Microgrid resilience: a holistic and context-aware resilience metric

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Abstract
Microgrids present an effective solution for the coordinated deployment of various distributed energy resources and furthermore provide myriad additional benefits such as resilience, decreased carbon footprint, and reliability to energy consumers and the energy system as a whole. Boosting the resilience of distribution systems is another major benefit of microgrids. This is because they can also serve as a backup power source when the utility grid’s operations are interrupted due to either high-probability low-impact events like a component failure or low-probability high-impact events—be it a natural disaster or a planned cyberattack. However, the degree to which any particular system can defend, adapt, and restore normal operation depends on various factors including the type and severity of events to which a microgrid is subjected. These factors, in turn, are dependent on the geographical location of the deployed microgrid as well as the cyber risk profile of the site where the microgrid is operating. Therefore, in this work, we attempt to capture this multidimensional interplay of various factors in quantifying the ability of the microgrid to be resilient in these varying aspects. This paper, thus, proposes a customized site-specific quantification of the resilience strength for the individual microgrid’s capability to absorb, restore, and adapt to the changing circumstances for sustaining the critical load when a low-probability high-impact event occurs—termed as—context-aware resilience metric. We also present a case study to illustrate the key elements of our integrated analytical approach.

Keywords Microgrid · Resilience · Resilience-metric · Resilience quantification · Risk assessment · System operation

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1 Introduction

1.1 Background and literature review

Energy systems are undergoing a major transformation as countries around the world work towards meeting their decarbonization targets. Shaping this transformation are the factors like new clean energy technologies (distributed energy resources and energy storage) as well as the need for continuous and dependable electricity supply as electrical is a quintessential component of modern life. Energy systems have long been categorized as a part of a country’s critical infrastructure because of this reliance of the modern economy on electricity [1]. In this environment, the ability to keep lights on in the event of a natural disaster or a cyber-incident has become a major concern for the power systems community. Compared to the larger grid, microgrids represent a subcategory of power grids, which when connected to the utility grid, are often designed to sustain the critical load in case of a power outage of the utility grid. In this way, the microgrids help strengthen the resilience of the distribution grid [2]. On the other hand, microgrids are the only source of electricity in the places like a remote island and therefore are designed to operate in isolated mode. The resilience of microgrid, in such remote settings, becomes all the more important.

The process of infusing resilience capabilities within a particular microgrid requires infrastructural as well as operational procedure changes [3]. Since the resilience of microgrids is an important consideration during the design and construction phase of greenfield projects, it follows that there should be a way to quantify the degree or the strength of the resilience capability of the microgrid which can guide the design decisions. Hence, the resilience metric. Are the existing standardized reliability metrics such as Customer Average Interruption Duration Index (CAIDI), System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI) not good enough to assess the resilience capabilities of a system? We briefly answer this question before venturing into the detailed discussion and proposed formulation of the resilience metric.

To understand the need for a different metric to quantify resilience, a distinction between the often interchangeably used terms reliability and resilience must be made. Reliability can be defined as the ability of the energy system, specifically the power system, to deliver electricity in quantity and with the quality that is required. The quantity is demanded by the users and the quality is determined by the nature of the end-use devices (inductive, capacitive, resistive load). Reliability is generally measured by the aforementioned interruption indices. Reliability, therefore, is a measure of the system’s capability to keep the lights on in a consistent manner depicting a binary view of the system performance—systems can either be functional or failed. On the other hand, the word resilience stems from the root resilio which means to leap or spring back. Resilience is concerned with the ability of a system to recover and restore normal operations when a high-impact event hits. The National Infrastructure Advisory Council [4] defines critical infrastructure resilience as: “...the ability to reduce the magnitude and/
or duration of disruptive events. The effectiveness of a resilient infrastructure or enterprise depends upon its ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event”. Our previous work has dealt with a detailed definition and interpretation of the concept of resilience (subsection 2.2 in [3]). Given the explicit differences between the terms reliability and resilience, it is clear that different metrics are needed to measure and quantify these two related yet distinct concepts aiding the efficient operations of energy systems.

The concept of resilience has been extensively explored in the context of power systems (i.e. the centralized utility grid). For example, Wang et al. [5] and Jufri et al. [6] provide a comprehensive review of the research on resilience of the power systems under natural disasters. The key strategies in realizing resilience in power systems are reviewed in [7]. Whereas Vugrin et al. [8] evaluate the effect of the resource constraints on the resilience of bulk power systems. Assessment of power systems resilience in case of the hurricane is conducted in [9]. Fang et al. focus on investment optimization in power systems with the objective of building resilience against attacks [10]. Resilience indicators are proposed for the evaluation of energy infrastructure in [11]. A load restoration framework based on distribution automation technology in the context of power system resilience is presented in [12].

