were improved as more variables and constraints were removed, the removal of certain variables and constraints were more effective at accomplishing this goal.

To understand the source of solve time improvement, we reviewed changes in problem size. In the CLP – ALL scenario, the number of rows, columns, and nonzeros were all reduced from the full model, as seen in

Figure 4. As a result of the iterative sequential solving process in ReEDS, discussed previously in Section 1.1, the size of the problem increases significantly as the model progresses to years further into the future. In general, it was observed that a reduction in problem size helped the problem solve faster.

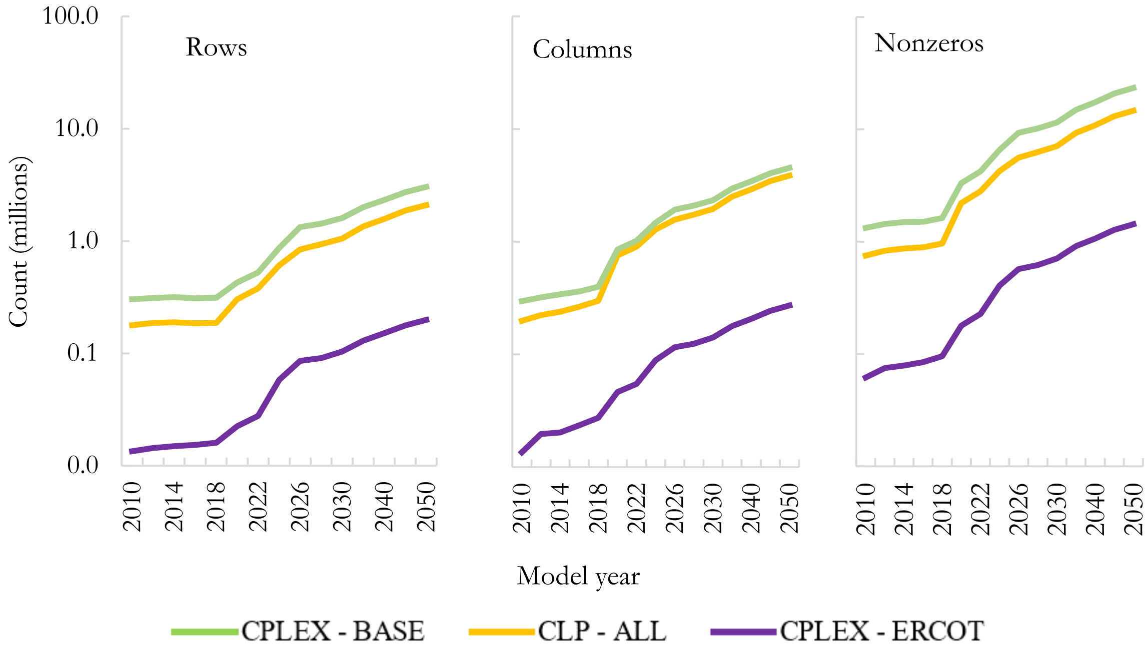

Figure 4.

Model output

When a model formulation is adjusted to improve solvability of the model, the modified formulation may yield different results from the full-featured model. Past efforts in electricity system capacity expansion modeling have compared the trade-offs of model resolution, solve time, and outcomes [37, 38].

Here we evaluate the impact of using reduced-form ReEDS problem instances on select model output metrics, including national CO_2 emissions, installed capacity, and system cost. We limit our inspection to scenarios that were solved by CLP for all model years (RPS OR; CAP TECH RPS OR; and ALL) and compare them to the BASE scenario solved by CPLEX (as the BASE scenario was not solved by CLP).

Figure 5 shows the deviations in CO_2 emissions from the BASE scenario. The emissions deviations become more dramatic after 2022. This is in part due to how ReEDS treats historical years differently, as previously discussed. However, aside from that model characteristic, the RPS OR scenario deviates the least when compared to the other scenarios that also ran through 2050. A general observation can be made that when the renewable portfolio standards are omitted from the model scenarios, emissions increase significantly. This is confirmed by calculating the cumulative emissions over the entire modeling horizon and weighting each year to account for the step size (e.g., 2030 represents 2 years; 2045 represents 5 years). We find that the corresponding increases in cumulative CO_2 emissions from BASE for runs ALL, CAP TECH RPS OR, and RPS OR are approximately 5.9%, 5.7%, and 1.7%, respectively. This is an indicator that while CLP can solve a modified ReEDS scenario, it cannot solve high renewable energy and/or low carbon scenarios within 10,000 seconds per solve year on the machine tested.

