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Electrical grid resilience framework with uncertainty☆

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ABSTRACT

Resilience in our electrical grid is imperative to the well being of society after events such as natural disasters or cyber attacks. To justify the development of resilience improvements in the grid, metrics are needed to quantify the improvement and cost benefit. These resilience metrics need to consider the inherent uncertainty in the grid, which arise from elements such as variable load and generation. This paper presents a method to include uncertainty in the proposed resilience framework. The resilience framework is demonstrated on a 2000-bus synthetic grid with a transient contingency simulated as a hurricane type event with numerous line outages. Varying amounts of distributed energy resources (DERs) at 0%, 10%, 20%, and 50% of load amount are included in the system and assessed for their system resilience impact and cost-benefit with and without uncertainty evaluated using Monte Carlo simulation.

1. Introduction

The ability of a power system to resist, respond, and recover from a catastrophic event are key factors commonly used to define the resilience of the power system. Resilience is often described in reference to low probability, high impact events. These types of events can be caused by environmental threats and human threats, such as cybersecurity attacks. The occurrence of extreme weather due to climate change has increased the frequency and duration of power outages in the United States between 2002 and 2012 [1]. Typical environmental threats that put the electrical grid at risk include hurricanes, winter storms, floods, wildfires, and earthquakes [2]. Weather-related electrical outages have cost the U.S. economy between $20 billion to $55 billion annually [3]. Human threats from cyber attacks are also emerging and have shown a source vulnerability in the electrical grid [4,5]. The cyber attack on Ukraine's electrical grid caused power outages for approximately 225,000 customers [6]. There is a need to enhance the electrical power grid's resilience by hardening it against these threats as they become more prevalent [7].

Numerous resilience based improvements have been suggested including: microgrids [8–10], improved dispatch and scheduling of resources [11–13], flexible local resources (such as generation, load, and energy storage) [14,15], and optimal switch placement [16]. The key to widespread implementation of such resilience-focused improvements will be the adoption of an established set of resilience metrics that quantify the resilience value and cost-benefit. The quantification of resilience in power systems is an emerging field, with several proposed resilience metrics, such as the resilience triangle and trapezoid [17,18]. However there is not a consensus on an established set of resilience metrics and existing reliability based metrics are not sufficient for valuing resilience.

The work in [19] provides extensive review of resilience metrics for power systems and proposes a resilience metric framework and notes few proposed metrics follow a utility-centric view of power systems. The proposed resilience metric framework bases its metrics on the U.S. Presidential Policy Directive 21 [20] which defines resilience on four components: withstanding capability, recovery speed, preparation/planning capacity, and adaptation capability. These metrics quantify the variables necessary to describe the four components, however a metric to describe the overall resilience of the system is missing. Further review is performed in [21], which makes an important differentiation between reliability and resilience. This work notes reliability metrics are inadequate to quantify resilience due to their inability to address topological flexibility, identifying critical infrastructure, cooperation with customers, and potential preventative measure evaluation. Valuable contributions are made in [22] providing

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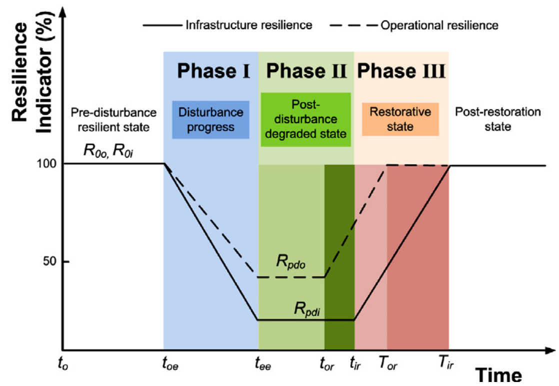


Fig. 1. Resilience trapezoid [23].

insight and classification of resilience in power systems and highlighting the need for cost-benefit studies of proposed resiliency improvements.

Perhaps the most accepted and well known metric for electrical grid resilience is the resilience trapezoid proposed in [23], which is pictured in Fig. 1. This builds on the works in [24–27] and applies the framework to power systems. The resilience trapezoid assesses the resilience of the system through three phases, the disturbance progress, the post-disturbance degraded state, and the restorative state. The resilience trapezoid is an extension of the resilience triangle, proposed in [17], which only accounts for the first phase. Further use of the resilience trapezoid is performed in [18], to show how the impact of improvements made in specific resilience phases affect the overall resilience on the system. Another important contribution to resilience metrics is the severity risk index introduced in [28]. This incorporates probability of event and impact as a method evaluate resilience risk. However, this work does not include a cost-benefit analysis.

Another proposed set of resilience metrics are from the controls systems perspective in [29]. The metrics from [29] are illustrated in Fig. 2. In this work the metrics are not applied towards power systems however they add an important contribution, the resilience threshold, to the resilience framework. There can be considerable overlap between reliability and resilience, and reliability metrics can be used to evaluate resilience type events. However, a difference between where resilience and reliability metrics are applied is often the magnitude and predictability of a disturbance, where resilience encompasses well beyond N-1 due to unpredictability of events and potential for uncertain N-k types of contingencies. With resilience it can be assumed that there is a certain threshold of degradation that might not be possible to prevent. Instead, the focus is on minimizing the degradation and recovering quickly. The resilience threshold marks the maximum acceptable level of degradation due to a catastrophic event. This level could relate to total loss of load in the system or retained critical loads. Similar to the

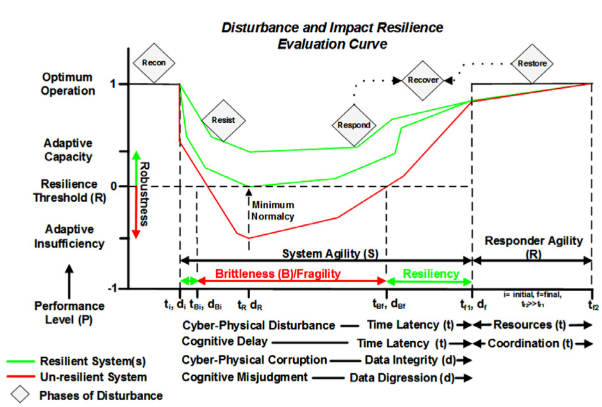


Fig. 2. Disturbance and impact resilience evaluation curve [29].

resilience threshold, [22] identifies a permissible range.

In [30,31], the metrics of adaptive capacity and insufficiency from Rieger [29] are applied to power systems. Adaptive capacity of the system is provided as a manifold describing the available active and reactive power at a node which could be injected if necessary in response to a disturbance. However, the adaptive capacity through the resilience phases of an event is not shown and the resilience threshold is not applied.

Unaccounted for in any of the proposed metrics is the quantification of uncertainty in the system, versus uncertainty of the event, and how that impacts the resilience metric. There is inherent uncertainty in electrical grids, such as load amounts and variable resource generation amounts. Extensive work in reliability studies has been performed to quantify the risk due to uncertainties in elements of the system, such as wind generation [32,33]. Similar to how quantification of uncertainty from system elements has been applied to reliability metrics, this uncertainty needs to be accounted for in resilience metrics. A resilience metric should either quantify the risk associated with the metric due to uncertainty or de-rate the metric. Risk associated with uncertainty due to probability of event, as previously mentioned, was introduced in [28], however this does not also account for uncertainty within elements of the system.

This paper introduces a resilience metric framework and methodology to compare resilience improvements, the cost-benefit of improvements, and a method to de-rate the resilience of the system due to uncertainty within its elements (e.g., DERs). This resilience framework incorporates the controls systems resilience framework presented in [29] and the resilience trapezoid presented in [18]. Building from Panteli et al. [18], the area is used to compare improvements while accounting for the resilience threshold. The main contribution of this paper is the introduction of the framework, which proposes the use of the resilience threshold and cost-benefit analysis for power system resilience metrics.

The proposed framework is assessed by considering a hurricane event that causes line outages across a 2000-bus synthetic grid overlaid on the region of the Electric Reliability Council of Texas (ERCOT). With this case study we evaluate the dynamic response of the system to create a more accurate estimate of load loss in the system to the hurricane event. The performance metric used to evaluate resilience performance is energy not served, as area under the curve from load loss. The resilience benefit of varying amounts of distributed energy resources (DERs) additions to the system is tested, and quantified using the proposed framework. Then, uncertainty in the DERs generation amount is considered, and the de-rating of the adaptive resilience due to this uncertainty is demonstrated.