Microgrid’s role and significance in enhancing the resilience of the power systems has also been studied in the literature to a large degree. System-level assessment of reliability and resilience provision from microgrids is presented in [13]. A method for load restoration through a microgrid formation strategy is proposed in [14]. Similarly, evaluation of microgrid’s ability to serve as a resilience resource of the utility grid is studied in [15–17]. But the question of microgrid’s own resilience in the face of low-probability high-impact events such as natural disasters and cyber-attacks remains relatively unexplored. Attempts have been made in the literature at attacking this question from a specific angle of windstorms [18] but they lack a comprehensive exploration of the problem space. Such an all-inclusive view should account for various types of events and the multi-dimensional interplay of microgrid’s infrastructural and operational aspects in both physical and cyber planes. This comprehensive study of the problem can be approached either in qualitative or quantitative ways.

Our previous work has presented a qualitative approach to assessing the resilience of microgrids [3]. In the current work presented here, we employ a quantitative approach to assessing microgrid resilience. We present a resilience metric formulation that accounts for various threats and vulnerabilities associated with those threats within a microgrid. We take a probabilistic approach to arrive at a metric that captures the interplay of the threat, vulnerability, and vulnerability impacts within a microgrid. The need and relevance of this work are further established in the following subsection.

1.2 Relevance and contribution

Resilient microgrids, when designed with needed capabilities, can effectively provide a reliable and robust supply of backup power, withstand threats, adapt to
continually changing circumstances during the event of an unusual disturbance, and trigger either automated or semi-automated restorative actions after the disaster has passed. However, the challenge lies in the determination of an effective design—on a case-by-case basis. For example, if a microgrid is situated in a coastal area, close to sea level, then the effective design choice, against a specific threat of hurricane-induced flood, would be to situate the on-site generation at a height. The solution seems simple enough in this case. However, this seemingly straightforward solution does not empower the microgrid with resilience against cyber-threat or fire-hazard. This example gives a peek into the complexity of the issue at hand—which is quantification considering all possible threats, vulnerabilities, and vulnerability impacts in parallel.

It is important to note that the topic of microgrid resilience, including its mitigation measures, has techno-economic, social-economic, and socio-technical aspects interwoven into it; where there are wide variations in the human judgment of the risk and existing vulnerabilities in the system as well as economic considerations. Figure 1 demonstrates this interwomen nature of various aspects with a venn diagram. Therefore, the quantification of microgrid resilience is not a one-size-fits-all problem. Instead, employing an approach rooted in the mathematical foundation of risk assessment through probabilistic method (Monte Carlo Simulation), but the overall methodology molded on a case-by-case basis, and guided by a well-informed framework will yield results that are optimal from a real-life deployment perspective. This work, therefore, intertwines mathematical risk assessment methodology with human expert knowledge about the risk-vulnerability profile of a given site and paints a holistic picture of this problem’s solution space in the social-technical domain. The real-life decision-making around introducing resilience-interventions (mitigations), therefore, will be highly benefitted with the proposed approach.

The proposed approach to determining the resilience metrics is holistic because it considers both physical and cyber layers of the microgrid, at the same time it is context-aware because it is considering both operational and infrastructural aspects for arriving at a metric. The specific contributions of the work are as follows:
• We propose a resilience hierarchy for assessing the multi-faceted nature of the microgrid resilience concept.
• We layout the framework for a context-aware and holistic quantitative resilience metric that can be used for assessing the resilience potential of a given microgrid design.
• We demonstrate the workings of the proposed framework for determining the resilience baseline of a microgrid through a detailed case study.
• We present an approach to employ the resilience baseline for identifying the most effective interventions, which can then prioritized over other possible interventions, that can help enhance the resilience capabilities of the microgrid.

1.3 Article structure

Section 1 laid out the background and motivation for this work and listed our contributions to the research question of microgrid resilience quantification. The rest of the article is organized as follows. Section 2 establishes the foundational interpretation of microgrid’s resilience capabilities in this work and further presents our proposed identification of the hierarchical relationship between infrastructural and operational resilience dimensions of the microgrid. A novel framework for microgrid resilience metric calculation is introduced in Sect. 3. Section 4 presents a case study conducted based on the proposed framework and Sect. 5 concludes the article with a discussion of future research directions.