To mitigate the effects of excluding the state RPS constraints, a practitioner could apply a renewable production incentive within the objective function to serve as a proxy for REC payments to renewable energy sources. Ultimately, practitioners must decide which sacrifices in model features are most appropriate given the analysis questions of interest. In a high-penetration renewable electricity future, state-specific RPS policies may no longer be binding. However, the regionality of RPS policies may have implications on renewable energy deployment in the near-term planning horizon, and thus the appropriate incentives should be captured in the model even if they are simplified.

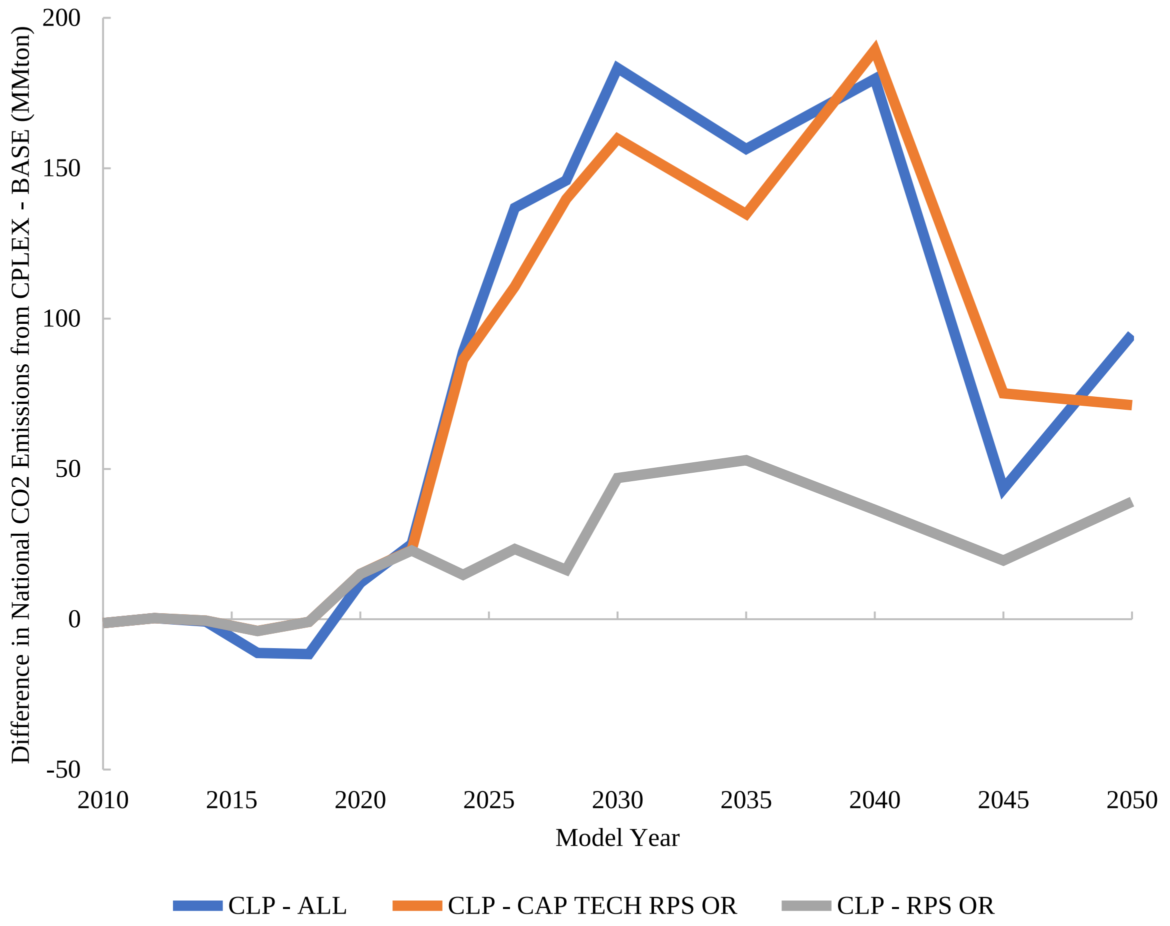

Figure 5.

Figure 6 summarizes the deviations in national capacity from the BASE scenario for select technologies that experienced the most significant fluctuations, including coal, combined cycle natural gas, offshore wind, onshore wind, utility PV, and 4-hour batteries. The RPS/OR scenario resulted in the least significant deviations except for the wind-offshore technology. For this technology, all scenarios responded with the same changes from BASE.

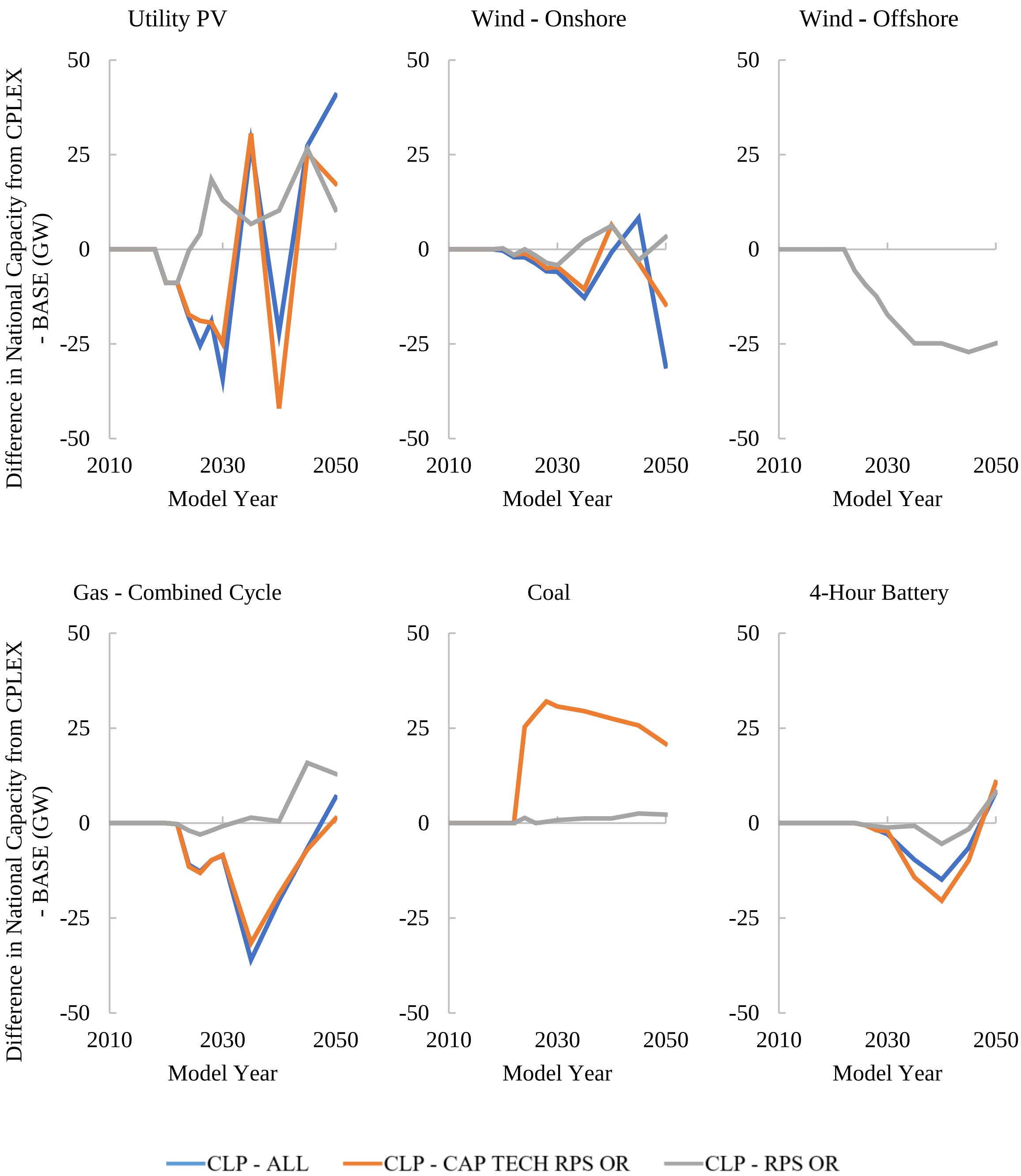

Figure 6.

