Resilience in planning: Its relationship to Reliability and a practical implementation guide

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Abstract Extreme weather events are a growing threat to power systems and can cause critical failures in the grid, leading to significant power outages. The concept of Resilience in the context of power systems has been poorly understood, especially how it relates to the concept of Reliability. This paper proposes a framework that clarifies the relationship between these two terms. Using Power Systems Planning as an example to bridge the methodological gap between these concepts, it also proposes a method to calculate the Value of Resilience to enable entities to clearly identify the costs and benefits of Resilience-driven investments. Gaps in modeling tools and policy are identified that need to be addressed in order to practically implement the proposed framework. The findings of this paper have implications for and can be generalized to the design, operation, and planning of power systems in the face of increasing threats from extreme weather events.

Keywords: Resilience, Planning, Reliability, Extreme Events, Policy, LOLE

1. Introduction

The number of High Impact Low Frequency (HILF) events like ice storms, winter freezes, and heat waves has been increasing in recent times and these events are projected to increase in the future [1], [2]. In the power systems world, the term 'Resilience' is associated with characteristics the electric grid should possess to withstand and react to these HILF events. There has been a recent influx of papers and reports that put forth the basic concepts around Resilience, but most of these are high-level papers that lay out frameworks to think about extreme events vis-à-vis power systems but do not describe the implementation details [3]–[5]. To the best of the authors' knowledge there have been only two publicly available studies to date that implement an end-to-end,[*] albeit narrowly focused, quantitative resilience analysis on a real network [6] [7]. One reason for the dearth of implemented studies is the lack of a common understanding and contextualization of the term 'Resilience,' especially how it relates to the concept of 'Reliability,' something that is well-understood within the industry. Confusingly, 'Reliability' is often conflated with 'Resilience.'

Just like Reliability, Resilience can itself mean operational resilience, supply resilience, T&D resilience, or even cyber resilience. Using the category of generation planning as an example, Section 2 aims to clarify the definitions of and the relationship between 'Reliability' and 'Resilience.' Then in Section 3, a framework is proposed that bridges the methodological gap between Reliability and Resilience planning. This framework also allows for the calculation of a 'Resilience value.' Section 4 concludes the paper.

2. Defining Resilience: Background and Context

There is no uniform definition of Grid Resilience that's widely adopted by the industry. Multiple agencies and research institutes have defined Resilience in policy proposals and research projects. For example, FERC defines it as *"The ability to withstand and reduce the magnitude and/or duration of disruptive events, which includes the capability to anticipate, absorb, adapt to, and/or rapidly recover from such an event"*[8]. NARUC has defined it as *"Robustness and recovery characteristics of utility infrastructure and operations, which avoid or minimize interruptions of service during an extraordinary and hazardous event"*[9]. Resilience definitions generally focus on a system's ability to withstand, reduce the impact, and rapidly recover from disruptive events. Two key characteristics are common across most of these definitions. First, they point to different phases of system performance during a disruptive event; for example, "prepare," "absorb," "adapt," and "recover," also referred to as the "Resilience trapezoid" in some reports (See Figure 1). Second, Resilience is event-specific and is typically evaluated against specific disruptive HILF events. For example, the grid characteristics needed to weather an ice storm are very different than those required to withstand an earthquake.

[*] 'End-to-end' here implies that the study systematically analyzes extreme events and proposes a concrete set of investments that are aimed to improve the system's response to extreme events.

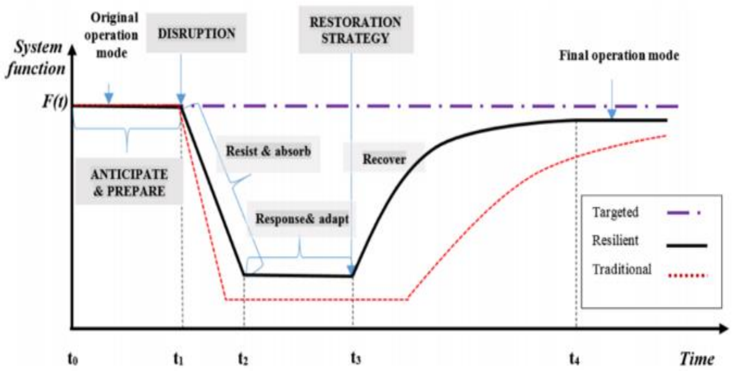

Figure 1: Schematic performance of a resilient power system during a disruption [10]

To better understand Resilience and eventually evaluate the cost-effectiveness of corresponding investments, it is important to understand the term's relationship with Reliability. Existing literature does not provide a clear answer here. Most studies use the term Reliability without mentioning Resilience. In Reliability studies that do mention Resilience [11], it is usually an afterthought with no detailed characterization of what it comprises. In the following section, this relationship between Reliability and Resilience is explored, starting with an appropriate definition of Reliability. It should be noted that the frameworks, examples, and metrics provided in this paper are not meant to be prescriptive. Rather their goal is to clarify oft overlooked or ill-defined concepts surrounding Resilience and provide a practical guide to conducting Resilience studies.