2 What does it mean for the microgrid to be resilient?

The United States Presidential Policy Directive (PPD21) [1] defines the term “resilience” explicitly to mean “the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents.” With many other variations of the power system resilience definitions presented in the literature [19], we establish the baseline of what is being considered as a ‘resilient microgrid’ in this work. It is the ability of the microgrid to:

• Be resistant against the potentially damaging event
• Be absorptive of the impact of the disturbance introduced by the event, without losing the critical load\(^1\)
  
  o By having needed redundancies (UPS supply, for example);
  o By being operationally adaptive (continuing to serve the critical load, by rerouting the available energy from generation resources which are able to supply power during and after the event);

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\(^1\) Critical loads are those loads to which power supply has to be maintained under any circumstances. They are usually specified as the percentage of the total site load.
• Rapidly restore the normal operations after the event has passed

  o Through automated or semi-automated operations restoration;
  o Or in case of partial infrastructure damage, trained personnel capable of operating partially-activated assets in manual operational mode;
  o Or in case of infrastructure damage to the point of losing all significant assets, by having required resourcefulness in terms of availability of the spare physical parts for the repair;

• Be infrastructurally adaptive

  o In case of partial or total infrastructure damage, a system designed with upgraded resilience features in physical as well as cyber dimensions that can operate in semi-automated mode;

The competence of the microgrid in the aforementioned aspects addresses all the phases it goes through when experiencing a low-probability high-impact event (i.e. hurricane, sabotage). These four capabilities of the microgrid form the foundational pillars for the discussion and quantification of its resilience strength. Resilience, therefore, has wide-reaching implications that can span large geographical areas (especially in the case of the utility-grid connected microgrid) and factor into performance at all system levels both during calamities and after such events have passed. Moreover, it is important to note that the restoration phase does not always have a straightforward path. Depending on the degree of infrastructural damage, the restoration process may take from minutes to weeks, or in some cases months.

“Operational resilience”, on the other hand, is introduced in a policy document from the US government in the context of needing to “make the system better able to absorb the impact of an event without losing the capacity of function” [20]. Whereas, “infrastructural resilience” encompasses the robustness of the building blocks of the microgrid in both hardware and software dimensions; also calls for sufficient redundancy in those building blocks, and allows for sufficient resourcefulness to resolve issues with sufficient rapidity to continue operating at normal or near-normal performance levels. For delivering the objective of keeping the critical load ‘on’ means the system should be resilient in both dimensions, the intertwined nature of these two is discussed later in the following sub-section.

It is also worth noting that resilience is associated with the ability to sustain and recover from low-probability high-impact events, which is differentiated from reliability that primarily revolves around strengthening the system to sustain through high-probability low-impact events occurring during normal operations. Reliability, however, does form one component of the larger resilience equation. In other words, for a system to be resilient, having reliable performance is a necessary condition but not a sufficient one, i.e. being reliable does not guarantee that the system will be able to sustain critical load in the face of external threats. This distinction between resilience and reliability leads to the discussion of classifying the events (or external threats), which are considered low-probability high-impact events against which the system’s resilience should be quantified. For quantifying the resilience of the
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Microgrid, the threats being examined in this study are external threats, i.e. external perturbation introduced in the energy system as a result of natural disasters, unusual weather conditions, and a planned physical or cyber-attack. A blizzard resulting in unusual heating load spikes or a heatwave causing cooling loads to overload the microgrid beyond expected demand are examples of low-probability high-impact external threats. A detailed description of the threats to the microgrid is provided in [3]. On the other hand, deviation from normal operations due to internal component malfunctioning is not an external threat to the system. For example, non-malicious chance failures of microgrid controller that occur due to unforeseen complex edge cases in highly sophisticated control algorithms because of insufficient testing is not an external threat against which the controller can be made resilient [21, 22]. This kind of event comes under the umbrella of component (hardware component in this case) failure issue, which needs to be studied under the reliability domain, which is termed as cyber-security for the software dimension. Similarly, an inverter failure due to internal fault is not a kind of threat resilience would be measured against [23]. This event, as the previous one, gets categorized as a reliability-related issue. The measures to prevent such events should be addressed during the planning/design process with the goal of maintaining desired reliability levels.

Having established a clear differentiation between the threats pertaining to resilience and the disturbances related to reliability, we now delineate the interdependencies amongst the operational and infrastructural aspects of the microgrid performance as it relates to the microgrid resilience quantification. It would not be unseemly to suggest that the resilience performance of the microgrid, both during and after catastrophic events, is greatly impacted due to the high degree of interdependence between these two aspects (infrastructural and operational)—especially when compared with the utility grid’s resilience. That is because for the utility grid, due to its interconnectedness and geographically wide-stretching transmission and distribution networks—(1) there are more than one generation plants that could supply the power to critical loads if the power lines are not completely damaged or rendered unfunctional, (2) there may be potentially more inertia to bring the system back to normal operational limits after the external disturbance has ceased. On the other hand, in the case of the microgrid, if the critical generation asset is destroyed, then this infrastructure damage could bring down the whole microgrid since redundancy in the generation assets is generally very difficult to maintain due to economic reasons. The following sub-sections elucidate this twirled nature of the operational and infrastructural dimensions of the microgrid.