The remainder of the paper is organized as follows. Section II presents the proposed resilience metrics and methodologies. In Section III, a case study is performed of a high impact event to demonstrate the use of the metrics and methodologies. The paper concludes with Section IV which explains the key takeaways along with the authors' ideas for improvements to the proposed framework and for resilience metrics for power systems in general.

2. Resilience framework metrics and methodologies

The resilience framework integrates the resilience trapezoid framework based in power systems applications from Panteli et al. [23] and the resilience control system framework from Rieger [29]. The benefit of incorporating the controls system perspective is to introduce the concepts of the resilience threshold, minimal normalcy, adaptive capacity, and adaptive insufficiency. These control systems concepts introduce vocabulary that enable resilience assessments in power systems to incorporate the effects of communication and network architectures related to smart grid advances and cybersecurity. These concepts are outlined below [29]:

- Minimum Normalcy: The minimum acceptable operation capacity of the system.
- Resilience Threshold: The level of operation set by minimum normalcy.
- Adaptive Capacity: The ability of the system to adapt or transform from impact and maintain minimum normalcy.
- Adaptive Insufficiency: The inability of the system to adapt or transform from impact, indicating an unacceptable performance loss due to the disturbance.

The key to these concepts is the resilience threshold. In high impact events it can be assumed that there will be some system degradation. The resilience threshold marks the maximum acceptable level of degradation. The performance metric used to set this threshold in power systems could be amount of load loss, retention of critical loads (such as hospital and emergency response), available spinning reserves, frequency nadir or other regulatory requirements. The classification of the resilience trapezoid, the three phases of an event, and the components that describe and quantify those phases are applied from Panteli et al. [23]. The three phases of the event are disturbance progress, post-disturbance degraded state, and restorative state. These perspectives are combined to establish the resilience framework as illustrated in Fig. 3. The times outlined in the framework illustration denote: t_d start of the disturbance phase, t_{pd} start of the post-disturbance phase, t_r start of the restorative phase, and t_{pr} start of the post-restorative phase.

The resilience trapezoid shape is inverted in the proposed framework, in comparison to the works it builds from, to retain consistency with the evaluation performed in the case study. The case study uses the performance metric of loss of load, where the performance degradation increases with an increase of loss of load. In Fig. 3, two system responses are shown. The un-resilient system response displays how the system operation level exceeds the resilience threshold. The resilient system response conversely displays how the system doesn't exceed that threshold.

Using the framework outlined in Fig. 3, the adaptive resilience system metric is calculated from the area of the trapezoid. There are two areas of the trapezoid with the implementation of the resilience threshold. These areas are the adaptive capacity area and the adaptive insufficiency area. The adaptive insufficiency area is subtracted from the adaptive capacity area to calculate the adaptive resilience of the system. These areas are exhibited in Fig. 4 and calculated in Eq. (1).

$$\text{Adaptive System Resilience} = \sum_{n=1}^{N} t_s(\,T - O_n) \tag{1}$$

The time is denoted by n, the length of the time step is t_s, the resilience threshold is T, and the operating level is denoted by O. This area metric describes the adaptive resilience of a system. Then the benefit of a change or improvement made to the system can then be assessed by the change in the adaptive resilience metric. The cost-benefit of such a change or improvement to the system can be evaluated using:

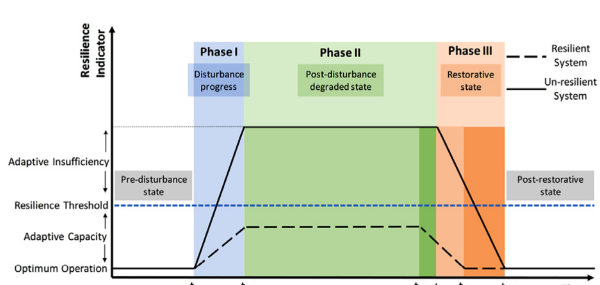


Fig. 3. Resilience Framework.

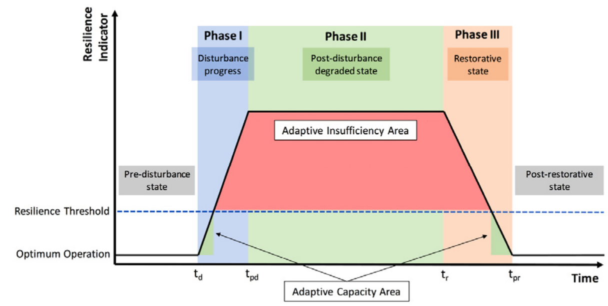


Fig. 4. Adaptive Resilience Metric.

$$\text{Cost-Benefit} = \frac{\text{Cost of System Degradation}}{\text{Event Duration}} - \frac{\text{Cost of Change}}{\text{Event Probability}} \tag{2}$$

where the event probability is provided in hours equal to the number of hours in the number of years that the event or scenario is expected to possibly occur. For example, an assessed scenario simulating a "hundred year flood" would be expected to possibly occur in one hundred years. The event probability would then be 100 times 8760 h in a year, to describe that the event is likely to happen once during a 876,000 h period of time. Putting the probability in hours provides a common time step to compare event duration. The event duration is also provided in hours, which is the number of hours from t_d to t_{Pr}. The cost of change could be based on incentives or payments for DERs, cost of transmission upgrades, or cost of redispatch or scheduling of resources. Examples of the cost of system degradation are energy not served cost or regulatory fees. The cost-benefit is then given in cost per hour. This allows for easy comparison of benefits between changes to the system being consider for enhanced system resilience. This simple cost-benefit method and metric aims to address the need to assess cost-benefit and worth of resilience improvements.

Uncertainty is another necessary element to consider when implementing resilience metrics. Depending on the state of the system at the beginning of an event, the system might be more or less susceptible to instability which can have an impact on the resilience of the system. Methods have been developed for assessing the risk of event uncertainty on resilience in power system [32]. This paper proposes a method to account for system uncertainty in the resilience metric.

This method de-rates the resilience metric by the uncertainty in the system from the elements of greatest concern or variability. Examples of elements in the electrical grid with great variability include variable resources such as solar and wind generators, load amount, and DERs. The uncertainty due to the chosen elements can be quantified by any sampling method. Other appropriate uncertainty methods for use with this framework include uncertainty sampling methods such as probabilistic collocation or Latin Hypercube sampling. From this quantification it is proposed to re-rate the adaptive resilience system metric by calculating the metric from the conservative 95% confidence interval. Fig. 5 demonstrates how the use of the 95% confidence interval will re-

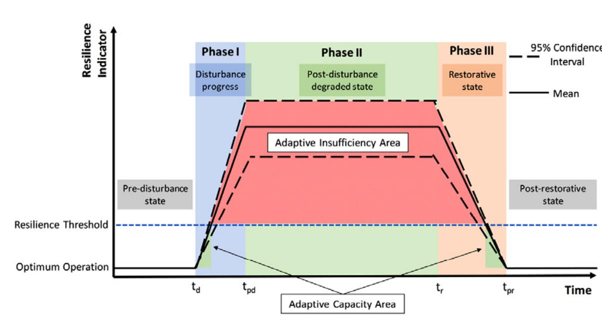


Fig. 5. Adaptive resilience metric with uncertainty.

rate the adaptive resilience metric.

De-rating of the resilience metric due to uncertainty is a necessary step for understanding the full impact of changes aimed to improve the resilience of the system. This is especially important if control of variable resources or DERs is to be considered as a resilience improvement to the system. The effect that such uncertainty can have on the adaptive resilience and cost-benefit is demonstrated in the case study.

3. Case study of adaptive resilience metrics

The adaptive resilience metrics and methodology presented in Section 2 are demonstrated using a hurricane event that causes line outages to a synthetic grid overlaid on the geographical footprint of Texas. The addition of varying amounts of DER generation aimed at improving the resilience of the system is considered. The adaptive resilience, cost-benefit, and de-rated metrics due to uncertainty in the DER generation amount are calculated for the original system and the system with each of the changes listed.

3.1. Methodology

3.1.1. Test case

The 2000-bus synthetic grid power system test case [34] is used to perform the simulations in this study. This test case contains dynamic models for all the machines so dynamic simulations can be performed. This test case was enhanced to include basic underfrequency and undervoltage protection relays on the generators and loads, and overcurrent protection relays on the lines. This provides a simple but more realistic load loss response to the event. An addition, wind generation machine, governor, and exciter models are added to the test case. The enhanced test case is publicly available [35].

3.1.2. Event simulation

The high impact event simulated in the case study was of a theoretical hurricane passing through the south eastern area of Texas. The hurricane results in several line outages over the course of 30 s. The timeline of the event is presented in Table 1. The listed lines were chosen due to their location in the “Coast” Area, and their loss causing significant load loss. The line outages were simulated with a three phase to ground fault followed by opening of both ends six cycles after.

The degradation phase–Phase I–of the event was simulated as a transient stability contingency in PowerWorld. The post-disturbance and restorative phases–Phase II and Phase III–were calculated using mean time to recover (MTTR) for the load. The MTTR assumed for this case study was 100 MW per hour. The amount of load loss found in the last time step of the transient stability contingency simulation was used for the first time step of Phase II. The amount of load loss in Phases II and III are calculated at an hourly time step using the assumed MTTR. The results are separated in the steady state response and the dynamic response. The dynamic response covers the first 30 s. The steady state response assumes zero load loss at the first time step, then the results from Phase II and Phase III begin at the second time step. Both responses are plotted to demonstrate the dynamic effects of the changes to the system, and the long term impacts of those dynamic effects.

Table 1
Hurricane event timeline.

Time (s)	Line Outage
1	Line 7206 to 7294
1	Line 7294 to 7239
1	Line 7294 to 7405
4	Line 7204 to 7428
4	Line 7205 to 7073
6	Line 7263 to 7204
8	Line 7076 to 7422
9	Line 7105 to 7187
9	Line 7003 to 7264
9	Line 7105 to 7205

This case study does not consider how the uncertainty inherent within the event impacts the resilience metric as other works have suggested methods for that assessment, instead it considers the probability of such an event causing a specific contingency. Adding uncertainty analysis in the event and contingencies is a target of future work. It is also important to note that determining the best cases and contingencies to study for these theoretical high impact low probability events is non-trivial and has significant impact on the resilience metric results. However, it is out of the scope of this paper to discuss or determine best methods for developing high impact low probability events to simulate. Additionally, only the inclusion of primary frequency response services are considered in this study. The incorporation of secondary frequency response, such as automatic generation control, would be beneficial for demonstrating increased resilience, but is out of the scope of this paper. However, tools such as Multi-Area Frequency Response Integration Tool (MAFRIT) [36] could be used to simulate both primary and secondary frequency response together.

3.1.3. Metrics

The performance indicator of expected energy not served (EENS) was used to evaluate the adaptive resilience of the system. EENS is a commonly used reliability metric by utilities. The use of this metric is to illustrate that already established and used metrics, such as EENS, can be adapted to provide meaning and value in terms of resilience [37].

The resilience threshold use in this case study is based on the North American Electric Reliability Corporation (NERC) standard BAL-002-0, disturbance control performance [38]. This standard states that *as a minimum, the Balancing Authority or Reserve Sharing Group shall carry at least enough Contingency Reserve to cover the most severe single contingency*. Therefore, the resilience threshold in this case study was set to the maximum amount of load loss from any single contingency. The maximum amount of load loss from any contingency was calculated from an $N-1$ transient contingency assessment of the original system that contained all the protection relays for the generation, loads, and lines, as to more accurately simulate load loss.

3.1.4. Resilience improvements

The system is tested with the addition of varying amount of DER generation. This study includes the DER_A model in PowerWorld to enable simulation of DERs with trip settings and voltage support as denoted in [39]. The DER generation amount is based on the total amount of load, set to a percent of the total load. The tested DER generation amounts as a percent of load are: 0%, 10%, 20%, and 50%. The inclusion of studying the resilience impact of DER generation is due to the increased interest in using DERs for improving power system stability, both for voltage stability [40] and frequency stability [41,42].

3.1.5. Uncertainty

The uncertainty quantification used in this case study demonstration was performed using the Monte Carlo sampling method. The DER amount was sampled from 0% to 10%, 0% to 20%, and from 0% to 50% of the load amount at each load using a uniform distribution. A set of 500 simulations were run on PowerWorld for each uncertainty range considered to gather data to calculate the mean, standard deviation, and confidence intervals for each time step of the simulations. The error of the confidence intervals was calculated as in [43].

3.2. Results and discussion

For ease of comparison the system with the specified amounts of DER generation and the system evaluated under different DER generation uncertainty ranges are here on referred to as the labels listed in Table 2. The average error in the calculated confidence intervals for

Table 2
System scenario labels.

Label	System Scenario
A	0% DER generation
B	10% DER generation
C	20% DER generation
D	50% DER generation
E	Uncertain DER generation ranging from 0 to 10%
F	Uncertain DER generation ranging from 0 to 20%
G	Uncertain DER generation ranging from 0 to 50%

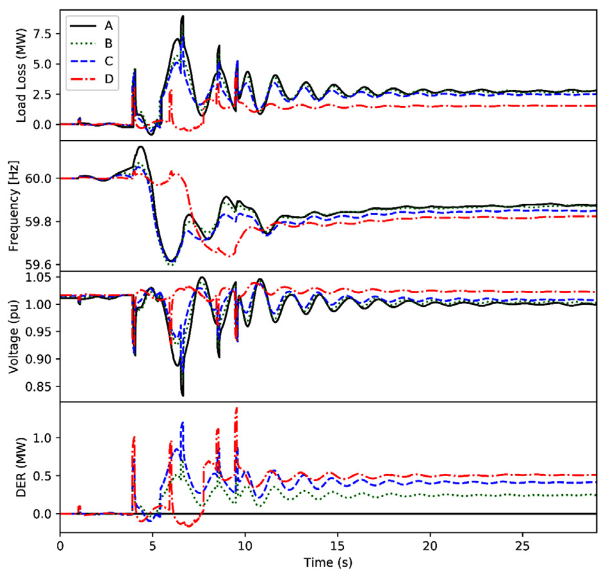


Fig. 6. Dynamic responses of Load 7432 for Scenarios A, B, C, and D.

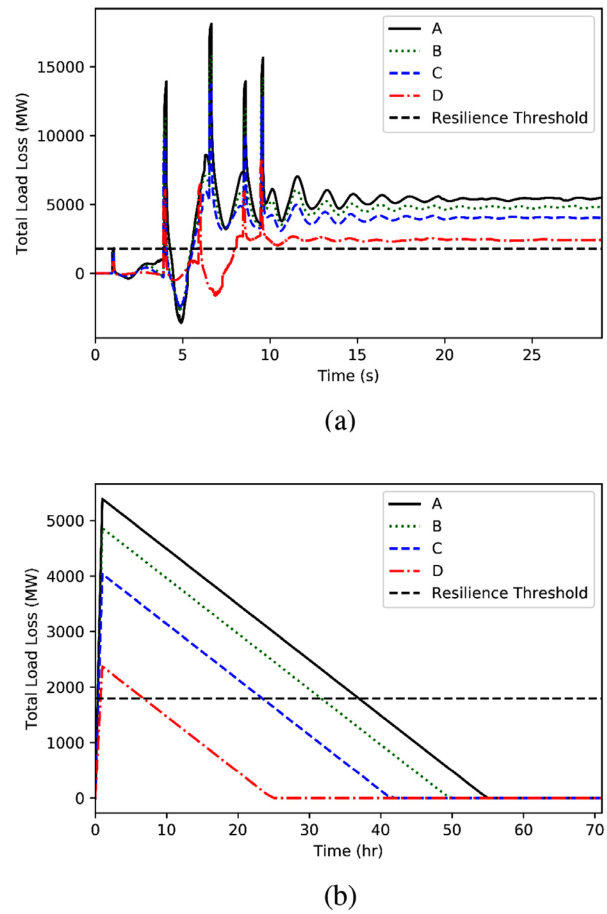


Fig. 7. Total load loss from Scenarios A, B, C, and D. (a) is dynamic response, (b) is steady-state response.

steady state simulation was 6.2% and for tranient simulation was 0.4%.

The results from the hurricane event are first compared on their dynamic responses. To demonstrate the effect of DER generation on the system the load MW, bus frequency, load voltage, and DER generation MW are compared for one load in the system. Fig. 6 presents the dynamic responses of Load 7432, which was chosen due to its proximity to the event and the fact that the load did not trip off.