What is Reliability?

Although there are many definitions of Reliability, for the purposes of this paper, NERC's definition is most useful. According to NERC [12], a grid possessing an Adequate Level of Reliability (ALR) is one that has the following six attributes:

1. The System is controlled to stay within acceptable limits during normal conditions;
2. The System performs acceptably after credible contingencies;
3. The System limits the impact and scope of instability and cascading outages when they occur;
4. The System's Facilities are protected from unacceptable damage by operating them within Facility Ratings;
5. The System's integrity can be restored promptly if it is lost; and
6. The System has the ability to supply the aggregate electric power and energy requirements of the electricity consumers at all times, taking into account scheduled and reasonably expected unscheduled outages of system components.

Note that NERC's definition of Reliability focuses on system operations during *normal* conditions or performance during *credible* contingencies. Moreover, the system is expected to be planned considering *scheduled* and *reasonably expected* unscheduled outages of system components. HILF events are by definition events that are not *normal* or *reasonably expected* – they are abnormal.* Although abnormal or extreme events are predicted to increase in frequency in the future [1], [2], there is very little data on the exact nature, duration, and physical course of these events. So, outages and contingencies these events impose on the grid cannot be 'reasonably' estimated. Figure 2 uses this normal-abnormal distinction to show that Reliability and Resilience are closely related to each other. In fact, Resilience is an extension of Reliability, as it is traditionally understood, to abnormal or extreme conditions.

* For the rest of the paper, the terms 'abnormal', 'extreme', and 'resilience' events are used interchangeably.

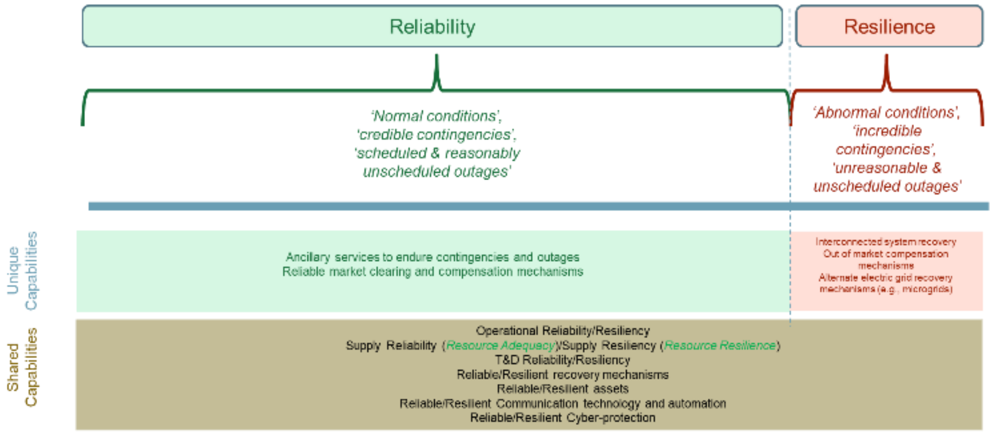

Figure 2: Resilience is an extension of Reliability to abnormal conditions

Figure 2 shows that components and features that make a system reliable often contribute to making it resilient and vice-versa. So, along with the concept of operational Reliability a corresponding Resilience concept must be defined as well. T&D Reliability has an analogous T&D Resilience concept. The distinction is the conditions under which these are defined – normal operating conditions vs extreme or abnormal conditions.

As mentioned in Section 1, for simplicity and to develop frameworks and methods, in this paper, the focus is on planning for Resilience in Generation. Nevertheless, the frameworks proposed in this paper are generalizable to T&D systems as well. Given the focus on generation planning in this paper, for the rest of the paper, unless explicitly mentioned, 'Resilience' refers only to Generator or Resource Resilience.

Defining Normal and Abnormal conditions

The previous section points to the importance of the distinction between normal and abnormal conditions. The next step is to define these conditions.

