Understanding the Computing and Analysis Needs for Resiliency of Power Systems from Severe Weather Impacts

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ABSTRACT

As the frequency and intensity of severe weather has increased, its effect on the electric grid has manifested in the form of significantly more and larger outages in the United States. This has become especially true for regions that were previously isolated from weather extremes. In this paper, we analyze the weather impacts on the electric power grid across a variety of weather conditions, draw correlations, and provide practical insights into the operational state of these systems. High resolution computational modeling of specific meteorological variables, computational approaches to solving power system models under these conditions, and the types of resiliency needs are highlighted as goal-oriented computing approaches are being built to address grid resiliency needs. An example analysis correlating outages to 1km day-ahead weather from two historical winter storms, calculated on a large cluster using a combination of interpolated and extrapolated inputs from multiple instrumented sites to workflows that produce primary meteorological outputs, is shown as initial proof of concept.

CCS CONCEPTS

• Applied Computing • Information systems → Information systems applications • Computing methodologies → Modeling and simulation

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KEYWORDS

Power grid, resiliency, extreme weather, computational approaches, analysis.

1 Introduction

Advances in technology such as electrification of vehicles and buildings are increasing customer electricity demand and customer expectations of power system reliability [37]. At the same time, increases in frequency and intensity of extreme weather events continue to challenge energy reliability across the United States power grid. Since the year 2000, many studies have found that the leading causes of large electricity outages are weather related [26, 1, 19]. These challenges must be addressed to identify strategies for performance under extreme weather conditions and assess potential grid weaknesses in order to mitigate the reduced grid performance and improve the resilience and reliability. Additionally, gas availability, (including contractual and physical supply disruption), seasonal availability constraints, and infrastructure limitations; and transmission availability and congestion must be addressed [24]. In recent years, researchers have applied machine learning (ML) techniques to predict power outages based on winter weather, land use, grid asset status, vegetation management and other conditions [5, 23, 7, 35]. Here we outline the issues associated with extreme weather and grid resilience, demonstrate a cold weather use case for which correlation and machine learning methods are applied, and discuss how large computing facilities can help predict and facilitate energy reliability and resilience.

2 Background

We provide an overview of the effects of severe weather such as extreme heat or cold, high winds, and flooding on the power system followed by an introspection of the state of the power system under such constraints and particularly with increasing penetration of renewables.

2.1 Severe Weather

Increasing frequency and intensity of extreme weather events continues to raise concerns about the resilience of the electric grid to present and future climate and extreme weather hazards [3]. For example, increased severity of extreme weather events was the principal contributor to an observed increase in the duration of U.S. power outages between 2000 and 2012 [19]. Additionally, during the period of 2014–2018, a total of 891 events of power outages were reported to be caused by severe weather events [1].

Extreme weather and climate-related threats to electrical grid systems include heat waves, drought, wildfire, flooding, ice storms and damaging winds from high-energy hurricanes and tornadoes. For example, transformers and power lines are particularly vulnerable to persistent high ambient air temperature, which can cause short lifetimes or abrupt failure of these components. Average power output from these components decreases 0.7% to 1% per 1 °C increase in air temperature above 20 °C [21]. Additionally, the lifetime of a transformer is limited by the "hot spot" temperature, the highest temperature within the windings of the transformer, which can be much greater than the ambient temperature [32].

Severe drought can cause thermoelectric power plant water reservoir levels to drop below the level of intake valves that supply the cooling water to those plants, causing plants to stop or reduce power production [18]. Low anomalies in hydropower generation have expressed a strong linear correlation between low streamflow anomalies and generation [2]. Wildfires can consume support structures for electric grid assets; and heat, smoke and particulate matter from wildfires can affect the transmission capacity of power lines. For example, the insulators that attach the lines to the towers can accumulate soot and enable leakage currents; and ionized air in smoke can act as a conductor, causing arcing between lines or between lines and the ground [8].

Flooding poses risks primarily to underground transmission and distribution systems, as water seepage from flooding may follow electrical lines back to underground conduits and vaults and cause damage to both underground power lines and substations [15]. Ice storms can lead to ice accumulation on overhead power lines, stressing the lines and increasing the probability of line galloping and line breakage under moderate wind exposure [16]. Additionally, the combination of low temperature and high humidity can lead to natural gas pipeline and wind turbine freezing and shut down of these generation resources [10]. In fact, nearly half of all major outage events for the years 2015-2019 were caused by extreme winter weather associated with low temperatures, high winds, heavy snow, hail, and blizzards [11]. Finally, high winds can snap towers and poles and down power lines leading to further downstream electric grid asset failures as a result [12].

2.2 Impacts on Electrical Power Systems

Electrical power system reliability involves the performance of the electric grid against high probability, low consequence events. When we think of the electric grid's resilience to weather events, it involves the performance of the electric grid due to low probability, high consequence events such as hurricanes, earthquakes, and man-made threats. Resilience can be thought of as the ability of the grid to prepare for and adapt to changing conditions, withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents [24].

The future electric grid reliability and resilience investigations typically cover a balanced portfolio of all aspects of the bulk power system (BPS) from generation through end-use, e.g., transmission, generation, and demand [25]. Thermal generating units are the foundation of the grid, but due to renewable portfolios, decarbonization goals and cost competitiveness, the future of these generation units is in doubt. Natural gas is currently the fastest-growing source of electric power generation, according to data from the United States Energy Information Administration (EIA) Hourly Electric Grid Monitor (https://www.eia.gov/electricity/gridmonitor/dashboard/electric_overview/US48/US48). The increase in natural gas-fired generation was the result of recent low prices and natural gas-fired power capacity additions. Natural gas-fired generation has generally increased in most U.S. regions since 2015, according to data from the EIA Power Plant Operations Report (https://www.eia.gov/electricity/annual/pdf/epa.pdf). Annual electricity generation from natural gas power plants in the United States increased by 31% in the Northeast region, by 20% in the Central region, and by 17% in the South region between 2015 and 2019. In the western region of the continental United States, electric power generation from natural gas power plants remained relatively flat during the same period.

Wind and solar energy sources are becoming a larger portion of the grid and their presence may make operations more challenging in some ways, but also provide some significant benefits [28]. For example, when hurricanes hit, wind and solar will not be able to produce electricity generation during the duration of the storm. The winds will be too high and cloud cover will block solar from providing energy during the storm. However, distributed solar can help during these extreme events, as was seen in Florida, when the grid goes down and adds a local resilience effect that can keep power on in communities and help communities recover quickly. Renewables add another challenge to the system because they are uncertain and variable [33]. Large amounts of computing power will be needed to maintain sufficient forecasts and perform large-scale coordination of these renewable resources across regions to maintain reliability and resilience of the grid.

Large-scale weather patterns can affect multiple states and coordination across these regions can be challenging during severe weather events. It is likely that during this energy transition, we will need traditional energy sources such as natural gas to maintain reliability and resilience of the grid during these severe weather events. As we are able to build up our capacity for forecasting, storing large amounts of energy in the form of long-duration storage [34], and advanced controls of these assets [17], we will be able to transition to a 100% clean energy future.

In the near future, many local and regional policy transitions could begin to impact the reliability and resilience of the electric grid that is closely connected with the interdependency of the natural gas system, water systems and telecommunications infrastructure. In an effort to examine the reliability and resilience of the electric grid and natural gas transportation availability, our research identifies and describes the specific reliability and resilience metrics that can possibly be used.

2.3 Computational Aspects

Computing and computational approaches play a vital role in the operations and upkeep of the power sector [13, 22]. The computing needs are several and can be broadly decomposed into planning, operational, and extraordinary circumstance needs.

The planning needs can range from short-term day-ahead type of load and generation predictions to significantly longer term needs around infrastructure planning, siting, and resource planning. It is interesting to note that the level of uncertainty and the influence of externalities increases as we get into the longer time frames. Population movements, business opportunity changes, changing energy mix, and types of generation become important. With the increasing penetration of renewables and utilities and governments having certain clean energy targets, the understanding around future generation mix and types and length of energy storage is becoming increasingly complicated, and perhaps uncertain. Numerous computational and algorithmic tools are being developed to specifically address this problem. One such tool is the Hybrid Optimization and Performance Platform (HOPP) [14], which is a software tool that enables detailed analysis and optimization of hybrid power plants down to the component level. It has the capability to assess and optimize projects that contain combinations of wind (onshore and offshore), solar, storage, geothermal, and hydro. The HOPP platform aims to answer the crucial question "When and where do hybrid plants make sense, and how can we design them optimally?" HOPP leverages other computational tools to size, analyze, and design the hybrid power plants of the future, allowing for detailed output on a myriad of design conditions, from number and types of turbines to the overall layout and topology of assets within the system. An average case run of HOPP involving component scale analysis with an optimization objective can easily use a few hundred cores for several hours. Tools such as HOPP are particularly important as we begin to address the changing climate and its resulting impacts on our power systems.

When addressing large computing needs for the large-scale power systems, there are several limitations. For example, PSSE (product of Siemens) is a power system dynamics computational tool that simulates the impact of transient events on large power systems (up to 100K buses) to observe dynamic behavior in the 0.1 – 3.0 Hz range. This corresponds to both small signal stability and transient stability phenomena that have been identified as culprits in some of the largest blackouts in North America history. However, because of its prevalence in transmission planning departments of eastern North America utilities, there are significant datasets and models available in PSSE that are widely used in simulations of the US Eastern Interconnect or EI. Therefore, PSSE is often chosen as the primary electric grid simulation tool for computing high performance scenarios.

Likewise, PowerWorld has become widely used in the western North America utility community. Models and datasets compatible with PowerWorld and available through WECC (Western Electricity Coordinating Council) make it a natural choice to study scenarios in the US Western Interconnect or WI. Seeding these models with good data and at high resolutions is a continuing challenge.

On the operational side, the computational tools are quite mature and are designed with aspects of providing time-constrained analysis results. Many generation and transmission utilities have extensive home-grown software tools to address their unique needs. A sub-class of these software systems are designed to orchestrate control actions at various time scales (from sub-second to time-of-day). Huge challenges as well as opportunities are emerging in this area as the end use of energy applications are getting smarter offering up the ability to control the devices and be able to shape the nature of load demand for the grid. A number of new elements in the controllability of equipment are emerging, notably, the ability to organize a large number of end use devices in a reliable enough fashion to meet certain grid needs [38]. Model-predictive control, control-theory based approaches, reinforcement learning and transfer learning-based approaches, as well as statistical methods to are emerging. Having a large number of distributed energy resources adds grid stability issues in managing the real and reactive component in the power. Significant computational challenges exist in addressing the needs and maturing these approaches to the level of robustness needed for wide adoption. More specifically, some of the specific challenges are:

- The distributed devices have different levels of participation in their availability for control.
- For those that participate, human override of the controls is extremely common and unpredictable, even with incentives.
- These devices have a variety of communication protocols and non-standardized (often proprietary) standards.
- Individual devices exist their own surroundings and respond to changes to variables such as temperature. Having that level of observability of anticipated behavior is difficult and can invade on privacy.
- Their collective control is necessary to meet the needs of the future electric grid having high penetration of renewables. When shaping the load using control, transients can get introduced in the power system leading to instability.

The third category of computational needs are around severe events and extraordinary circumstances or scenarios. The nature of the computational needs is very cross-disciplinary. These situations could arise when extreme weather conditions are prevalent, or when certain human induced events cause disturbances in the grid.

There may be some weather events like a hurricane or snowstorm that may have a lead time of days. There could be other events that have very little lead time, such as earthquakes. The computational needs in such scenarios require the knowledge and setup that can predict the severity and extent of impact of the weather phenomenon to a level of sufficient confidence and then the ability to evaluate computationally the resulting impact on the power grid. Recent events such as the extreme hot and cold waves seen recently in Texas are pointing to a need to build more reliable mathematical constructs that can help understand the consequences using an interdependent system of systems approach.

Generation sources such as wind and solar have a distinct highly temporal dependance on the state of wind and cloud cover. Cloud cover, in particular, can be challenging to predict at near real-time timescales. Highly localized irradiance forecast with cloud cover are needed to anticipate solar production and both are notoriously difficult to obtain using standard forecast data. An emerging body of work is using sky facing cameras to anticipate photovoltaic power production factoring in weather conditions, cloud density, and the changing cloud positions [40]. These methods have value in the 5 – 15 minute time horizon; however, their reliability becomes questionable for longer timeframes.

Fortunately, instrumentation and the ability to collect fine resolution data, both spatially and temporally, is rapidly improving and paving the way for data-driven models to be built that are showing significant promise. Several Artificial Intelligence and data-driven methodologies are now being developed to address this need for the sector. The future grid having an increasingly larger share of distributed energy resources will force our hand to mature these models as we address power flow, stability, and resiliency needs.

3 Power Sector Impact Analysis

Herein we discuss the types of analysis needs starting with a discussion of cross-sector interdependencies, reliability versus resilience, and metrics to quantify them.

3.1 Cross-sector interdependencies

In 2019, 40% of the natural gas delivered by transmission and distribution pipelines went to electric power plants, 30% to industrial plants, and 30% to residential and commercial consumers. Gas transmission reliability is an important factor to gas generation units and distribution reliability should be analyzed for residential and commercial consumers. The distribution and transmission of gas pipelines are subject to different regulations which affect reliability analyses.

Modeling and analyzing the weather driven resilience of natural gas is necessary to understand its risks and its contribution to grid infrastructure improvement decisions to make it less vulnerable to weather-related outages and reduce the time it takes to restore power after an outage. An integrated electricity and natural gas analysis is highly recommended; however, performing one of these at regional to national scales involves the obtaining of natural gas flow data, the type, configuration, and operation of pumping stations, potentially pricing information, as well as current operational status of these units. A holistic approach suffers from being accurate enough because of the complicated data acquisition process.

The natural gas sector is but one of several other sectors impacting the analysis. The availability of coal and the supply chain for coal continues to be a need. The sector is, however, relatively mature and sufficient understanding exists to model these components well.

To integrate the natural gas interdependency, one can assume to begin with the generating capacity and demand projections from the North American Electric Reliability Council's or NERC's Long-Term Reliability Assessment and the Bulk Electric System (BES) transmission topologies as defined in its Western Electricity Coordinating Council (WECC) Anchor Data Set, Eastern Interconnection Reliability Assessment Group Multi-Regional Modeling Working Group (ERAG/MMWG) Data Set. From here one can calculate baseline regional power sector gas demands from present electricity delivery year through the end of delivery year by applying security constrained economic dispatch. The load demand can then be compiled along with demand projections for regional residential, commercial, and industrial natural gas demands from the most recent Energy Information Administration (EIA) Annual Energy Outlook Reference Case into Deloitte's MarketBuilder® North American Gas Model. Through the application of these demands, MarketBuilder® one can project the topology of natural gas flows in the natural gas pipeline network across the interconnected North American system along with regional natural gas prices that may be seen by market participants in future years.