2.1 Resilience hierarchy

Though infrastructure and operational resilience address two different constituents of the resilience quantification, they are neither mutually exclusive nor independent dimensions of microgrid resilience. Figure 2 depicts the proposed resilience hierarchy that illustrates the overarching concept of holistic resilience quantification. The core plan for making a microgrid resilient enough to serve the critical loads during
For the case when microgrid infrastructure (generation assets, inverters, connecting cables for local distribution, battery storage, controllers) is rendered non-functional by an extreme event, then the question of understanding operational resilience becomes irrelevant. Clearly, none of the critical load can be served and restoration of the hardware components (in case of physical damage) or rebooting of the control systems (aftermath of cyber-attack) is the primary concern in this scenario. If the physical infrastructure is completely damaged, then the timeframe to bring the microgrid back to its normal operation could extend to months. On the other hand, if the damage is partial and replacement of a few components is enough to get the microgrid into a functional form, then the resourcefulness (spare part inventory and off-the-shelf availability of the spare parts) aspect of microgrid resilience is put to test. Therefore, prioritizing the hardening of infrastructure (in both physical and cyber dimensions) provides the first line of defense against extreme events.

Nevertheless, for the scenario when the infrastructure is partially or fully functional, operational resilience becomes of prime importance. There are three phases through which microgrid’s operations progress—(1) before the event, (2) during the event, and (3) after the event. The next sub-sections.

### 2.2 Operational and infrastructural resilience

The operational resilience of a microgrid spans the phases from the first hit of the event till the system is back to the normal operation. The goal of operational
resilience is to make the system better able to absorb the impact of an event and continue functioning to supply the critical load. When looked at from the perspective of the physical layer of the microgrid, operational resilience requires the physical assets to endure the impact and keep functioning to serve the critical load. In the cyber dimension, operational resilience would require the analytics and controls layers of the microgrid to have the ability to detect a cyber-attack, defend it, block it, and all the while keep supplying the energy as needed.

The infrastructural resilience, on the other hand, calls for the ability to recover fast after the event—in case the infrastructure has been damaged during the event. The goal of infrastructural resilience is to minimize the time needed for the system to get back to its full functional capacity. For the physical layer, it would entail the repair or replacement of the damaged components. Whereas in the cyber layer, if the cyber-attacker has been successful in interrupting the operation, the ability to detect the passage of attack and isolate it exhibits the resilience capacity of the microgrid.

2.3 Interdependencies between cyber and physical layers

Although the cyber and physical layers of the microgrid can be broken down into separate planes for study and analysis purposes, in reality, they are tightly intertwined and operate in tandem at every point in time. Therefore, when a threat is posed on either of the layers, the vulnerability impacts can quickly trickle down to the other layer—rendering the microgrid stale. For example, a cyber-attack, aimed at falsifying the demand measurements (showing them abnormally high) can prompt the microgrid controller to up the energy supply by discharging the battery. The excessive supply can, in absence of adequate load, can throw the frequency out of balance causing a microgrid-wide blackout.

3 Microgrid resilience metric—a holistic assessment framework

Considering the definition of resilience as put forth earlier in this article, to holistically and quantitatively assess—“How resilient is this microgrid?”—a metric should account for the operational and infrastructural dimensions of the problem, and also be representative of the hardware and software features inherent to a tightly-knit cyber-physical system like a microgrid. For the metric to be relevant, the underlying formulation of the metric should be characterized by context-specific factors such as operational vs infrastructure resilience as well as situation-specific factors such as a flood or a cyber-attack. A better way to quantify the resilience of microgrids is to define it relative to the threats to which it is exposed and the performance it is expected to deliver should such adverse events be realized.

3.1 Components of quantitative analysis of resilience

We propose a unified resilience metric that is representative of the cumulative and weighted effect of threats, vulnerabilities, and vulnerability impacts on both
operational and infrastructural resilience of microgrid. In the context of this assessment, threats are defined as external low-probability high-impact events, either natural or human-caused, with the potential to adversely impact a microgrid’s ability to meet critical load or reliability objectives (i.e. hurricanes, terrorist attack). Threats are parameterized in terms of their probability of occurrence over a one-year duration at any level of severity, such that 100% probability threats are certain to occur every year, and 20% probability threats would be expected to happen once every 5 years. For clarification, the threat parameter describes the likelihood of a type of event happening, it does not describe what impacts are to be expected to occur during the event. Such probabilities are expressed as vulnerabilities which are described later in this section. Also, note that each threat is accompanied by a level of importance parameter, which is a scalar between zero and one that is representative of how much the threat should contribute to the cumulative metric; zero being not at all and one being of utmost importance. The level of importance allows the resilience assessment to be contextualized within the microgrid’s constituents’ values and objectives. Thus, a modeler may choose to assign a high level of importance to all conceivable threats, or, alternatively, amplify, diminish, or nullify the contribution of certain threats based on assessment priorities.