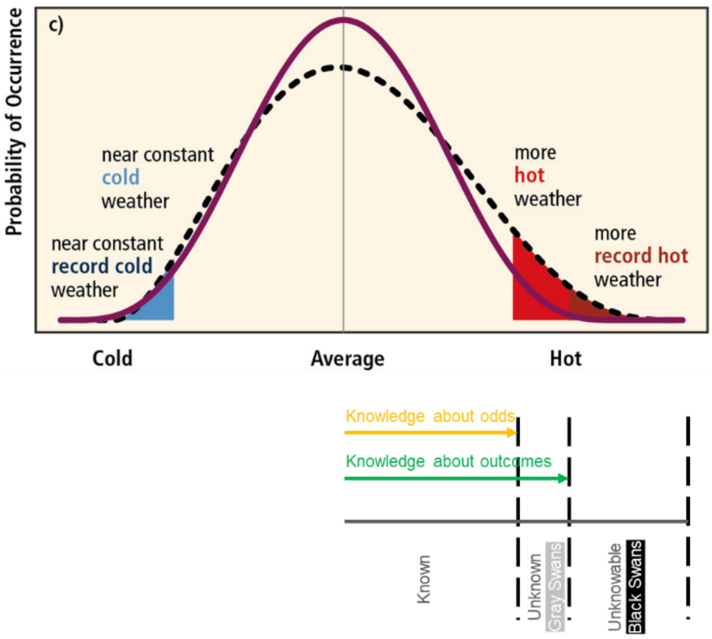

Figure 3: The entire distribution of events can be divided into three categories depending on the strength of historical data supporting estimates of their odds

Figure 3, which is a schematic adapted from the 2012 IPCC report [13] and shows changing temperature distributions, provides a good starting point. The solid line shows the historical temperature distribution while the dotted line represents the new distribution and indicates instances that were previously deep in the tails but occur more frequently under the new distribution.* 'Normal' conditions are those for which there is adequate historical data and operator input to reasonably estimate their odds of occurrence. Following [14], these are called 'Known' conditions. The next tranche of conditions are what [14] refers to as 'Gray Swan' events – these are conditions which may be increasing in frequency, but there is not enough historical data to reasonably estimate their odds of occurrence. For example, it is apparent that the number of major wildfires on the US West Coast are increasing, but it is not yet and may never be possible to predict their frequency of occurrence and where they will occur and the portions of the electric grid they will affect. So, the outcomes are known, but their odds are unknown. The last tranche of conditions is 'Black Swan' events for which, by definition, neither outcomes nor odds are known.

One key axiom in establishing the Reliability-Resilience nexus is that all events or conditions whose odds can be reasonably estimated using historical data or SME input, i.e., all 'Known' or 'Normal' events as defined above, should be considered within the regular planning process. For example, most utilities consider Resource Adequacy (RA) issues within their Integrated Resource Plan (IRP) processes. Market operators also consider RA issues through forward capacity constructs, either bilateral as in California and SPP or centrally cleared as in PJM or NYISO. Stochastic modeling techniques such as Loss-of-Load Probability (LOLP) modeling are typically used, wherein a wide range of weather and resource outages conditions are considered, spanning the distribution of normal events described above. A key for these techniques is that they require a reasonable estimate of the probability of such events occurring, since their output is based on the expected statistical frequency.

This leaves the Gray Swan events to be addressed in another way — through Resilience analysis. For these events, outcomes are known (or can be simulated), but odds are not. One difficulty associated with this distinction can be seen in Figure 3, which is that there appears to be a large overlap between tail-end events and HILF events (gray swan events) for which it is difficult to estimate probabilities.

How do current planning processes account for extreme events?

Most utilities already account for extreme events to some degree in their planning and operational requirements. There is also a general recognition that generation, transmission, and distribution capacity must be available and functional to the extent possible during extreme events and any outages must be quickly resolved. This is evident from the many natural gas contracts western utilities in the US have signed to firm up their portfolios. Utilities are also increasingly winterizing resources and expanding the operational temperature range requirements for PPA contracts. Another way in which tail events are already being considered in planning is by parameterizing indicators such as load or wind output with an appropriate high/low percentile value. For example, as part of ERCOT's RA calculations, peak load is represented using the 90th percentile of historical summer peak load while unplanned outages are characterized using the 95th percentile of historical forced outages [15]. Transmission planning typically uses heavy summer loads (CAISO uses 1-in-10 year loads) combined with a contingency (N-1 or N-1-1 depending on the planning process). Distribution planning is also usually done using 1-in-10-year loads. Beyond this assortment of practices however, there is no widely-accepted framework to account for extreme events in planning. This paper is an effort to peer behind the curtain and think systematically about them.