It is worth nothing that nuclear energy provides an alternate option that does not suffer from sudden ramps, can provide for adequate spinning reserve, as well as be extremely resilient. However, nuclear energy has historically been controversial even though some countries like France produce bulk of their energy from nuclear.

Emerging trends indicate the need to incorporate the status of communications infrastructure to approach a near-complete understanding of the state of the power sector.

The computational needs point to building systems-of-systems that have roots in graph-theory based models and analysis. The key is in adequately establishing the relationships between the various nodes and edges. The computing solutions heavily involve solving power flow models and using the outputs to derive the consequences on interdependent systems.

3.2 Reliability versus Resilience

A main differentiator between reliability and resilience is the frequency and impact of an event. Reliability focuses on assuring adequate electric grid operations in typical conditions, through real-time load and generator balancing, and operating equipment within defined limits. Resilience focuses on the operation of the electric grid during extreme and adverse events, which can be categorized as atypical and emergent conditions. Another distinction between reliability and resilience is that a system may be considered reliable without identifying a specific threat to the system. However, when discussing resilience, systems are considered resilient to a particular threat or set of threats. Hence, reliability metrics do not attribute the cause to the metric (e.g., a load is de-energized without regard to why or how), whereas resilience metrics do consider the cause (e.g., a hurricane caused the load to be de-energized). Therefore, resilience bridges the gap between the system response and a root cause.

3.2.1 Time-Dependent Analysis of an Event

An important aspect of resilience is its time-varying nature. Many of the basic elements of system resilience can be captured in different phases before and during a severe event as well as after the event, when the system has been restored. Figure 1 shows an illustrative generic resilience curve where a resilience indicator is used to quantify the resilience level of a power system during an event as a function of time. The resilience indicators are in the form of the following:

- The amount of generation capacity (MW).
- The load demand served or not served (MW).
- Number of transmission lines tripped.
- Number of outages.
- Number of customers not served.

In Figure 1, five different phases can be clearly seen: the pre-disturbance state, disturbance state, post-disturbance degraded state, recovery & restoration state, and the post-restoration state [24].

3.2.1.1 Pre-disturbance Phase

The pre-disturbance state is the operating point of the system before a severe event occurs. In this state, resources are prepositioned to prepare for an event. Remedial actions are set up to minimize the impact of the event. The metrics that are calculated in this phase include Loss of Load Probability, Planning Reserve Margins, etc. These metrics quantify the generation resource adequacy.

3.2.1.2 Disturbance Phase

The disturbance phase is the time between the start of the event to the end of the event. In this phase, the resilience indicator quantifies how fast and how low the resilience drops. This includes the amount of generation MW lost, load MW disconnected, and the rate at which generation, transmission lines, and customers are disconnected during the event.

3.2.1.3 Post-Disturbance and Degraded Phase

Following the end of the event and just before restoration is initiated is the post-disturbance degraded state. In this stage, the damages caused by the event are assessed and critical components required for recovery are identified.

3.2.1.4 Recovery and Restoration phase

A resilient system should demonstrate high restorative capabilities in order to restore disconnected customers and collapsed infrastructures. The recovery phase of the event commences at the time the system performance has reached its minimum level and ends at a point in time in which some minimally acceptable and stable level of system performance has been recovered through adaptive actions by the system and its human operators.

3.2.1.5 Post-Restoration Phase

Following the event and the restoration of the system to an acceptable operational state, the post-restoration phase begins. In this phase, the impact of the event and the performance of the network are thoroughly analyzed to identify the weaknesses and limitations of the network.

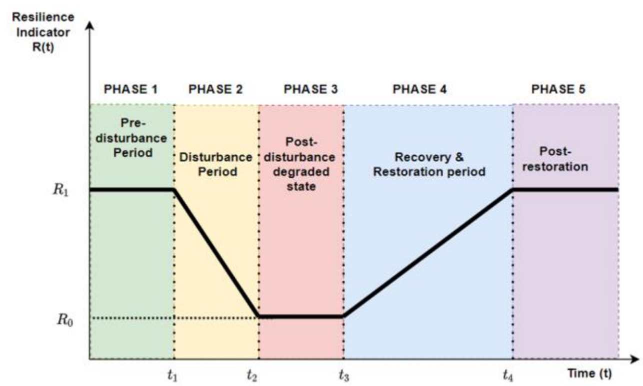

Figure 1: Multi-phase trapezoid curve [24].

3.3 Metrics for Resilience and Reliability

A discussion of reliability and resilience is incomplete without the inclusion of relevant metrics. We include a summary of the most important resiliency and robustness metrics [24]. The topic is vast and a full review is outside the scope of this exposition.