Each threat will also be associated with one or more vulnerabilities, which are direct adverse resilience impacts that occur as threats are realized (i.e. high winds take down power lines during a hurricane, saboteur destroys a transformer). Vulnerabilities are similarly parameterized in terms of their probability of occurrence should conditions for the threat be met. Consider the threat imposed by a hurricane, the likelihood of a flooding vulnerability being exploited may be higher for ground-mounted generation assets than rooftop generators.

Each vulnerability in turn has a distinct vulnerability impact on both operational resilience and on infrastructural resilience. Vulnerability impacts on operational resilience are parameterized in terms of the percent of critical load not served during a threatening event. A very high vulnerability impact on operational resilience would be one in which the supply of power is completely curtailed. Note, isolated damage to a subset of system components may not be sufficient to degrade operational resilience if the critical load is minimal, or if there is sufficient redundant generation. Vulnerability impacts on infrastructural resilience are quantified based on the ratio of restoration costs to the aggregate embedded cost of the system (i.e. an impact that destroys a single generator would reflect the proportional cost of restoring that system component to the capital costs of the total system). Note that restoration costs may include the value of lost load if the operator is liable for such losses. Moreover, while restoration costs may conceivably exceed system capital costs, vulnerability impacts are bounded between zero and one. The vulnerability impact parameter serves its purpose when calibrated as such to express a relative degree of impact; it need not express precise cost ratios.

The definition of system-level scope for vulnerabilities and vulnerability impacts (i.e. hurricane winds damage solar PV vs hurricane winds damage all generation capacity) is at the discretion of the modeler; what is important is that the vulnerability impact reflects the vulnerability as defined.
3.2 Parameterization

The framework we put forth for resilience analysis parametrizes threat and vulnerabilities based on likelihoods of occurrence, and vulnerability impacts on the degree of impact quantified as a percentage. In some cases, such precise numeric values can be estimated from historic trends or advanced site-specific modeling capabilities. We expect though in most cases such data does not exist, is overly burdensome to obtain, or exists within a high degree of uncertainty, especially when considering projections out into the future. A solution widely used in studies of risk analysis is to employ qualitative descriptions in place of quantitative data, often gathered from a group of experts. We begin with a qualitative assessment of parameters and extend these to quantitative ranges by means of the lookup provided in Table 1. Note that such mappings of severity descriptions to quantitative ranges are intended for providing a starting point for analysis; further differentiation of severity categories will help to refine the resolution of results where appropriate. Also, note that parameters may be expressed as groups of ranges (i.e. Very Low to Very High may describe the vulnerability impact of a single generation asset).

Diving deeper into Table 1, we see that a ‘very low’ threat would be one that we expect to have a 1–5% rate of occurrence in a year. In other words, we would expect to see this type of threat once every 20–100 years. Likewise, a ‘very low’ vulnerability is one that would only occur rarely if conditions for the threat were met. To understand vulnerability ratings, consider a simple microgrid consisting of a solar PV panel in an area proximate to mature trees and prone to high winds. While the high wind threat may be ‘very high’ if such events are common, the vulnerability to physical damage from a fallen tree during high winds may be ‘very low’ given that in only one in a hundred high wind events would wind-induced tree damage be expected to occur.

Building on this example, and to understand the operational resilience of this system, consider that this simple PV system has a series of solar PV panels connected in series to an inverter. In the event that a tree did fall we might expect a ‘very low’ loss of generation capacity if only one panel at the edge of the series is impacted such that only 1–5% of the critical load is lost. However, a strike farther down the series closer may cause a complete loss of critical load. Accordingly, we classify the potential operational resilience impact as ‘very low’ to ‘very high’. With more information about the

| Classification       | Range     |
|----------------------|-----------|
| Negligible           | 0–0.01    |
| Very low             | 0.01–0.05 |
| Low                  | 0.05–0.2  |
| Moderate             | 0.2–0.5   |
| Considerable         | 0.5–0.7   |
| High                 | 0.7–0.9   |
| Very high            | 0.9–1     |

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likelihood of tree damage outcomes on the system, we would be able to say that the distribution of operational impacts is more likely to occur towards the higher (or lower) end of the impact spectrum. Moreover, an intervention that parallelizes panels (i.e. or physically hardens this infrastructure) may reduce the importance of anyone component such that we drop the worst-case scenario impact on operational resilience to ‘moderate’ or even ‘low’. Finally, to understand infrastructural resilience consider that the microgrid’s vulnerability to physical damage from trees is only expected to damage a subset of panels. Proportional to the capital costs of the total system, such repair or replacement costs may constitute no more than 50%, and with this presumption, we would identify a ‘very low to moderate’ impact on infrastructural resilience.

3.3 Monte Carlo analysis procedure

A microgrid’s resilience assessment begins with listing all relevant threats to a system, inclusive of severe weather events (i.e. thunderstorms), natural disasters (i.e. earthquakes), and human factors (i.e. terrorism). Threat likelihoods are parameterized as described above and assigned a level of importance. Next, vulnerabilities for each threat are contextualized to possible outcomes for system components (i.e. the threat of a hurricane may expose the vulnerability that PV panels may be damaged, but not pose a risk of damage to a well-protected generator) and parameterized. Likewise, vulnerability impacts on operational and infrastructural resilience are parameterized for each vulnerability.

Having established quantitative ranges for threats, vulnerabilities, and vulnerability impacts we employ a Monte Carlo approach to sample an empirical range of potential resilience outcomes for the microgrid. The fact that we are establishing quantitative ranges highlights the degree of uncertainty this problem-space involves. Therefore, the use of the Monte Carlo method which relies on repeated random sampling to obtain numerical results is justified. The underlying concept behind the choice of this method is the use of randomness to solve the problem of obtaining an empirical range of potential resilience outcomes, which are deterministic in principle yet probabilistic in interpretation. We first assess operational and infrastructural resilience separately, according to the same procedure now described.

For each identified and parameterized threat and vulnerability combination in the resilience category (i.e. operational or infrastructural), we compute a residual resilience score as described by the function in Eq. (1), shown below, 1 million times. On each iteration, we insert a threat, vulnerability, and vulnerability impact value at random from within the prescribed bounds of each parameter. The mean of all iterations is then compiled into a metric for the risk.

\[
f(l, v, t, i) = \text{threat level of importance}(l) \times \text{probability of threat}(t) \\
\times \text{probability vulnerability}(v) \\
\times \text{impact of vulnerability}(i) \forall l, v, t, i \in (0, 1)
\]

The resulting mean risk for each threat and vulnerability combination is then aggregated into an aggregate resilience score as described in Eq. (2) below.
where $R$ is the resilience score. Finally, after having computed both operational and infrastructural resilience scores, we combine the two into a total risk score by means of simple averaging as follows:

$$RST = 1 - \frac{(RSI + RSO)}{2}$$

where $RST$ is the Risk Score Total, $RSI$ is Risk Score Infrastructural, and $RSO$ is Risk Score Operational. Given the variability in the number and types of potential threats and vulnerabilities to which a microgrid may be exposed, such an empirically derived risk score is not intended to be compared across sites. Instead, this metric best employed as a baseline for assessing intervention alternatives at the site.

Having established a baseline, a modeler employing this methodology can assess the relative effectiveness in terms of total reliability by adjusting the initial parameterization then rerunning the analysis.

In the following sections, we provide a case study to illustrate the types of threats, vulnerabilities, and vulnerability impacts one would consider in assessments of microgrid operational and infrastructural resilience. We establish an approximate location and feasible set of generation technologies to enable us to make reasonable assumptions about magnitudes and distributions of threats, vulnerabilities, and vulnerability impacts.

4 Case study—coastal community in New England

Let us now consider a small residential town on the New England coast that has built a grid-tied microgrid to sustain critical services during a larger utility grid outage. In the event of a grid failure, this system will keep powered municipal facilities, medical centers, emergency centers, and other food and financial service providers. The microgrid consists of 1 MW rooftop solar PV, a 1 MW wind turbine, 8 MW natural gas generators, as well as 4 MW (8 MWh) battery storage and above-ground distribution lines.

4.1 Threat, vulnerability, and impact assessment

We next describe in detail the threat, vulnerability, and vulnerability impact rankings for this site, which is outlined in Table 2 below and incorporates qualitative mappings described in Table 1 above. Please note that in these assessments, we make reasonable attempts to bound the distribution of each ranking’s intensity. However, since this example is intended to demonstrate how to determine a baseline and assess intervention alternatives, rather than determine a site-specific resilience assessment for the specific location, we do not consult expert opinion or attempt to base ranges on published figures. We also assign an importance level of one to all...
| Threat                | Threat probability and importance | Vulnerability                                                                 | Vulnerability probability | Impact on operational (% critical load lost) | Impact on infrastructure (effort of repairing system) |
|-----------------------|----------------------------------|-------------------------------------------------------------------------------|----------------------------|---------------------------------------------|--------------------------------------------------------|
| Hurricane             | **Probability**                  | Clouds and rain lead to PV generation losses                                 | Considerable               | Negligible to low                          | Negligible                                             |
|                       | **Moderate to considerable**     |                                                                                | 0.5–0.7                    | 0–0.05                                      | 0–0.01                                                 |
|                       | **0.2–0.7**                      | High winds leads to turbine generation losses                                | Low to moderate            | Negligible to low                          | Negligible                                             |
|                       | **0.2–0.5**                      |                                                                                | 0.2–0.5                    | 0–0.2                                       | 0–0.01                                                 |
|                       | Importance                        | High winds damages PV                                                         | Low                       | Negligible to moderate                     | Negligible to moderate                                  |
|                       | **1**                            |                                                                                | 0.05–0.2                   | 0–0.5                                       | 0–0.5                                                  |
|                       | High winds damages turbine       |                                                                                | Low                       | Negligible to moderate                     | Negligible to moderate                                  |
|                       | **0.05–0.2**                     | High winds damage distribution                                                | Low                       | Negligible to moderate                     | Negligible to moderate                                  |
|                       | **0.05–0.5**                     | heavy rains/storm surge damages generator                                      | Low                       | Negligible to moderate                     | Negligible to moderate                                  |
|                       | **0.05–0.2**                     | Heavy rains/storm surge damages storage                                        | Low                       | Negligible to moderate                     | Negligible to moderate                                  |
|                       | **0.05–0.2**                     |                                                                                | 0.05–0.2                   | 0–0.5                                       | 0–0.5                                                  |
|                       | Severe winter storm              | Snow and ice lead to PV generation losses                                      | Considerable               | Negligible to very low                    | Negligible                                             |
|                       | **Probability**                  |                                                                                | 0.5–0.7                    | 0–0.05                                      | 0–0.01                                                 |
|                       | **High**                         | Snow and ice lead to turbine generation losses                                | Very low to low            | Negligible to low                          | Negligible                                             |
|                       | **0.7–0.9**                      |                                                                                | 0.01–0.2                   | 0–0.2                                       | 0–0.01                                                 |
|                       | Importance                        | Snow, ice, and wind damages PV                                                | Very low to low            | Negligible to moderate                     | Negligible to moderate                                  |
|                       | **1**                            |                                                                                | 0.01–0.2                   | 0–0.5                                       | 0–0.5                                                  |
|                       | Snow, ice, and wind damages turbine | Snow, ice, and wind damages turbine                                           | Very low to low            | Negligible to moderate                     | Negligible to moderate                                  |
|                       | **0.01–0.2**                     |                                                                                | 0.01–0.2                   | 0–0.5                                       | 0–0.5                                                  |
|                       | Snow, ice, and wind damages Distribution | Snow, ice, and wind damages Distribution                                      | Very low to low            | Negligible to moderate                     | Negligible to moderate                                  |
|                       | **0.01–0.5**                     |                                                                                | 0.01–0.5                   | 0–0.5                                       | 0–0.5                                                  |
| Threat                  | Threat probability and importance | Vulnerability | Vulnerability probability | Impact on operational (% critical load losT) | Impact on infrastructure (effort of repairing system) |
|-------------------------|----------------------------------|---------------|---------------------------|----------------------------------------------|-----------------------------------------------------|
| Severe thunderstorm     | **Probability** | **High** 0.7–0.9 | **Importance** 1 | clouds and rain lead to PV generation losses | Considerable 0.5–0.7 | Negligible to very low 0–0.5 | Negligible 0–0.01 |
|                         | High winds leads to turbine generation losses | Very low to low 0.01–0.2 | Negligible to low 0–0.2 | Negligible 0–0.01 |
|                         | High winds and rain damage PV | Very low to low 0.01–0.2 | Negligible to low 0–0.2 | Negligible to low 0–0.2 |
|                         | High winds and rain damage turbine | Very low to low 0.01–0.2 | Negligible to low 0–0.2 | Negligible to low 0–0.2 |
|                         | High winds and rain damage distribution | Very low to low 0.01–0.5 s | Negligible to low 0–0.2 | Negligible to low 0–0.2 |
|                         | Lightning causes electrical system damage | Very low 0.01–0.05 | Negligible to high 0–0.9 | Negligible to moderate 0–0.5 |
| Hail                    | **Probability** | **High** 0.7–0.9 | **Importance** 1 | Infrastructure damage to PV | Very low to low 0.01–0.2 | Negligible to very low 0–0.5 | Negligible to Very Low 0–0.5 |
| Threat      | Threat probability and importance | Vulnerability | Vulnerability probability | Impact on operational (% critical load lost) | Impact on infrastructure (effort of repairing system) |
|------------|----------------------------------|---------------|---------------------------|---------------------------------------------|------------------------------------------------------|
| High wind  | Probability Moderate to considerable 0.2–0.7 | Considerable 0.5–0.7 | Negligible to low 0–0.2 | Negligible 0–0.01 |
|            | Importance 1                        |               |                           |                                             |
|            | High winds leads to wind generation losses |               |                           |                                             |
|            | Infrastructure damage to PV         | Very low to low 0.01–0.2 | Negligible to low 0–0.2 | Negligible to low 0–0.2 |
|            | Infrastructure damage to turbine    | Very low to low 0.01–0.2 | Negligible to low 0–0.2 | Negligible to low 0–0.2 |
|            | Infrastructure damage to distribution | Very low to low 0.01–0.2 | Negligible to low 0–0.2 | Negligible to low 0–0.2 |
| Flooding   | Probability Low to moderate 0.05–0.5 | Very low to moderate 0.01–0.5 | Negligible to considerable 0–0.7 | Negligible to Considerable 0–0.7 |
|            | Importance 1                        |               |                           |                                             |
|            | Infrastructure damage to generator  | Very low to moderate 0.01–0.5 | Negligible to considerable 0–0.7 | Negligible to Considerable 0–0.7 |
|            | Infrastructure damage to storage    | Very low to moderate 0.01–0.5 | Negligible to considerable 0–0.7 | Negligible to Considerable 0–0.7 |
| Earthquake | Probability High 0.7–0.9            | Very low 0.01–0.05 | Negligible to low 0–0.2 | Negligible to Low 0–0.2 |
|            | Importance 1                        |               |                           |                                             |
|            | PV damage                           | Very low 0.01–0.05 | Negligible to low 0–0.2 | Negligible to Low 0–0.2 |
|            | Turbine damage                      | Very low 0.01–0.05 | Negligible to low 0–0.2 | Negligible to Low 0–0.2 |
|            | Generator damage                    | Very low 0.01–0.05 | Negligible to considerable 0–0.7 | Negligible to Considerable 0–0.7 |
|            | Storage damage                      | Very low 0.01–0.05 | Negligible to considerable 0–0.7 | Negligible to Considerable 0–0.7 |
|            | Distribution damage                 | Very Low 0.01–0.05 | Negligible to considerable 0–0.7 | Negligible to Considerable 0–0.7 |
| Threat                      | Threat probability and importance | Vulnerability | Vulnerability probability | Impact on operational (% critical load lost) | Impact on infrastructure (effort of repairing system) |
|-----------------------------|----------------------------------|---------------|----------------------------|---------------------------------------------|--------------------------------------------------|
| Tornado                     | Probability High 0.7–0.9 Importance 1 | PV damage     | Very low 0.01–0.05         | Negligible to low 0–0.2                      | Negligible to Considerable 0–0.7                    |
|                            | Turbine damage                   | Very low 0.01–0.05 | Negligible to low 0–0.2     | Negligible to Considerable 0–0.7             |
|                            | Generator damage                 | Very low 0.01–0.05 | Negligible to considerable 0–0.7 | Negligible to Considerable 0–0.7             |
|                            | Storage damage                   | Very low 0.01–0.05 | Negligible to considerable 0–0.7 | Negligible to Considerable 0–0.7             |
|                            | Distribution damage               | Very low 0.01–0.05 | Negligible to considerable 0–0.7 | Negligible to Considerable 0–0.7             |
|                            | Inverter damage                  | Very low 0.01–0.5 | Negligible to high 0–0.9    | Negligible to moderate 0–0.5                 |
| Electromagnetic pulse       | Probability Very Low %1.2–0.5 Importance 1 | Operation shutdown | Very low to low 0.01–0.2 | Negligible to considerable 0–0.7 | Negligible 0–0.01 |
| (non-lightning)             |                                  |               |                            |                                             |                                                  |
| Fuel price spikes           | Probability Low 0.01–0.2 Importance 1 | Operation shutdown | Very low to low 0.01–0.2 | Negligible to considerable 0–0.7 | Negligible 0–0.01 |
|                            |                                  |               |                            |                                             |                                                  |
| Drought                    | Probability Moderate 0.3–0.5 Importance 0 | –              | Negligible 0–0.01          | Negligible 0–0.01                           | Negligible 0–0.01 |
| Threat                  | Threat probability and importance | Vulnerability | Vulnerability probability | Impact on operational (% critical load lost) | Impact on infrastructure (effort of repairing system) |
|------------------------|----------------------------------|---------------|---------------------------|---------------------------------------------|-----------------------------------------------------|
| Tsunami                | Probability Negligible 0–0.01     | Negligible    | Negligible 0–0.01         | Negligible 0–0.01                           | Negligible 0–0.01                                   |
| Wildfire               | Probability Negligible 0–0.01     | