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Quantitative Power System Resilience Metrics and Evaluation Approach

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***Abstract* — Power system resilience is an emerging topic and plays an essential role in helping power industry understand and respond to the increasing threats of extreme weather events. The first step of power system resilience analysis is to introduce metrics to quantify the resilience reasonably. Existing resilience metrics are typically restrained by the limited data for extreme event modeling and fall short in terms of physical interpretation and comparability. This paper develops novel quantitative metrics to evaluate power system resilience in pre- and post-event contexts. The developed metrics illustrate clear physical meanings and can be effectively used to compare resilience across different systems under different extreme events. Moreover, the developed metrics can be applied to both transmission and distribution systems. Simulation on a distribution system is employed to validate the effectiveness of the proposed resilience metrics and resilience evaluation approach.**

***Index Terms*—Power system resilience, resilience metrics, resilience quantification**

I. INTRODUCTION

Nowadays, the operation of power and energy systems faces numerous challenges introduced by climate changes, such as energy demand surge caused by heatwaves and hydro generation shortage caused by droughts. Among these challenges, the number of outages is believed to rise because of the increasing frequency and intensity of extreme weather events [1]. The recent 2021 power outage in Texas highlighted the necessity to understand, analyze, and deal with such extreme events to minimize the damage [2].

In this context, power system resilience is proposed to capture the performance of power system under the influences of extreme events [3]. In general, power system resilience can be defined as the capability of a power system to maintain its performance (e.g., generation, load, and voltage) and speedily recover damages after a high-impact low-probability (HILP) event. Many research works have been done in the area of power system resilience, including definitions, modeling approaches, evaluation metrics, and methods and strategies to improve power system resilience [4]-[10]. Among them, defining appropriate power system resilience metrics and quantification methods is critical before moving forward to discussing models and approaches to analyze and improve resilience. As an emerging topic, several resilience metrics have been proposed referring to existing metrics in other fields such as graph theory and power system reliability [11]-[12]. Although these metrics can reflect one or several key features of resilience, the following drawbacks can be identified: i) existing resilience metrics are either nonquantitative or quantitative but do not provide a clear physical interpretation; ii) existing metrics rely heavily on historical data/record to evaluate event impact and grid vulnerability, which may not always be available or reliable given the nature of HILP event; and iii) it is difficult to compare the resilience of different systems that may suffer from different types of events using existing metrics.

To overcome these drawbacks, this paper develops quantitative metrics for power system resilience evaluation and discusses the evaluation approach. The proposed quantitative metrics are designed such that each metric corresponds to a term that is meaningful to the power industry. The heavy reliance on extreme event data is relieved by dividing the resilience quantification into two stages: pre-event stage that evaluates resilience in general, and post-event stage that uses the known event data to quantify resilience against that specific event scenario. Moreover, the developed resilience metrics have better comparability than existing ones, thus making them suitable to compare the resilience of power systems with diverse characteristics and different types of threats.

II. RESILIENCE EVALUATION

A. *Typical Resilience Evaluation Process*

Take the resilience against extreme weather events as an example, existing methods typically take the following steps to analyze resilience, as shown in Fig. 1.

1. <u>Event modeling</u>: model extreme event intensity, propagation paths, and influencing radius using either historical or forecast data.
2. <u>Impact assessment</u>: with a modeled event, its impacts on the power system infrastructure are evaluated using historical vulnerability and frangibility records.
3. <u>Outage analysis</u>: with identified vulnerable sections of the grid, potential outage scenarios will be generated using probabilistic analysis and Monte Carlo simulation.

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4. Resilience evaluation: simulate power system response using the generated outage scenarios and evaluate resilience using the resilience trapezoid developed in [3].

However, power system resilience evaluation is a challenging task, given the nature of HILP events. The scarcity of HILP event data, especially before the event happens, results in two challenges: i) HILP event model construction with limited data, and ii) accuracy of HILP event modeling. Another concern is associated with the second step (impact assessment). Existing operating records can be used to evaluate the reliability of power apparatus during normal or close to normal conditions. When influenced by an extreme event that has indicators exceeding historical operating conditions, it is challenging to evaluate the functionality accurately using historical data. Take the planning studies as an example, where power systems want to strengthen their grid and implement preventative measures to deal with potential threats. Following the four steps shown in Fig. 1 is likely to introduce significant error and discrepancy in extreme weather modeling step and the impact assessment step due to the lack of historical data and forecast error.

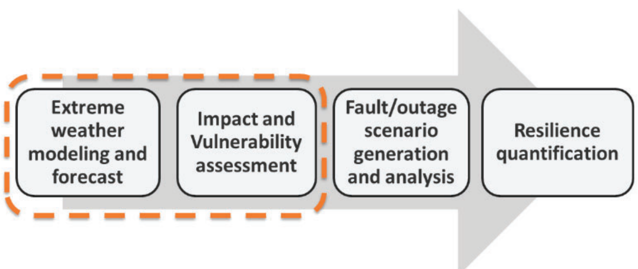

Fig. 1. Typical resilience evaluation steps.

B. Bypass Event Modeling Challenges

The first two steps in Fig. 1 (highlighted by the dashed box) have been identified as the challenges to resilience quantification. On the other hand, resilience analysis also relies heavily on the extreme event, as the same system may perform completely differently against different events. To bypass the event modeling challenges while maintaining reasonable resilience quantification results, i.e., skip the first two steps highlighted by the dashed box in Fig. 1, this paper proposes to evaluate power system resilience from two perspectives: pre-event evaluation and post-event evaluation.

Pre-event evaluation investigates the resilience performance of a power system without the knowledge of the extreme event information. Post-event evaluation is conducted after the occurrence of an extreme event when event data and impacts are known. In other words, the pre-event evaluation provides a generic resilience assessment, whereas the post-event evaluation is case-sensitive and evaluates power system resilience in a specific scenario.

- Pre-event evaluation: Instead of modeling the nature of extreme events, the focus is placed on the direct causes of power outages—faults and maloperations. The resilience of a power system in the pre-event context estimates the system operating level when losing a number of facilities or a certain percentage of its nominal capacity. Pre-event estimation makes no assumption on the event, so the quantification represents resilience in general.
- Post-event evaluation: With a given extreme event, the resilience performance can be directly assessed using event data. The response of a power system to the extreme event can be directly analyzed in the post-event context without worrying about event modeling. Note that the post-event evaluation provides an event-specific resilience assessment that helps operators to re-evaluate the optimal response strategy against the same or similar event.

In both cases, event modeling and impact assessment can be bypassed. Moreover, the combination of pre- and post-event resilience evaluation help provide a more comprehensive insight into resilience. As shown in Fig. 2, a system with better post-event performance (e.g., system 1 performs better under event *c*) does not indicate it should have a better pre-event resilience evaluation (e.g., system 2 has better overall pre-event resilience evaluation considering three events *a*, *b*, and *c*), and vice versa.

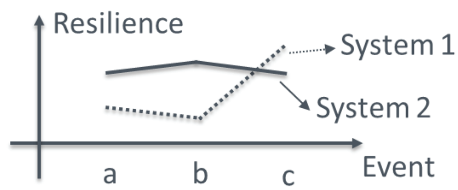

Fig. 2. Resilience in general vs. resilience in specific event.

III. Proposed Quantitative Resilience Metrics

A. Metric for Pre-Event Resilience Quantification

The pre-event resilience evaluation aims to provide a general assessment of system response after a major disturbance without accurate knowledge of extreme events. An ideal pre-event metric should contain the following three key attributes:

- Event insensitivity: The pre-event resilience metric should not be built upon the accurate/forecast data of a specific event.
- Physical interpretation: The pre-event resilience metric should have a clear physical interpretation, e.g., denoting a physical quantity that has a clear meaning and can be easily understood/accepted by power industry.
- Comparability: The pre-event resilience metric assesses the resilience in general, thus it should be able to compare the expected resilience of different systems with diverse features against different types of events.