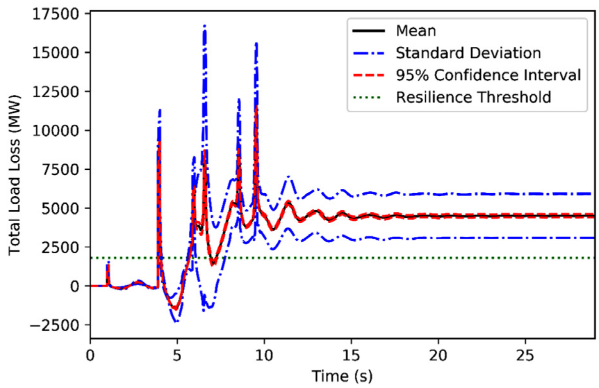
As the DER generation amount increases, there is a reduction in load loss. The 50% scenario has the lowest amount of load loss. In this study, no re-dispatching of resources was performed, which requires the slack bus to compensate for the increase in DER generation. This increased stress on the slack bus is perhaps the cause of the slightly increased voltage and depressed frequency found with increases of DER generation. In reality such an imbalance would only occur if there was a sudden change, as the day ahead or real-time markets would be based on forecasted load, which has embedded forecasts for DER generation. It is likely that with re-dispatching of resources based on optimal power flow that greater stability and load retention would be realized. Therefore this study's benefits are conservative. This comparison of DER generation amounts shows how penetration can affect load loss and overall system instability during a high impact event. These significant differences highlight the need to access uncertainty in DER generation amounts due to the wide ranging results shown in Fig. 6. How these DER generation amounts affect the total load loss is shown for both the dynamic and steady state response in Fig. 7.

Due to the difference in starting load loss amount in the steady state response, the overall load loss due to the entire event decreases proportionally. Where the addition of DER generation makes an impact on the resilience in the system is in the reduction of degradation of the system in Phase I. While this study focuses on how DER generation changes the transient response which impacts the degradation phase of the event, other resilience gains are made in other phases as well. An improvement on this study would be to evaluate how these DERs could create increased impact in Phase II and Phase III through the implementation of microgrids. Additionally, other resilience improvement methods such as faster recovery response could create impact in Phases II and III.

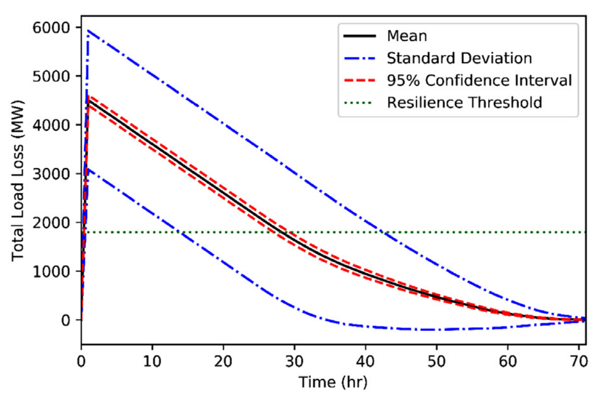
The effect of the DER generation uncertainty to the total load loss for both dynamic and steady state responses are illustrated in Fig. 8 for system scenario G with an uncertainty range or 0 to 50% DER generation. System scenarios E and F resulted in similar responses, therefore system scenario G responses are displayed as representative of all three scenarios.

For the adaptive resilience metric considering uncertainty, the response of the lower 95% confidence interval is used to calculate the metric. The response of the lower 95% confidence bound is overall lower than the result of the 50% DER generation seen in Fig. 7. This is an expected but an important result to note as this lower response implies a lower adaptive resilience metric and lower cost-benefit, which are shown and discussed below. This highlights the need to consider uncertainty in test cases that include variable elements. This is whether or not these elements are being implemented as a method to improve resilience or already exist as uncertain elements in the system, as the resilience impact will be changed, and in this case lowered. Therefore to perform accurate cost-benefit analysis to provide as a basis for improved decision making, uncertainty in the variable elements of the system needs to be considered.

The cost-benefit analysis for this case study is based on EENS. Therefore the cost-benefit equation, Eq. (2), is calculated with the following variables outlines in Eq. (3).



(a)



(b)

Fig. 8. Uncertainty Results with maximum DER penetration of 50% (a) dynamic response (b) steady state response.

$$\text{Cost-Benefit}=\frac{(\text{EENS})(\text{Electricity Cost})}{55\ \text{hours}}-\frac{(\text{DER Sell Back Rate})*(\text{DER MW amount})}{(10\ \text{years})*(8760\ \text{hr/yr})} \quad (3)$$

We assume the event probability to be 10 years and the event duration was simulated to be 55 h with no improvements made. The electricity cost is assumed to be 9 cents/kWh, and the DER sell back rate is assumed to be 9.6 cents/kWh based on Texas distribution utility prices and in this study assumed to be constant. The inclusion of DERs in variable bulk electricity markets could impact the cost benefit however is out of scope for this study. The adaptive resilience metrics were calculated for each of the scenarios. The EENS is calculated from the simulations, and the DER amount is calculated as the specified percentage of the total load. For scenario E, with uncertain DER amount, the DER amount used for cost-benefit analysis is 10% as that is the upper range of the uncertainty range which would be the theoretical installed capacity of DER generation. The actual DER generation could be anything under the 10%. Similarly system scenarios F and G used 20% and 50% respectfully for the DER amount used in cost-benefit analysis. The adaptive resilience improvement metric is the difference in the adaptive resilience metric from Scenario A to the Scenario in question. The resilience framework metrics are calculated from the steady state responses. The resulting adaptive resilience metric results are reported in Table 3.

From the results in Table 3, one can see that the greatest cost-benefit is due to the highest amount of DER generation tested, at the rate of $193,930 per hour. However, when uncertainty in DER generation is considered the cost-benefit drops to $64,138 per hour, seen in scenario G. In this study, even when considering uncertainty across system scenarios E-G, 50% still has the greatest cost-benefit. However it is seen how that cost-benefit drops when compared to non-variable DERS. Interestingly, scenario F has a lower resilience metric than the original scenario A. It is possible that there is a certain percentage of DERs within the range of 10–20% that causes a larger amount of instability than the other ranges which causes this drop in adaptive resilience. This points out the need to consider and study the transient stability due to the contingencies of a large event as the transient stability can have lasting impacts in terms of long term resilience.

Table 3
Adaptive resilience metric case study results.

System	Adaptive resilience (MWh)	Resilience improvement (MWh)	Cost-benefit ($/hr)
A	−20,397	-	-
B	6858	27,237	44,562
C	43,982	64,361	105,303
D	98,157	11,856	193,930
E	−16,973	3406	5566
F	−30,516	−10,137	−16,603
G	18,839	39,218	64,138

For other system improvements the uncertainty might highlight an optimal amount of the variable resource that maximizes resilience and cost-benefit. Additionally, if a resilience based improvement is being decided off a cost-benefit threshold, adding the uncertainty could reduce the cost-benefit to below that threshold making it no longer a viable option. All these reasons highlight the need to incorporate uncertainty of the variable elements of the system into the resilience metric analysis.

From the results provided, the utility who owns this grid could chose to incentivize or build out a specific amount of DERs on the system, or make a certain amount of DERs controllable for dispatch. The metric framework presented here provides the resilience and cost-benefit justification for such actions. This framework can be used by utilities to aid their decision making process for future improvements and investments in their system as part of their planning process. The cost-benefit of an improvement could be extrapolated across several low probability high impact events, showing potential increased cost-benefit when considering several events.

4. Conclusion

This paper presents a resilience framework whose main contributions are to provide a metric and assessment method to account for uncertainty within elements of a power system and to quantify cost-benefit of resilience-based improvements to the system. We discuss the need to account for system uncertainties and cost-benefit analysis in resilience assessments. We demonstrate the proposed adaptive resilience metrics using a case study simulating a hurricane event that causes line outages across the southeast coast of Texas. A 2000-bus synthetic grid test case overlaid on the geographical footprint of ERCOT, which included dynamic models for generators and protection relays, was used to perform dynamic simulations of this event. The addition of varying amounts of DER generation were evaluated for their resilience benefit. The adaptive resilience metrics were calculated for the seven system scenarios with various amounts of DER generation, ranging from 0% to 50% with cases considering uncertain DER generation from 0 and up to 50% of the total load amount. It was shown how the adaptive resilience metrics can be used to effectively de-rate the resilience metric due to uncertainties, providing realistic and conservative resilience metrics, and how the resilience metric can be used to implement cost-benefit analysis. This cost-benefit analysis is useful for comparing proposed improvement measures and assist in deciding whether or not to invest in certain resiliency improvements of the system. Future work to improve this resilience framework will include computationally faster uncertainty quantification methods, improved event development methods, and the inclusion of co-simulation of communication networks to model cyber attacks.

Declaration of Competing Interest

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

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