Figure 7 summarizes the deviations in the objective function from the BASE scenario. The cumulative percent differences in system cost from BASE for ALL, CAP TECH RPS OR, and RPS OR are 1.31%, 1.22%, and -0.24%, respectively. The fuel cost increases are likely because of the increase in conventional generation in the system capacity due to the elimination of the RPS constraints. Across the different scenarios, the transmission cost experienced the most negative percent change from BASE. This can be explained by the fact that the model solution is relying on fewer renewable energy resources and more on centralized resources, therefore requiring less transmission infrastructure. Taken as an average across the different cost variables, the CAP TECH RPS OR scenario had the most significant percent change in magnitude from the BASE scenario.

The ReEDS modeling results are mostly prescriptive through the 2020 model year, as these are historical years, but we allow ReEDS to build combustion turbine gas technologies during these years as a slack variable for maintaining model feasibility in historical years.

The graphs in Figure 5 through Figure 7 highlight deviations from the BASE run across different metrics. The magnitude of the deviations became more substantial beyond the year 2022. The scenarios with fewer constraints eliminated (i.e., fewer model formulation modifications) resulted in less significant deviations from the BASE scenario. As modelers attempt to improve the solvability of their chosen model on open-source solvers, they should stay mindful of the modifications that result in the fewest constraint eliminations to produce results closets to the original model formulation.

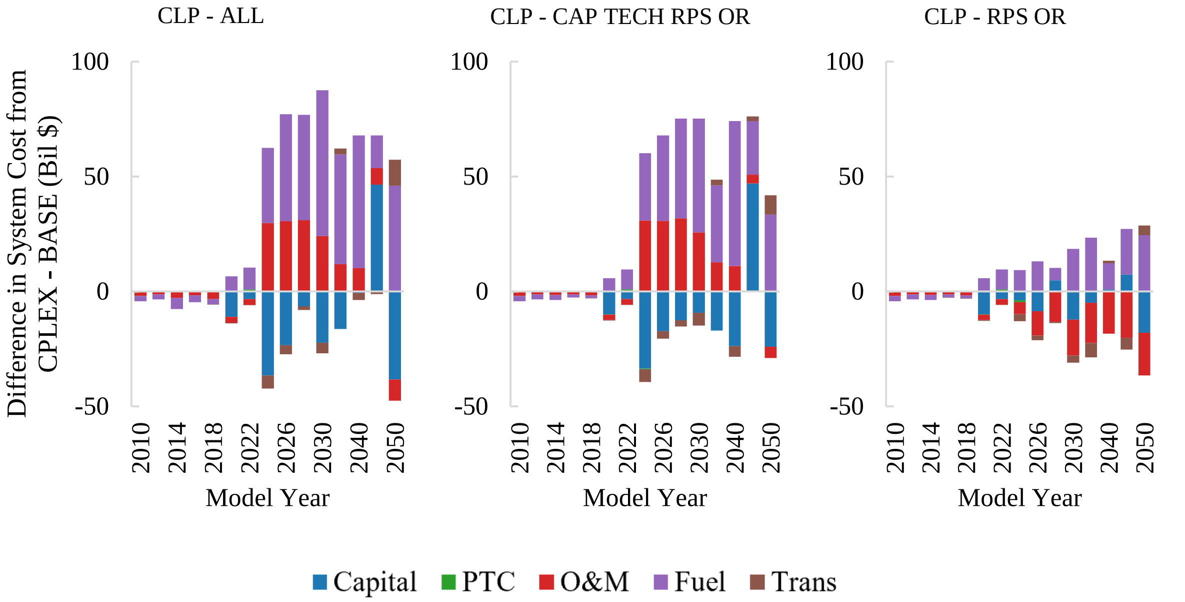

Figure 7.