In pre-event evaluation context where event data is not available, the scenarios should focus on the direct cause of power outages—failures and malfunctions of the grid. In fact, various types of extreme events will first influence the normal functionality of the grid before causing outage issues to the customers. To name a few cases: i) a hurricane causes several 500kV transmission lines to trip; ii) a heatwave results in heavy loading in an urban area, leading to bus undervoltage and line overloading issues; and iii) a cyberattack causes a generating station to shut down completely. These cases are the results of completely different event which are extremely difficult to model in the pre-event context. However, their impacts on the grid are easier to anticipate, i.e., causing failures and malfunctions of the grid. Therefore, modeling the failures and malfunctions of the grid is a viable solution in pre-event context.

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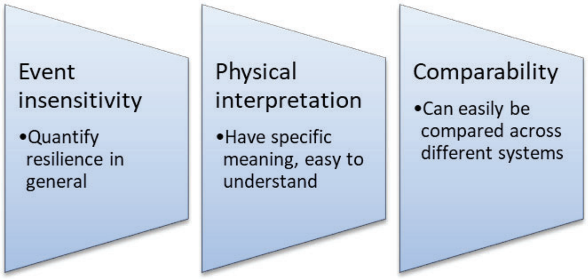


Fig. 3. Key attributes of a successful pre-event resilience metric.

Focusing on grid failures and malfunctions, the key question to be addressed is to construct a reasonable scenario to represent the failure without losing generality. A new metric named performance-damage-duration (PDD) is developed to quantify the capability of the power system to maintain a certain level of performance (e.g., load supply) when suffering from a certain level of disturbance, for a predefined period. The PDD metric contains two main parameters, performance/damage (X) and duration (Y), which is defined as:

$$X \coloneqq \max_{X \in [0,1]} \left\{ \inf_{s \in S, t \in [0,Y]} P_{s,t}^{1-X} \geq X \cdot P_{s,t} \right\} \tag{1}$$

where S denotes the set of possible damage scenarios that represent the damage level X, $P_{s,t}$ denotes the nominal load consumption at time t, $P_{s,t}^{1-X}$ denotes the uninterrupted load supply at time t when suffering from damage X. In Equation (1), inf is the infimum function that captures the worst cases of $P_{s,t}^{1-X}$ among all scenarios in S.

This PDD metric is a unified metric formulation for both transmission systems and distribution systems. With a fixed duration Y, a higher X indicates a higher resilience evaluation result in the pre-event context. Similar conclusion can be reached if X is fixed. To understand the meaning of this PDD metric, several examples are given below assuming Y is fixed:

- Let $X = 1\%$, it means the system can provide sustainable power supply to at least 1% of its nominal load when losing 1% of its infrastructure/capacity, in the worst-case scenario. Modern power systems typically satisfy this criterion because they are *N*-1 reliable. Equation (1) aims to maximize X, so X can be pushed to a higher value.
- If X is raised to 20%, it means the system can provide sustainable power supply to at least 20% of its load when losing 20% of grid infrastructure/capacity, in the worst-case scenario. This becomes more challenging because losing several critical elements indicates a very severe disturbance. If the failures can be properly isolated and control scheme can sectionalize the grid into self-sustained islands/microgrids, the criterion in Equation (1) may be accommodated if the system is strong, i.e., resilient.
- The ideal case is when X reaches 100%, meaning that no load curtailment occurs during the duration of Y when the grid is completely down. An example is a microgrid system where every customer has a sufficiently large battery and backup generator. Therefore, no customer relies on microgrid and its upstream transmission system for power supply. Although $X = 100\%$ does not seem realistic for now, it is intuitive to imagine this kind of power grid has the highest resilience against major disturbances.

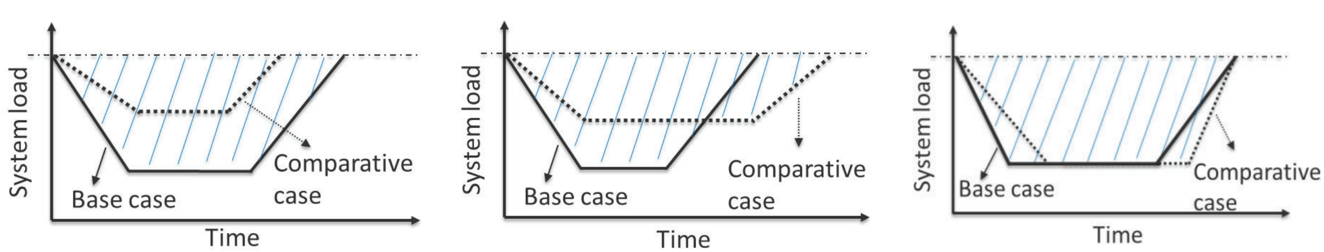
Therefore, using the developed PDD metric to evaluate system resilience is to find the maximum X and Y that a system can tolerate. Furthermore, the developed PDD metric satisfies all three criteria shown in Fig. 3. First, the PDD metric does not employ event models or data and is insensitive to the type, nature, and characteristics of the event. Second, the PDD metric has a clear physical meaning according to its definition. Given the values of X and Y, one can easily infer the performance of the power system without needing to be familiar with the features of the system. Third, the PDD metric can easily be used to compare resilience across different systems. For example, system *A* has better PDD evaluation (e.g., higher X and Y) than system *B*. It is reasonable to conclude that system *A* has better resilience in general even if these two systems have very different configurations and suffer from various types of threats.

B. Metrics for Post-Event Resilience Quantification

In post-event resilience evaluation, accurate event data can be employed to analyze and improve system responses. The commonly used approach is to model the event and system response using a resilience trapezoid [3], as shown in Fig. 4.

The key to post-event resilience evaluation is to derive metrics from the trapezoid. Among existing resilience metrics, the most used metric is the amount of energy curtailment, or the economic loss/damage caused by the event. Referring to Fig. 4(a), this metric corresponds to the total load energy shed (E^{shed}) due to the HILP event. However, E^{shed} alone does not always capture the resilience performance, several examples are provided in Fig. 4.

In Fig. 4(a), the system load curve of the comparative case (dot line) is higher (i.e., superior) than the base case (solid line). Using E^{shed} can reach the same conclusion that the comparative case has better resilience than the base case in Fig. 4(a). However, the base case and comparative case in Fig. 4(b) and Fig. 4(c) share the same amount of energy curtailment E^{shed}, yet displaying very different performance against the same event. It is clear that E^{shed} alone cannot successfully illustrate the resilience in Fig. 4(b) and Fig. 4(c).



(a) (b) (c)

Fig. 4. Resilience trapezoid comparisons.

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Therefore, additional metrics should be introduced to evaluate resilience. Here we propose to use two primary metrics and one secondary metric to capture the two core concepts of resilience. The primary metrics are:

- Total energy curtailment $E^{shed} := \int_0^t P^{shed}(t)dt$
- Peak load curtailment $P^{peak} := max_t P^{shed}(t)$

The secondary metric aims to capture the capability of the system to withstand and recover from an extreme event, which is defined as:

- Resist/recovery ratio $R^s := T^D/T^R$, indicating the robustness and resilience of the system. T^R represents the total time horizon of the resilience trapezoid, T^D denotes the duration that the system degrades from its nominal operating point to the worst operating level. The ratio $R^s = T^D/T^R$ integrates and normalizes T^D and T^R, and this ratio R^s ranges from 0 to 1.

For the same event, a smaller T^R indicates a faster restoration speed, and a larger T^D normally indicates: 1) the system is more robust, i.e., degrade at a slower speed; 2) customers have more time to react to the HILP event, which may reduce their economic loss caused by the outage. Therefore, a larger R^s can be used to imply a more robust system. An ideal system with optimum resilience performance will have minimal values of E^{shed} and P^{peak}, and a maximal value of R^s.

With the set of metrics E^{shed}, P^{peak}, and R^s, the resilience of base case and comparative case in Fig. 4(b) and Fig. 4(c) can be assessed. In Fig. 4(b), two cases have the same E^{shed}, but the comparative case has smaller P^{peak}. In Fig. 4(c), both cases have the same E^{shed} and P^{peak}, while the comparative case has a larger R^s. Thus, it is reasonable to conclude comparative case is more resilient in Fig. 4(b) and Fig. 4(c).