A close examination of current practices reveals several problems with how extreme events are considered:

- The most common (and frequently only) way utilities consider extreme events is through depiction of high loads in planning where an arbitrary cutoff such as 1-in-2 years, 1-in-10 years, 95th, or 97.5th percentile are modeled within the RA process. While the exact standard and number used is a secondary point, load is just one (certainly the most important) of the many indicators of extreme events. There are many other variables such as contingencies, transmission ratings, level of market support, and crew response which become very important during extreme events but are currently not adequately considered in planning.
- Most extreme event considerations are done post-RA/IRP as add-on investments or adjustments. Utilities signing natural gas contracts to firm up generation supply is an example of this. Current planning standards do not explicitly incentivize firm generation leaving utilities to make manual adjustments to portfolios. This not only leads to inefficient allocation of resources but might also lead to unnecessary increases in both electricity costs and emissions.
- Furthermore, current practices for considering abnormal events are often housed in processes that are both ad-hoc and are procedurally divorced from RA planning and operational strategy. There is no comprehensive understanding of how the different parts fit together and serve to mitigate the worst impacts of extreme events on the utilities' service territory. As a result, investments that bring both Reliability and Resilience benefits might not be valued appropriately or even identified.

* Although this schematic shows more extreme hot-weather events, its generalizable to both extreme hot- and cold-weather events.

A single analytical and procedural framework that addresses both Reliability and Resilience considerations effectively will help mitigate the aforementioned problems. The dividing line between normal and abnormal events may be fuzzy, but both types of events need to be explicitly considered in this framework, while avoiding double-counting events. Additionally, a separate value for Resilience needs to be calculated that will help entities quantify investments' costs and benefits, and justify budgets targeting Resilience-specific investments (See Section 3 for more details).

3. Bridging the gap between resource planning and Resilience planning

RA frameworks generally use established probabilistic frameworks that capture key challenges for power systems. However, this framework is only effective when probabilities and correlations are well known. A complementary Resilience framework can capture additional extreme event related key challenges beyond the scope of LOLP models. However, since probability estimates are not known,[*] individual scenario analysis and robust sensitivity analysis around probabilities of scenarios is the best that can be done. The following sections expands on the implementation of these ideas.

Bridging the gap between traditional RA frameworks and Resilience should be done gradually using a walk-jog-run approach (See Figure 4). Merging these frameworks requires adjustments to established RA procedures, in terms of modeling, data collection, and stakeholder engagement. As such, it is prudent to first pilot and test these concepts and methods and allow for their maturation (in the walk and jog phases) before using a single framework to evaluate RA and Resilience investments (run phase). Even while focusing on Resilience, probability distributions that inform RA studies must be continually updated based on all the latest available historical data. It is necessary to do this to ensure that the RA process considers all new data that helps in bringing extreme events into the 'RA fold'.

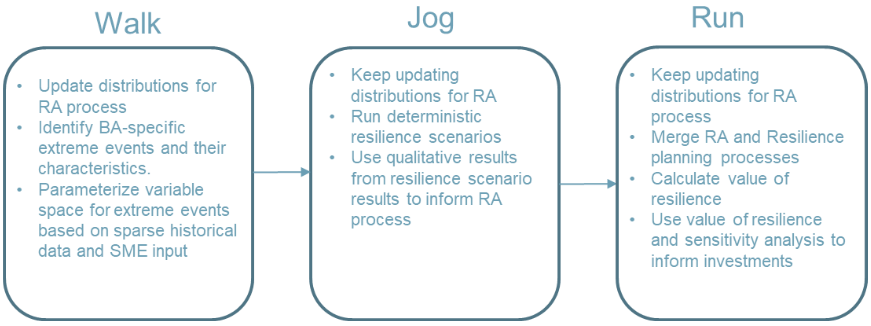

Figure 4: Walk, Jog, Run approach to bridge the gap between traditional RA frameworks and Resilience planning.

Walk stage: In this stage, an identification exercise is carried out by the Balancing Authority (BA) or Utility to detail the type and nature of extreme events the Balancing Authority Area (BAA) or Utility service area may expect to face in the near future. For example, the Texas-DSW region faces both heat waves and ice storms. Once identified, these events are parameterized to enable their modeling in a simulation tool. For example, ice storms can be defined by different levels of extreme temperatures, weather-correlated generator outages, reduced external market support, and T&D outages. The sparsity of historical data on gray swan events means this exercise will necessarily be informed by inputs from both historical data and SMEs. The extreme event identification and parameterization will be used in the subsequent jog and run stages when these events are simulated in production cost simulation models.