3.3.1 Resilience metrics

The following are some of the important resilience metrics [24]:

a. FLEP metric: This is a time-dependent resilience metric that captures the performance during the different event phases in terms of how Fast the resilience drops, how Low it drops, how Extensive it is, and how Prompt is the recovery.
b. Severity Risk Index: The SRI is a metric where generation loss, transmission loss and load loss events are aggregated into a single value that represents the risk to the Bulk Energy System.
c. Dynamic Resilience Indicator: The DRI addresses the need for an overall resilience measure for shorter periods of time.

d. Cumulative customer energy not served
e. Critical customer energy demand not served
f. Time to operational recovery

3.3.2 Reliability metrics

The notable reliability metrics include the following and most are self-explanatory [24]:

a. Planning Reserve Margin: This is a primary metric used to measure resource adequacy and is measured as a percentage of additional expected capacity over demand.
b. Loss of Load Probability (LOLP) measures the probability of a system daily peak demand exceeding available resources.
c. Loss of Load Expectation (LOLE) is the expected number of days per time period for which the generation capacity becomes insufficient to serve the demand.
d. Effective load Carrying Capacity (ELCC) is the amount of incremental load a resource can reliably serve.
e. Expected Unserved Energy (EUE) is the summation of the expected number of megawatt hours of demand that will not be served in a given time period as a result of demand exceeding the available capacity across all hours.
f. System Average Interruption Frequency Index (SAIFI)
g. System Average Interruption Duration Index (SAIDI)
h. Customer Average Interruption Duration Index (CAIDI)
i. Customer Total Average Interruption Duration Index (CTAIDI)
j. Customer Average Interruption Frequency Index (CAIFI)

It should be noted that SAIFI, SAIDI, CAIDI, CTAIDI and CAIFI are primarily used for the analysis of electric distribution systems.

3.3.3 The FLEP Metric Set

The FLEP metrics [5] is a time-dependent resilience metric set that captures the performance of a network during the different phases associated with an event. It includes how Fast (Φ) resilience drops, how Low (Λ) resilience drops, how Extensive (E) the post-degraded state becomes and how Promptly (Π) the network recovers to its pre-event state [5]. Figure 2 summarizes the FLEP (ΦΛΕΠ) metric set

Phase	State	Description	Symbol
1	Disturbance Progress	How fast resilience drops	Φ
2	Disturbance Progress	How low resilience drops	Λ
3	Post-disturbance degraded state	How extensive is the post-disturbance degraded state	E
4	Recovery and Restoration state	How promptly does the network recover	Π

Figure 2: FLEP Metrics Set.

Figure 3 shows the mathematical representation of the FLEP metric set, The Φ-*metric* is evaluated by estimating the slope of the resilience curve during the disturbance phase, while the Λ-*metric* is defined by the resilience degradation level at the end of the event at t_2. The *E-metric* is simply the time that the network remains in the *post-disturbance degraded state* is given by $t_3 - t_2$. The Π-metric is defined by the slope of the resilience recovery curve which considers both the resilience improvement during this phase and the time required for achieving this required for reaching this resilience level [6]. Complementing the "ΦΛΕΠ" resilience metrics system, an additional metric can be used, i.e., the *area* of the trapezoid. The *area* metric is expressed as the integral of the trapezoid for the duration of the event.

Metric	Mathematical Expression	Unit
Φ	$\frac{R_0 - R_1}{t_2 - t_1}$	MW/hours, No. of lines tripped/hours, No. outages/hours, No. of unserved customers/hours
Λ	$R_1 - R_0$	MW, No. of Lines tripped, No. of outages, No. of unserved customers
E	$t_3 - t_2$	Hours
Π	$\frac{R_1 - R_0}{t_4 - t_3}$	MW/Hours, No. of lines restored/hours, No. of restored customers/hours
Area	$\int_{t_1}^{t_4} R(t)dt$	MW X hours, No. of lines in service X hours, No. of outages X hours, No. of customers X hours

Figure 3: Mathematical representation of the FLEP Metric set.

3.3.4 Severity Risk Index (SRI)

The SRI is a metric where generation loss, transmission loss and load/demand loss events are aggregated into a single value that represents the risk to the Bulk Energy System. It can serve as a resilience indicator of the power system over a longer period. The score can show the best and poorest performance of the grid within weeks, months, or a year.

As shown in Figure 4, the SRI is the sum of three weighted components: percentage of generation lost, percentage of transmission lines tripped, and the percentage of load disconnected. To calculate the SRI, each element (generation, transmission, and load loss) is weighted by a pre-determined factor. It can be written as:

$$SRI = \beta_1 G + \beta_2 T + \beta_3 L$$
$$\beta_1 + \beta_2 + \beta_3 = 1$$

Where G is the percentage of Generation lost per hour/day, T is the percentage of Transmission lines tripped per hour/day, L is the percentage of load disconnected per hour/day, β_1, β_2, and β_3 are the weighting indices. NERC calculates a daily SRI for the BES with $\beta_1 = 0.1, \beta_2 = 0.3$ and $\beta_3 = 0.6$

Metric	Mathematical Expression	Unit
Φ	$\frac{R_0 - R_1}{t_2 - t_1}$	MW/hours, No. of lines tripped/hours, No. outages/hours, No. of unserved customers/hours
Λ	$R_1 - R_0$	MW, No. of Lines tripped, No. of outages, No. of unserved customers
E	$t_3 - t_2$	Hours
Π	$\frac{R_1 - R_0}{t_4 - t_3}$	MW/Hours, No. of lines restored/hours, No. of restored customers/hours
Area	$\int_{t_1}^{t_4} R(t)dt$	MW X hours, No. of lines in service X hours, No. of outages X hours, No. of customers X hours

Figure 4: Mathematical representation of the FLEP Metric set.

3.3.5 Dynamic Risk Index (DRI)

The authors have been involved in the development of the DRI to address the need for an overall resilience measure for shorter periods, e.g., minutes to hours. As shown in **Figure 5**, the DRI is also the sum of three weighted components:

- RR: The measure of reactive reserves, e.g., the phase angle separation between areas/regions of interest.
- LL: the Loadability limit, e.g., the point of maximum load, i.e., the tip of the nose curve.

- FA: Measure of frequency agility e.g., the percentage of frequency nadir.

Mathematically, the DRI is written as:

$$DRI = \alpha_1 RR + \alpha_2 LL + \alpha_3 FA$$
$$\alpha_1 + \alpha_2 + \alpha_3 = 1$$

Figure 5: Severity Risk Index (SRI) and Dynamic Resilience Indicator (DRI)

4 Computational Methods to Support the Analysis and Prediction

As evidenced, the need for applying the state-of-the-art in computing and computational approaches is important to enhance the resiliency of our power systems in the increasingly complex and dynamic nature of power systems. The entire range of computing and computational approaches are likely expansive. We limit this discussion to the computing approaches that are relevant for the objective of delivering resiliency during severe weather events.

4.1 Ensemble methods for severe weather

A large body of work exists that has elevated the use of ensemble methods to derive an understanding of the mean and spread of future weather forecasts. For power systems, the effects are often localized and individualized forecasts at that spatial granularity are unavailable and unreliable. There is a significant computational cost for running these ensembles and in particular, for generating dynamic nested grids for regions of significant interest. The Weather Research and Forecasting model, one of the more popular tools for weather prediction, scales well; however, its preprocessing and postprocessing involving initialization, domain decomposition, and input/output do not scale well. Ensemble scenarios require the parallel setup of different initialization conditions or parametrizations. A well-designed setup that automates most of the steps can easily consume a dedicated HPC system. Nested grids typically provide for adding higher temporal and spatial resolution in certain areas of interest within the computational domain. Each nest adds complexity and sometimes the calculations can get into indeterminate regimes that are difficult to anticipate. I/O can easily be in the 100s of TBs for an ensemble run.

The demands of a setup of high-performance computing resources in an operational close-loop environment is challenging. The costs of setup and maintaining such systems is prohibitive. Still, the benefits of having more accurate weather forecasts are highly desirable. This will translate to improvements across all metrics of reliability and resiliency as utilities will find themselves more streamlined in responding to such events.

4.2 Model development of resulting impacts

Arguably, the most significant and far-reaching impact could be had from reliably translating the anticipated severity of a weather event to the nature of impact expected on the power system. This is usually approached using fragility curves, which are essentially transfer functions that map certain variables in the weather prediction to a level of adverse impact on the power system. Some of these fragility curves can incorporate additional factors in its assessment. Building out a computational capability that can take in the complex power system network and its current state and dynamically resolve the impacts as a severe threat comes in and unfolds can have outstanding benefits. Not only can they help the operators reliably anticipate system outages, they can also help operators devise alternate solutions as certain parts of the network go down. Building in layers of maturity, some of these decisions can be automated and computed on the fly to be presented as potential options for the final decision at the operator level.

4.4 Controllability-based approaches with distributed energy resources

There is a healthy need for devising scaled up end-to-end optimization solutions that involves the control of participating hardware devices. This is a very complex landscape as there could be tens of thousands of devices that offer up controllability. Usually, the space heating and water heating appliances are the top targets for energy flexibility, but even the subset of these have numerous firmware versions, device protocols, and varying level of participation in such programs. Impending externalities such as severe heat or cold requires load management and curtailment. As such, the assured delivery of a quantified amount of load flexibility is still not mature. Fluctuating generation from renewables and right-sizing energy storage continues to be multi-objective optimization problem. Assuring robustness in such decentralized systems with varying penetrations of different distributed energy resources is an emerging computational challenge.

An additional aspect of the deep controllability problem is equity and energy justice [9]. The electric power grids tend to be less robust and reliable in historically disadvantaged geographies and communities. The quality of building construction and the availability of sufficient participating devices could vary significantly. The amount of assumed available demand flexibility in such communities could adversely affect their existing quality of life. At the same time, the penetration of distributed energy resources in these communities may itself be a challenge. Therefore, any control development that spans large geographic areas must assure a quality of service that does not adversely impact such communities.

4.5 Situational awareness and visualization

There is a distinct need for the advancement of situational awareness tools and advanced visualization capabilities for the integrated assessment of severe weather and power systems. This manifests as a multi-scale problem as the relevant time scales of weather phenomena could be in the order of minutes to hours while their impacts on the electric grid propagate in the order of seconds. Having the ability to fold in decision support tools, as discussed earlier, would offer up an ability to enhance the situational comprehension of unfolding events.

4.6 Role of Artificial Intelligence

This discussion would be remiss without the inclusion of emerging artificial intelligence approaches that hold tremendous promise. AI has pervasively touched every realm of our lives including the topic of our discussion. There are efforts underway that use AI for weather predictions, for controls development, and to devise data-driven decision science tools. Deep neural networks, surrogate modeling, gaming adversarial networks, and multiple other approaches are showing huge promise in weather predictions [41] and other applications. In particular, huge gains in run time have been observed using surrogate models. Our view is that AI is a very powerful tool and that it can substantially improve on various challenges outlined in this paper. We also believe that the challenges highlighted are fundamental in their own way and that the drive for resiliency in our power system is ongoing.

5 Preliminary Results from two Cold Weather Use Cases

We now illustrate the analysis of two cold weather events to further anchor our discussion with real-world examples.

In February of 2021, Winter Storm Uri caused electricity power outages for 4.5 million customers and left many without power for several days [6]. In February 2022, Winter Storm Landon [27], caused tremendous outages across a 2,000-mile-long expanse of snow and ice from the Southern Rockies and Plains into the Midwest and northern New England. To examine the impacts of these storms on electricity customers in Texas during these periods, we employed a Pearson's correlation coefficient analysis and a Random Forest machine learning method to understand the relationship between gridded (1 km spacing) daily weather variables and county-level daily customer outages recorded during these events.

5 Correlation of Outages to Weather

The correlation analysis evaluated the strength of the relationship between the relative movements of two variables, meteorological conditions, and percentage of customer outages, using Pearson's correlation coefficient. In the case of Winter Storm Uri, the percentage of customer outages in each Texas county on a given day were strongly and positively correlated to the percentage of customer outages the day before. It can be interpreted from this result, and it was certainly observed during the storms, that outages persisted in the same regions for several days. Additionally, maximum daily temperature and daily average incident short-wave radiation were positively correlated with outages, an unexpected but interesting outcome. There were no strong negative correlations observed.

The same type of correlation performed using data for Winter Storm Landon, did not show any strong positive or negative correlations. However, minimum temperature and snow water equivalent were weakly positively correlated to the percentage of customer outages on the next day. Finally, a Pearson's correlation using Texas county-level data from both storms showed that while daylight average incident shortwave radiation and cumulative snow water equivalent on a given day were weakly positively correlated to the percentage of customer outages the next day, and average vapor pressure, maximum and minimum temperature and cumulative precipitation were more highly and negatively correlated with the percentage of customer outages the next day, the highest positive correlation occurred in the combined dataset again between outages on consecutive days (Figure 2).

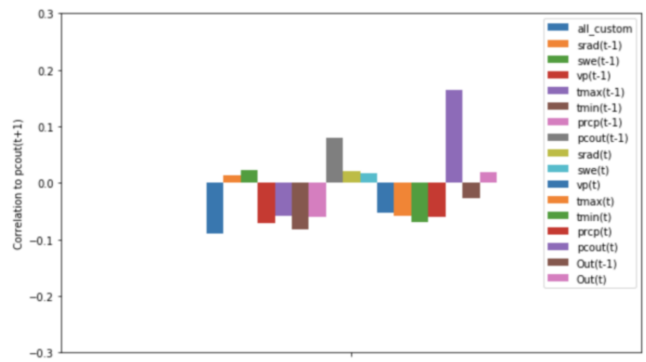

Figure 6. Visualization of the result of Pearson's correlation of the percentage of next-day customer outages (t+1, x-axis) in Uri and Landon winter storms to each of the weather and outage variables. The y-axis shows the strength and sign of the correlation [4].

5.2 Random Forest Analysis

For the Random Forest (RF) analysis, we used the daily weather and outage data for five days each from the two winter storms, to determine whether yesterday's weather information can predict tomorrow's outages. Data for this analysis focused on Texas outages for both storms. 90% of the data were used for training the model to predict the percent of outages in each affected county in Texas and 10% of the data were used to validate the result. These results showed a small positive correlation for Winter Storm Uri of yesterday's weather to today's outages, with a root mean squared error (RMSE) of 9.793. Results from using the same geographical data for the 2022 Winter Storm Landon showed a lower RMSE of 7.224 indicating that there is a greater positive correlation among the weather variables and the percentage of customers outaged during that storm. Combining the Texas county data from both winter storms provided the best correlation among weather variables and outages, and produced the lowest RMSE at 6.125, indicating that prediction from the combined data from both storms was better than that of either Uri or Landon alone.

5.3 Data and Methods Employed for Cold Weather Use Cases

Meteorological data for Winter Storms Uri (February 13-17, 2021) and Landon (February 2-6, 2021) were obtained for the state of Texas from the Oak Ridge National Laboratory's (ORNL) Daymet Version 3 [36]. The meteorological data included maximum and minimum daily temperature, daylight average incident short-wave radiation, cumulative precipitation, snow water equivalent and average vapor pressure calculated using a combination of interpolated and extrapolated inputs from multiple instrumented sites to workflows executed on a large computing cluster. Data were averaged spatially to the county level to match customer outage counts. County level customer outages were obtained from the archives of the Department of Energy (DOE) Environment for Analysis of Geo-Located Energy Information (EAGLE-I [31]) situational awareness platform for near real-time energy status.

The Pearson's Correlation and Random Forest analyses performed used components of the Advanced data SCiENce toolkit for Non-Data Scientists (ASCENDS) tool [20, 30], which is a set of command-line and web-based tools for performing data analysis and machine learning. Among the methods supported by ASCENDS are linear, logistic and other types of regression, random forests, support vector machines and neural networks.

The Pearson correlation algorithm in ASCENDS that was used for this study is:

$$r = \frac{\Sigma[(X[:,i] - mean(X[:,i])) * (y - mean(y))]}{(std(X[:,i]) * std(y))} \tag{1}$$

with the X matrix including all weather and outage variables, and y representing the outage predictions. In the above equation, std refers to the standard deviation of the data distribution.

ASCENDS' Random Forest tool is an implementation of the Python Scikit-learn Random Forest (RF) Regressor [29], a non-parametric model that fits a selected number of classifying decision trees to various samples subset from the data.

5.4 Computational Enhancements

The analysis illustrated here highlights how data was sourced from multiple places (Daymet, EAGLE-I, etc.) and both machine learning and statistical approaches (ASCENDS) were used for the preliminary analysis. Daymet is a 1km x 1km gridded daily dataset for North America while EAGLE-I houses about a decade of 15-minute resolution customer outage data at the utility and county resolution. For a robust setup, a system-of-systems approach that can source data from various systems, run computational models, perform machine learning, and run statistical techniques is needed. Furthermore, when the next hurricane unfolds, a system that can provide insights that are significantly more advanced would position the electrical power systems sector much more resiliently.

5.6 Collecting Electric Grid Data for a winter storm case

This process of acquiring data starts by collecting historical weather, power generation/consumption, and natural gas production/consumption data of an area. This identifies the worst cold year by analyzing the historical weather data. It is relatively effortless beyond this to model scenarios with having extreme winter weather in a certain area.

Additionally, one can analyze the forced outage rates (FOR) of conventional generators, including different type of units, based on historical outage rate data such as winter storm Uri. Historical FOR data of transmission lines can be integrated. This eventually can model the impact of extreme weather conditions on load demand using winter weather parameters (WWP) during winter storms in an area. Additionally, it is relatively easy to investigate the impact of a winter storm on natural gas demand (an interdependent asset). Analyzing the impact of winter storm Uri on pipeline operations and natural gas production is critical to validate any use case.

5.7 5.7 Use Case of an Impact of a Winter Storm on Electric Demand

To model the impact of cold weather on electric load, historical load data and weather data is needed during winter (Jan., Nov., and Dec.). Firstly, we can calculate the WWP value using the following equation:

$$\begin{cases} WWP = Temp - (0.5 \times (Wind - 10)), if\ Wind > 10 \\ WWP = Temp, if\ Wind \leq 10 \end{cases}$$

where, Wind = Wind velocity in MPH, Temp = Dry bulb temperature. For each load zone, we used linear spline fitting functions to map the relationship between WWP and electric load.

The relationships between WWP and load of AE, Dayton, and COMED zones are shown in **Figure 7**. With the decrease of WWP value, the daily maximum load increases. At WWP values greater than 40, there appears to be minimal load response to weather conditions.

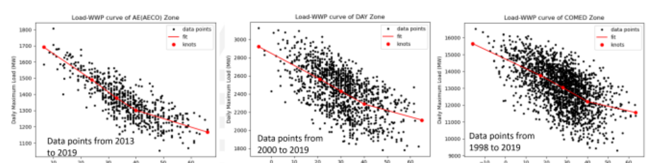

Figure 7: The impact of WWP parameter on load of AE, Dayton, and COMED

6 Conclusion

The paper presents a discussion on the resiliency and reliability needs of the electrical power sector with respect to severe weather conditions. A computing audience relevant introduction to the reliability and resiliency approach used in power systems was presented followed by a dialogue on the computing and computational needs to achieve a higher state-of-the-art in power systems resiliency. Two use cases of severe cold weather with subsequent analysis were presented to highlight the possibilities that could result with computational advancement in the field.

The end goal of such systems is ultimately to prevent the loss of life and property. It will require bridging across multiple sectors and domains. This is somewhat inevitable and forced in many ways by the distributed nature of renewables. The computing and computational community will have a significant role as the world transitions over to cleaner sources of energy.

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