C. *Pre-Event Resilience Evaluation Approach*

Event data can be directly used in post-event resilience evaluation. Pre-event resilience evaluation, on the other hand, is not straightforward. In fact, to derive the X value is comparative to solving a large number (typically unknown) of *N-k* contingency analysis problems, even with a fixed value of Y.

Hence, a simplified evaluation approach is proposed to approximate the PDD metric with the duration Y fixed (i.e., only need to estimate the X value). The detailed procedures to approximate the PDD metric is summarized in Algorithm 1.

Algorithm 1

1: Initialize capacity of system elements (e.g., generation, line, transformer, etc.) and close all circuits
2: Open a closed circuit with the largest capacity.
3: Calculate the level of damage $X1$ (%) and run power flow to derive the level of load supply $X2$ (%). If $X2 \geq X1$, the criterion (1) is met and jump to step 5. If $X2 < X1$, proceed to step 4.
4: Reclose the opened circuit. If all circuits have already been opened, proceed to step 5. Otherwise, open a new circuit that was originally closed and has the second largest capacity and return to step 3.
5: If all circuits have already been opened, return $X2$ as the estimated value of X, terminate the algorithm. Otherwise, return to step 2.

IV. Simulation Validation

The IEEE 123-bus test feeder [13] is employed to validate the performance of the proposed metrics. The peak load capacity is 3500 kW, and the following cases are simulated:

- Case 1: 0% photovoltaic (PV) penetration.
- Case 2: 50% PV penetration (total capacity is 1750 kW), 83 small-size PVs are deployed in a scattered manner.
- Case 3: 25% PV penetration (total capacity is 875 kW), 83 small-size PVs are deployed s in a scattered manner.
- Case 4: 50% PV penetration (total capacity is 1750 kW), 6 large-size PVs are deployed.
- Case 5: 25% PV penetration (total capacity is 875 kW), 6 large-size PVs are deployed.

For post-event resilience analysis, 10 sets of event scenarios are created, each of which contains 20 distribution line outages that are randomly generated. The simulation timeframe is 6-hour with 1-minute time-resolution. The load and PV power are assumed to be constant during the 6-hour timeframe.

A. *Pre-Event Resilience Quantification Results*

Table I reports the pre-event resilience evaluations of the studied 5 cases. Two existing metrics, namely the branch count effect and the repetition of resources [11], are also compared.

TABLE I Pre-Event Resilience Evaluation Results

Case	Branch count effect	Repetition of sources	Proposed PDD metric (%)
1	131	0.01	8.59
2	131	0.92	50.99
3	131	0.92	22.50
4	131	0.08	29.41
5	131	0.08	22.21

For cases 1-5, the branch count effect is constant because the topology remains unchanged. The repetition of sources depends on the location and number of generation sources, it has the same value for PV case 2 and 3 (case 4 and 5). It is clear these two metrics only capture some network features of the grid while ignoring electrical parameters such as load distribution and generation capacity.

For the proposed PDD, case 1 has the worst pre-event resilience because there is no PV. Case 2 has the highest pre-event resilience evaluation results because: 1) it has the highest PV penetration level (50%); and 2) it has the most dispersed distribution in the microgrid, meaning that the system is more robust against distribution lines failures. Case 3 and case 5 have very similar pre-event evaluation despite having very different PV capacity distribution. This is because the capacity of a single PV unit in case 3 is too small and may not be sufficient to supply its local load, not to mention supplying its neighboring loads suffering from major disturbances. Therefore, when PV penetration is low, the bottleneck issue to be addressed is to increase PV penetration. When the total PV generation capacity becomes larger (e.g., 50% in cases 2 and 4), improving microgrid resilience will require a more dispersed PV unit distribution.

B. *Post-Event Resilience Quantification Results*

Fig. 5 and Table II report the resilience trapezoids and post-event evaluation results in scenario 10. Three comparative

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metrics, namely degradation rate, degradation intensity, and recovery rate [3] [12] are also compared in Table II.

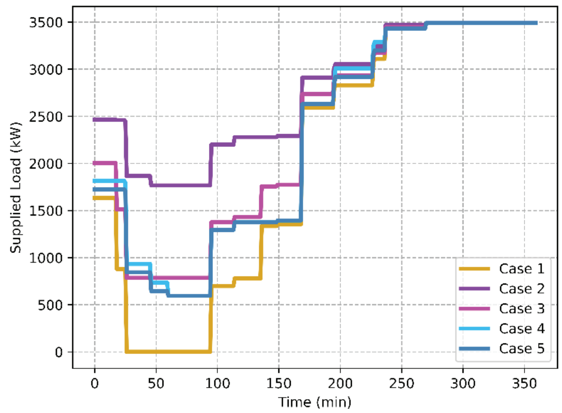

Fig. 5. Resilience trapezoids of 5 cases in event scenario 10.

TABLE II POST-EVENT RESILIENCE EVALUATION RESULTS

Case	Degradation rate (kW/hr)	Degradation intensity (hr)	Recovery rate (kW/hr)	E^{shed} (kWh)	P^{peak} (kW)	R^s
1	7756	1.15	1203	8814	3490	0.10
2	2200	0.82	594	4443	1723	0.17
3	6011	0.57	777	6894	2705	0.10
4	2848	0.58	998	7236	2895	0.23
5	2848	0.58	998	7387	2895	0.23

TABLE III COMPARISON OF PRE- AND POST-EVENT RESILIENCE EVALUATION

Case	Pre-event ranking	Average post-event ranking	Highest post-event ranking	Lowest post-event ranking
1	5	5	5	5
2	1	1.1	1	2
3	3	3.1	2	4
4	2	2.3	1	3
5	4	3.5	3	4

According to Fig. 5, case 2 has the best resilience performance while case 1 is the worst. Cases 3-5 have similar resilience trapezoid shapes, but case 3 is slightly better than cases 4 and 5 because its performance curve is generally more superior than the other two cases. However, the comparative metrics in Table II will rate cases 4 and 5 higher because of the slower degradation rate, similar degradation intensity, and faster recovery rate. Using the developed set of metrics, case 3 performs better because of its smaller E^{shed} and P^{peak}. Although case 3 falls short in terms of R^s, it is still considered better than cases 4 and 5 because R^s is not a primary factor in post-event resilience evaluation. Therefore, the developed set of metrics provides a more reasonable post-event resilience quantification.

C. Discussions

Table III compares the pre-event resilience evaluation results and the post-event resilience evaluation results in the simulated 10 scenarios. Note that the pre-event ranking based on the proposed PDD metric is very consistent with the average post-event ranking obtained from 10 different event scenarios. What's more important is that PDD evaluation does not rely on any event data. This proves that the proposed PDD metric can illustrate system resilience without event modeling and event data, thus fits the pre-event resilience evaluation context.

Table III validated that power systems with a higher pre-event resilience rating are expected to perform better with major disturbances. But with a certain scenario, this conclusion may not be true (e.g., case 4 has a highest ranking of "1" in Table III, indicating it has the best resilience performance in certain event scenarios despite case 2 has the best average post-event ranking and is also rated highest in pre-event evaluation). Therefore, Table III proves that pre- and post-event metrics are complementary to each other and supports the idea to use pre-event PDD metric for general resilience quantification and post-event metrics for resilience evaluation in specific scenarios.

V. CONCLUSIONS

This paper develops quantitative pre- and post-event resilience metrics for comprehensive power system resilience analysis. A new resilience metric named PDD is proposed to evaluate resilience in the pre-event context, and a set of metrics are developed to evaluation resilience in the post-event context. The developed resilience metrics do not rely on historical data or accurate event forecast, and demonstrate better comparability compared to existing ones. Simulation results on a distribution system validate that the developed resilience metrics are more effective and consistent. Given the increasing threats of extreme events, the developed resilience metrics can help power industry to analyze resilience and secure grid operations in the presence of major disturbances.

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