Jog stage: In this stage, the identified extreme events and their parameters can be simulated. In this case, production cost simulation using software such as PLEXOS is appropriate (although depending on the problem, the simulation type can vary). Based on insights from the walk-stage, different levels of these events can be simulated. Consider the above example of Ice Storms and Heat waves as being the most concerning threats to a DSW utility. Figure 5 shows a schematic that depicts possible scenarios to simulate within each threat. Levels 1, 2, and 3 indicate increasing severity of the event. Each level is parameterized by bespoke changes to system characteristics such as load, fuel supply, and generator outages. The stress generated by these parameters on the system increases with increasing levels of the simulated event.[†]

[*] If they are known, they should be included in the RA process (not in Resilience) as they would fall under 'reasonably expected unexpected outages'.
[†] The scenarios need not be deterministic. Stochasticity can be added for example, to simulation of generator outages.

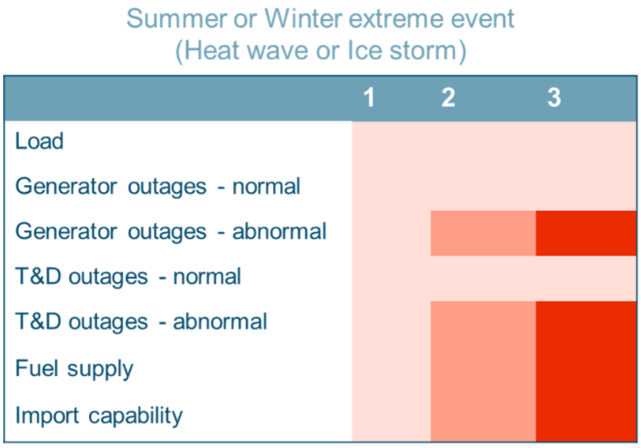

Figure 5: Example simulations to test and understand system performance under increasing levels of stress under a summer or a winter extreme event

The simulations proposed here are production cost simulations and so indicate how well a specific resource portfolio, presumably informed by a robust RA assessment, performs during HILF events. Some useful metrics to evaluate portfolio performance during extreme events are average hours of lost load, maximum load lost, average lost load duration, and total quantity of unserved energy. Based on these metrics, portfolios with identical RA characteristics (e.g., meeting a 1-day-in-10-year LOLE standard) can be evaluated against each other to compare their performance during extreme events. The insights derived from this process are used as qualitative inputs into portfolio development to, potentially, improve their performance during extreme events. This iterative process can be repeated until the BA is satisfied with the portfolio or a budget constraint is met.

Is there a need for an explicit Resilience target?

The next step (in the Run stage) is to directly use RA and Resilience scenarios in the same mathematical model to inform portfolio investment decisions so that the resulting portfolio helps the system meet both Reliability and Resilience goals. But before that can be done, the question of the need for Resilience planning targets must be answered, specifically, a.) how far do current RA standards such as LOLE help with meeting Resilience needs and, b.) are separate Resilience metrics that quantify system performance during extreme events necessary?

Consider Figure 6 from [7] which shows how portfolios that all meet the same Reliability (LOLE) standard differ greatly in performance during a specific simulated extreme event.* Portfolios that are meant to be equally 'reliable' result in very different durations and magnitude of outages during extreme events. In this specific example, one portfolio has more than 2.5 times the duration and magnitude of outages during extreme events even though both portfolios have the same LOLE. In fact, this discrepancy is to be expected as sustained extreme events fall outside the envelope of events considered in traditional planning methods.

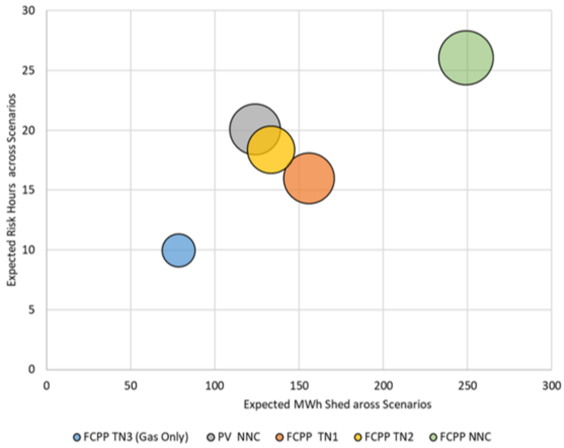

Figure 6: Different resource portfolios with the same LOLE have varying performance during extreme events

* Performance here is measured by duration of outages, size of the outages, and single largest outage when simulating the portfolios in extreme weather (critical) week.

An explicit Resilience goal is also required to specify a resilience target in capacity expansion models. Consider a mathematical optimization model that builds a least-cost portfolio (as most capacity expansion models used in IRPs do). Reliability is usually modeled through a Reliability standard, which is given as a constraint to the model. This is generally either the LOLE directly or a proxy that is informed by it, for example, a Planning Reserve Margin (PRM). The model then optimizes the portfolio and meets this standard. Currently, there is no widely agreed upon Resilience target. A target would ensure that the resulting portfolio meets the Reliability and Resilience goals while also being least-cost.

A Resilience target could be based on the metrics discussed above, for example, peak MW lost during extreme events, or the duration of the event. During Resilience events such as an ice storm, since the duration of the outage is most important, a metric designed around the longest possible outage seems appropriate.

Once an appropriate target has been agreed upon that has been informed by insights from the walk and jog stages, it can be modeled as a constraint in the capacity expansion optimization model in a similar manner to how a PRM is used to constrain solutions to meet RA goals. Answering the question of the type and nature of Resilience target is an area of open research.

Run stage: In this stage, the goal is to merge the RA and Resilience processes so that the final portfolio that is built has all assumptions baked into it and contributes to both system Reliability and Resilience.

Figure 7-A is a stylistic representation of the traditional RA process and Figure 7-B shows a framework that comprises both Reliability and Resilience conditions. The Resilience module of Figure 6-B drives changes to the RA investments so that the final set of investments meet both Reliability and Resilience standards.

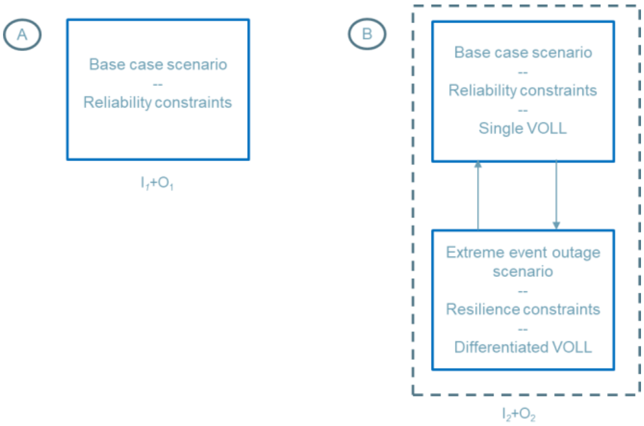

Figure 7: A) Traditional RA optimization problem, and B.) The proposed framework combining RA and Resilience planning

The key caveat though is that it is impossible to assign reasonable probabilities to the Resilience conditions. The translation of these probabilities in RA models is typically as weights on sampled conditions (usually represented as hours or days) in the objective function of an optimization problem. In the absence of a way to accurately estimate probabilities to the Resilience conditions based on historical data, a worst-case approach, or testing multiple sets of relative weights to Reliability and Resilience conditions must be used. In particular, SMEs can help augment historical data by identifying operationally the worst historical events or times when operations were "tight" for their regions.

A portfolio that meets both Reliability and Resilience targets (Figure 7-B) will be more expensive (or at least not cheaper) than a portfolio that meets the Reliability criteria alone (Figure 7-A). At any given set of relative weights between the Reliability and Resilience conditions in 6-B, the incremental cost of Resilience is given by the difference between objective values of Figure 7-B and Figure 7-A. Changing the weights on Reliability and Resilience conditions and solving 6-B at each set of weights enables the plotting of an efficient frontier that shows the incremental cost of a portfolio (compared to its cost from 6-A) versus the net Resilience benefit it brings. This frontier represents the tradeoffs between costs and Resilience benefits and can be used by the BA to evaluate and justify its investments. A stylistic example of such a trade-off curve is shown in Figure 8. For a given cost (Resilience budget), the steeper the curve is, the higher the Resilience benefit.

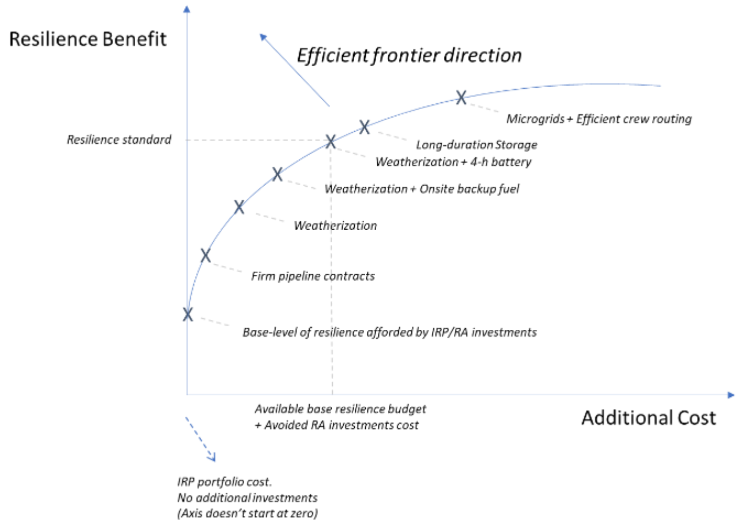

Figure 8: Trade-off curve for Resilience investments

Assuming these are both cost-minimization problems, the difference between the objective values of the models represented in Figure 7-B and Figure 7-A is the incremental cost of resilient supply. This cost accounts for changes in both the investment costs and the resulting operational cost over the modeling horizon. The BA can then consider this cost and evaluate its tradeoff with Resilience benefits and other non-modeled benefits to justify the investment. For example, Figure 9* from [7] shows how adding progressively longer duration batteries to a portfolio improves its performance during a simulated Summer extreme event. Note the green bubble moving from the right top corner of the Figure to the bottom left.

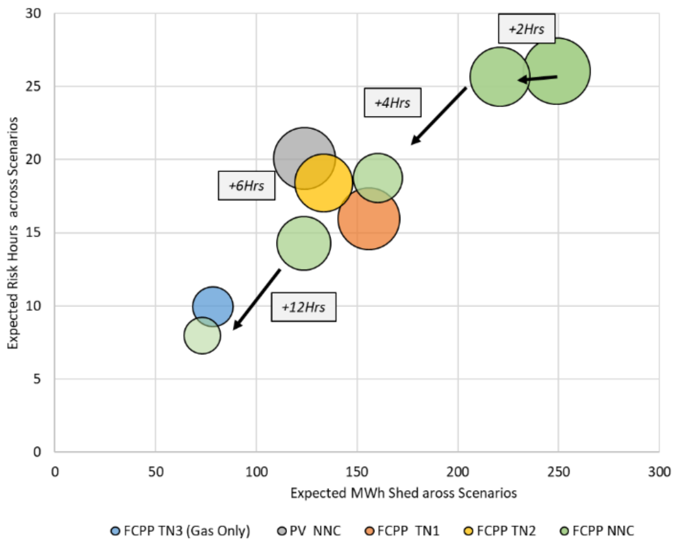

Figure 9: Increasing storage duration results in similar performance under Summer extreme events

Practical considerations: Serving identified beneficiaries and needed policy support

The framework shown in Figure 7-B separates out the Reliability and Resilience modules of the model. Both modules are solved in tandem and the final set of investments, I_2, represent those that not only meet Reliability standards, but also additional standards imposed by Resilience considerations. The difference between objective values of Figure 7-B and Figure 7-A is the cost of Resilience.

* Shows same set of portfolios as Figure 6.

While the entire grid is planned for a base level of Reliability, establishments such as hospitals, defense establishment, and emergency services might need to be restored quickly during a Resilience event.* One modeling and practical challenge is ensuring Resilience investments serve customers who need priority during extreme events. But how do you do this when the same investments serve all customers? One practical way for this to be implemented is if policy makers step in and establish Resilience clusters – geographical areas that need to meet a Resilience target on top of a Reliability standard. These Resilience clusters are assigned a higher/differentiated Value Of Lost Load (VOLL) in the simulation which would translate into a higher Resilience benefit. On a practical level, this also greatly simplifies the problem of allocating scarce resources such as crew and spare parts during extreme events. Crews deployed to Resilience clusters can restore power to the entire cluster quickly without having to individually identify and restore power to high-need customers.

In summary, using the framework proposed above, all areas will meet the Reliability standard, and depending on how differentiated the VOLL in the Resilience module is and policy's success in implementing clusters, targeted customers will have a higher level of Resilience (although because of the interconnected nature of the grid, all customers will have some Resilience benefits even with a base VOLL level).

This modeling and policy framework shows how Resilience planning can act as a bridge between conventional planning and conventional emergency management. It ensures that investments that bring both Reliability and Resilience benefits are identified, Resilience costs are calculated, and Resilience beneficiaries are identified. During extreme events, the framework allows beneficiaries to not only get a higher standard of electricity supply, but also enables utilities to prioritize limited labor to locations with higher Resilience value.

Practical considerations: Modeling tools needed

Another practical consideration is the suite of tools that are needed to model the impact of extreme events on electric grids. These are rare events and there is not a lot of historical data that can be used to determine and understand the impact of extreme events on the system. For example, modeling the impact of tropical storms on generator, transmission, or distribution facilities to predict the combinations of these infrastructure elements that would be part of an outage is challenging. Yet, such predictions are necessary to identify vulnerable points that need to be reinforced and ensure appropriate redundancies are built into the grid. This points to a need for simulation tools that make creative use of available sparse historic data, meteorological data, weather forecasts, and Subject Matter Expert (SME) input to simulate extreme events and estimate the path these events might take and the resulting impact on the physical components of the electric grid. There are two studies that show how these tools can be developed and used to identify Resilience investments. The end-to-end Resilience study [6] mentioned in Section 1 identifies vulnerabilities in the Tampa Electric system due to hurricanes by bootstrapping a small dataset of 184 storms (that came within 50 miles of TECO's territory since 1852). The second study is from California where PG&E is using Machine Learning techniques to learn from sparse data to estimate the wildfire risk for a given "pixel" of PG&E service territory [16]. Pixels with the highest risk can then be part of a targeted exercise to identify investments that mitigate wildfire impacts. Developing such tools to understand and predict the impact of extreme events on electrical infrastructure at a component level is a critical gap in existing tools and improvements in this direction will help inform investment decisions that mitigate the impact of extreme events.

4. Conclusion and discussion

This paper shows that it is impossible to talk about Resilience without addressing its relationship to Reliability as it is traditionally understood. This paper clarifies the relationship between these two terms and shows that Reliability deals with normal or reasonably expected events while Resilience deals with extreme events that are HILF in nature. The link between Reliability and Resilience is dynamic and as data keeps becoming available, weather, outage, performance databases, their distributions and the corresponding representative samples drawn must be continually updated and augmented with SME input to clearly classify events into the Reliability vs Resilience categories. Once this is done, depending on whether the BA is in the Walk/Jog/Run stages, the proposed implementation scheme in this paper will ensure that the resulting portfolio of investments meets both Resilience and Reliability standards. The example shown in Figure 5 and the proposed simulations and evaluation metrics all fit into Resilience frameworks previously proposed by previous reports such as those from IEEE PES Task Force [17] and Sandia National Labs [4]. The frameworks suggested by these studies can be seen for example, in Figure 7.

* Most hospitals are already on circuits that are designated as critical circuits and shielded from rotating outages.

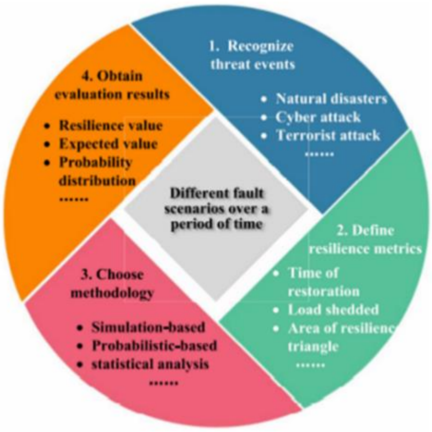

Figure 10: Power systems Resilience framework *[10]*

The example and the process discussed in Figure 5 follow this framework. Recognizing threats in summer (heat wave) and winter (ice storm), defining Resilience metrics such as duration of outage, peak load shed, average MWh lost, choosing production cost simulation, and ultimately calculating the cost of Resilience all meet steps 1,2,3, and 4 proposed in [10].

This paper builds on these previously-suggested frameworks and clarifies implementation details using the practical example of Generator Supply Resilience. It also fills in the missing pieces – Resilience's relationship with Reliability, proposing the need for Resilience target, proposing modeling frameworks that bridge the gap between traditional RA and Resilience frameworks, and ultimately identifying policy action and tools needed to make Resilience in planning actionable and minimize cost-shifts among customers.

Although this paper focuses on Resource Resilience (referred to as just Resilience throughout this paper), as shown in Figure 2, it is only part of what makes the grid resilient. Other Grid Resilience attributes such as T&D Resilience are important areas for future research for which the framework proposed in this paper can be used. The four steps identified by papers such as [10] and reports by IEEE Power & Energy Society [17] and examined as part of Supply Resilience in this paper (recognizing threats, defining metrics, choosing methodology, evaluating results) would have analogous counterparts in these areas as well and more investigation is needed here. As an example, SAIDI and SAIFI (System Average Interruption Duration Index and System Average Interruption Frequency Index), are commonly used distribution metrics, but large-scale events are generally excluded while calculating these values [18]. So, research into augmenting traditional Distribution Reliability metrics to account for Resilience is needed, similar to the discussion in Section 3 on Resource Resilience targets in planning.

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