Conclusions

In this study, we examine the potential for an open-source solver to compute solutions for a large-scale capacity expansion model of the U.S. electric power system. We identify the CLP solver as the most viable option to use for the ReEDS model based on several evaluation criteria, including: (1) it is free or low-cost access for all users, (2) it is open-source or publicly available, (3) it includes the interior point method, (4) it is easily linked through GAMS, and (5) it is represented and performed well in past benchmark studies. Compared to other studies discussed in this paper, we conduct an analysis on solver performance for an energy model and determine methods for how the solver performance (i.e., solve time speed) can be improved through modifications to the energy model formulation. While we find CLP to be the best candidate open-source solver for ReEDS, CLP may not be the best option for all models. A limitation of our study is that only one model was tested on several solvers. The ReEDS modeling community is not a complete representation of the energy system modeling community. Therefore, expanding this study to other large energy models would broaden the reach of this study's findings to more energy modelers. The techniques applied in this study to investigate the utility of open-source solvers on ReEDS can be used by other researchers on their own models of interest.

Although CLP was unable to solve the full-featured ReEDS model within the designated cutoff time of 10,000 seconds per solve year, it was able to solve reduced-form versions of ReEDS through the entire modeling horizon within the cutoff time. We reduce the problem size by excluding certain model features—regional emissions policies, endogenous retirements, carbon capture and storage technologies, state RPS policies, and operational reliability requirements—and reducing the dimensions of the problem. For the reduction of dimensions, we only explore a smaller spatial extent and fewer number of years modeled, but other dimensions could be reduced, including spatial resolution, temporal resolution, and technologies represented. For the runs with reduced spatial extent (i.e., ERCOT), CLP was able to solve ReEDS for all model years with all options turned on. Reducing the dimensionality allows practitioners to maintain the model features at the expense of lower-resolution model outputs. We compare the national-level emission, generation capacity, and objective function values of the reduced-form model scenarios with those of the full feature model and find noticeable differences in the results. The variation in the results will need to be considered by individual modelers in accordance with their project needs and goals. Some additional considerations for removing the constraints selected in this study are that a solution may not be compliant with state-specific renewable generation requirements without the state RPS constraint, and that a solution may not have sufficient capacity to meet unexpected changes in supply and demand without the OR constraint. Moving forward, since there will be instances of linear program open-source solvers struggling to solve very large problems, additional work to improve the solvers themselves can make them more useful to model practitioners.

Using open-source software to solve large energy system optimization models can increase the accessibility of energy model tools. This study offers techniques that will help enable the use of open-source solvers for energy system modeling for modelers regardless of their budget or available solver resources.

Figure Captions

Figure 1. CLP and CPLEX baseline solve times for the unaltered ReEDS model.

Figure 8. Baseline problem size for full ReEDS model.

Figure 9. Solve time summary.

Figure 10. Number of rows, columns, and nonzeros in the linear program ReEDS following formulation modifications.

Figure 11. Difference in national CO_2 emissions from CPLEX – BASE, 2010-2050.

Figure 12. Difference in national capacity from CPLEX – BASE ***by select technology****, 2010-2050. (All three scenarios are depicted in each chart, however, in the instance of the coal graph, CLP – ALL is not visible. The CLP – ALL results align with those of the CLP – CAP TECH RPS OR run for coal. In the instance of the offshore wind graph, CLP – ALL and CLP – CAP TECH RPS OR results are not visible because they align with the results of the CLP – RPS OR result.)*

Figure 13. Difference in system objective cost from CPLEX – BASE.

Acknowledgements

The authors would like to thank Daniel Steinberg, Alexandra Newman, and Patrick Brown for their assistance with the writing of this paper.

Funding

The work was supported by the Department of Energy: Strategic Priorities and Impact Analysis Office.

References

[1] M. Groissböck, “Are open source energy system optimization tools mature enough for serious use?,” *Renew. Sustain. Energy Rev.*, vol. 102, pp. 234–248, Mar. 2019, doi: 10.1016/j.rser.2018.11.020.
[2] “Temoa – Tools for Energy Model Optimization and Analysis.” https://temoacloud.com/ (accessed Jan. 13, 2021).
[3] “OSeMOSYS,” *OSeMOSYS*. http://www.osemosys.org/ (accessed Jan. 13, 2021).
[4] “News | Open Source Initiative.” https://opensource.org/ (accessed Feb. 17, 2021).
[5] “openmod - Open Energy Modelling Initiative.” https://openmod-initiative.org/manifesto.html (accessed Feb. 17, 2021).
[6] M. Heron, V. L. Hanson, and I. Ricketts, “Open source and accessibility: advantages and limitations,” *J. Interact. Sci.*, vol. 1, no. 1, p. 2, May 2013, doi: 10.1186/2194-0827-1-2.
[7] “solver:academic_programs_by_solver_partners [GAMS Support Wiki].” https://support.gams.com/solver:academic_programs_by_solver_partners (accessed Jun. 02, 2021).
[8] S. R. Thorncraft, H. R. Outhred, and D. J. Clements, *Evaluation of Open-Source LP Optimization Codes in Solving Electricity Spot Market Optimization Problems*.
[9] B. Meindl, M. Templ, B. Meindl, M. Templ, and T. Wien, *Analysis of commercial and free and open source solvers for linear optimization problems*. 2012.
[10] “Regional Energy Deployment System (ReEDS).” https://www.nrel.gov/analysis/reeds/index.html (accessed Jan. 17, 2021).
[11] “Request Access to Download Model.” https://www.nrel.gov/analysis/reeds/request-access.html (accessed Jul. 27, 2021).
[12] “ATB | NREL.” https://atb.nrel.gov/ (accessed Oct. 15, 2021).
[13] A. Martinez, *Integrated Canada-U.S. Power sector modeling with the regional energy deployment system (ReEDS)*. Golden, Colorado: National Renewable Energy Laboratory, 2013. Accessed: Apr. 23, 2021. [Online]. Available: {"https://purl.fdlp.gov/GPO/gpo40815":["purl.fdlp.gov"]}
[14] J. L. Ho, W. J. Cole, and E. Spyrou, “ReEDS-Mexico: A Capacity Expansion Model of the Mexican Power System,” National Renewable Energy Lab. (NREL), Golden, CO (United States), NREL/TP-6A20-70076, Sep. 2017. doi: 10.2172/1398375.
[15] A. Rose, I. (ORCID:0000000284917814) Chernyakhovskiy, J. Palchak, S. Koebrich, and M. Joshi, “Least-Cost Pathways for India’s Electric Power Sector,” National Renewable Energy Lab. (NREL), Golden, CO (United States), NREL/TP-6A20-76153, May 2020. doi: 10.2172/1659816.
[16] S. Sattler, J. Macknick, D. Yates, F. Flores-Lopez, A. Lopez, and J. Rogers, “Linking electricity and water models to assess electricity choices at water-relevant scales,” *Environ. Res. Lett.*, vol. 7, no. 4, p. 045804, Dec. 2012, doi: 10.1088/1748-9326/7/4/045804.
[17] R. L. Newmark, S. M. Cohen, K. Averyt, J. Macknick, J. Meldrum, and P. Sullivan, “Evaluating the Impacts of Climate Change on the Operations and Future Development of the U.S. Electricity System,” vol. 2014, pp. GC22A-01, Dec. 2014.
[18] E. Zhou, W. Cole, and B. Frew, “Valuing variable renewable energy for peak demand requirements,” *Energy*, vol. 165, pp. 499–511, Dec. 2018, doi: 10.1016/j.energy.2018.09.009.
[19] E. Ibanez, T. Mai, and L. Coles, “Analyzing the Deployment of Large Amounts of Offshore Wind to Design an Offshore Transmission Grid in the United States: Preprint,” National Renewable Energy Lab. (NREL), Golden, CO (United States), NREL/CP-5500-56262, Sep. 2012. Accessed: Oct. 15, 2021. [Online]. Available: https://www.osti.gov/biblio/1051891
[20] O. Zinaman, E. Ibanez, D. Heimiller, K. Eurek, and T. Mai, “Modeling the Integrated Expansion of the Canadian and U.S. Power Sectors with the Regional Energy Deployment System (ReEDS),” National Renewable Energy Lab. (NREL), Golden, CO (United States), NREL/TP-6A20-63797, Jul. 2015. doi: 10.2172/1215138.
[21] Y. Scholz *et al.*, “Speeding up Energy System Models - a Best Practice Guide,” Jun. 2020. https://gitlab.com/beam-me/bpg (accessed Jan. 18, 2021).
[22] “Standard Scenarios.” https://www.nrel.gov/analysis/standard-scenarios.html (accessed Apr. 19, 2021).
[23] E. Klotz and A. M. Newman, “Practical guidelines for solving difficult mixed integer linear programs,” *Surv. Oper. Res. Manag. Sci.*, vol. 18, no. 1, pp. 18–32, Oct. 2013, doi: 10.1016/j.sorms.2012.12.001.
[24] “BDMLP.” https://new.gams.com/33/docs/S_BDMLP.html (accessed Apr. 23, 2021).
[25] *coin-or/Clp*. COIN-OR Foundation, 2021. Accessed: Jun. 02, 2021. [Online]. Available: https://github.com/coin-or/Clp
[26] “GLPK - GNU Project - Free Software Foundation (FSF).” https://www.gnu.org/software/glpk/ (accessed Jun. 02, 2021).

[27] "Ipopt: Documentation." https://coin-or.github.io/Ipopt/ (accessed Jan. 17, 2021).
[28] *coin-or/Ipopt*. COIN-OR Foundation, 2021. Accessed: Jun. 02, 2021. [Online]. Available: https://github.com/coin-or/Ipopt
[29] "Introduction." http://lpsolve.sourceforge.net/5.5/Intro.htm (accessed Jun. 02, 2021).
[30] "MINOS 5.5." http://www.sbsi-sol-optimize.com/asp/sol_product_minos.htm (accessed Jun. 02, 2021).
[31] *Argonne-National-Laboratory/PIPS*. Argonne National Laboratory, 2021. Accessed: Jun. 02, 2021. [Online]. Available: https://github.com/Argonne-National-Laboratory/PIPS
[32] "BEAM-ME - Project." http://www.beam-me-projekt.de/beam-me/EN/Project/project_node.html (accessed Apr. 23, 2021).
[33] "SoPlex." https://soplex.zib.de/ (accessed Jun. 02, 2021).
[34] J. L. Gearhart, K. L. Adair, J. D. Durfee, K. A. Jones, N. Martin, and R. J. Detry, "Comparison of open-source linear programming solvers.," Sandia National Lab. (SNL-NM), Albuquerque, NM (United States), SAND2013-8847, Oct. 2013. doi: https://doi.org/10.2172/1104761.
[35] "MINOS - How to Buy." http://www.sbsi-sol-optimize.com/asp/sol_minos.htm (accessed Jul. 21, 2021).
[36] "SoPlex: Overview." https://soplex.zib.de/doc-2.2.1/html/index.php (accessed Jul. 21, 2021).
[37] "Decison Tree for Optimization Software." http://plato.asu.edu/bench.html (accessed Jan. 17, 2021).
[38] "CLP User Guide." https://www.coin-or.org/Clp/userguide/clpuserguide.html#presolve (accessed Mar. 25, 2021).
[39] "Solver Manuals." https://www.gams.com/latest/docs/S_MAIN.html (accessed Jan. 22, 2021).
[40] O. US EPA, "Sources of Greenhouse Gas Emissions," *US EPA*, Dec. 29, 2015. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions (accessed Jan. 22, 2021).
[41] D. Getman, A. Lopez, T. Mai, and M. Dyson, "Methodology for Clustering High-Resolution Spatiotemporal Solar Resource Data," National Renewable Energy Lab. (NREL), Golden, CO (United States), NREL/TP-6A20-63148, Sep. 2015. doi: 10.2172/1225896.
[42] "Intel® Xeon® Gold 5120 Processor (19.25M Cache, 2.20 GHz) - Product Specifications," *Intel*. https://www.intel.com/content/www/us/en/products/sku/120474/intel-xeon-gold-5120-processor-19-25m-cache-2-20-ghz/specifications.html (accessed May 02, 2021).
[43] B. A. Frew and M. Z. Jacobson, "Temporal and spatial tradeoffs in power system modeling with assumptions about storage: An application of the POWER model," *Energy*, vol. 117, pp. 198–213, Dec. 2016, doi: 10.1016/j.energy.2016.10.074.
[44] T. Mai, C. Barrows, A. Lopez, E. Hale, M. Dyson, and K. Eurek, "Implications of Model Structure and Detail for Utility Planning. Scenario Case Studies using the Resource Planning Model," National Renewable Energy Lab. (NREL), Golden, CO (United States), NREL/TP-6A20-63972, Apr. 2015. doi: 10.2172/1215187.

Supplemental Information

SI-1. ReEDS open-access repository

https://www.nrel.gov/analysis/reeds/request-access-form.html

SI-2. Initial Test with IPOPT

IPOPT will solve the ERCOT 2010 model instance. However, IPOPT assigns levels to variables that are excluded from the optimization. For example, IPOPT assigns a value of 10,000 to the investment variable for new concentrating solar power (CSP) within a region. However, new CSP investments are not permitted in historical years.

This variable has no impact on on the objective value nor constraints. Additionally, the variable is bounded between 0 (non-negativity) and 10000 (a default upper bound for new investment in ReEDS). However, there are no constraints within the formulation that force the variable to be zero at optimality.

The nonzero value of this CSP investment variable is valid, but not wanted. Therefore, Future work would identify where these variables appear in the model constraints and ensure they are excluded.

We were able to replicate this behavior for a modified version of the basic transport model. We excluded two variables from all equations except for two equation that are not binding. In this case, we expected the level of these two variables to be zero in the optimal solution. However, IPOPT (mumps) returns an optimal interior point solution where the levels for these two variables are nonzero.

STEP 1. Solve transport.gms using IPOPT and find x.l(i,j) = 0 for two routes (i,j) between plant 'i' and market 'j'.

```
----      83 VARIABLE x.L  shipment quantities in cases

             new-york     chicago      topeka

seattle        38.569     300.000
san-diego     286.431                 275.000


Z.l = 153.67499998467878
```

STEP 2. Declare set r(i,j) for valid routes (i,j) between plant 'i' and market 'j'. Let "YES" = route (i,j) is allowed; Let "NO" = route (i,j) is not allowed.

```
set r(i,j) 'valid routes between plant i and market j' ;
```

STEP 3. Initialize all routes to "YES" (valid routes), but then define two routes as "NO" (not valid). These are the two routes whose x.l are zero in STEP 1.

```
r(i,j) = YES ;

r('seattle','topeka') = NO ;

r('san-diego','chicago') = NO ;
```

STEP 4. Apply the set r(i,j) to all constraints.

```
cost..       z =e= sum((i,j)$r(i,j), c(i,j)*x(i,j));

supply(i).. sum(j$r(i,j), x(i,j)) =l= a(i);

demand(j).. sum(i$r(i,j), x(i,j)) =g= b(j);
```

STEP 5. Add a new equation to define the upper bound for x(i,j), but limit this equation to apply only to routes that are not valid, i.e., r(i,j) = NO.

```
supply_ub(i,j)$[not r(i,j)].. x(i,j) =l= 1000 ;
```

STEP 6. Solve this modified version of the transport model using IPOPT and find that x.l(i,j) is greater than zero for the two routes that are not valid:

```
----      83 VARIABLE x.L  shipment quantities in cases
```

```
             new-york     chicago      topeka

seattle        44.766     300.000     306.983
san-diego     280.234     306.983     275.000

Z.l = 153.67499998471507
```

SI-3. Python Code to parse MPS files

```
import raw_value streams as rvs

import pandas as pd


mpsfile=rvs.get_df_mps('mpsfile.mps')


def high_values(df,max_val):

    high_values = df[df['coeff'].abs()>max_val].copy()

    return high_values


def low_values(df,min_val):

    low_values = df[df['coeff'].abs()>min_val].copy()

    return low_values


mpsfile_high = high_values(mpsfile, 1000000)

mpsfile_low = low_values(mpsfile, .000001)


pd.Dataframe.to_csv(mpsfile_high,'mpsfile_high.csv')

pd.Dataframe.to_csv(mpsfile_low,'mpsfile_low.csv')
```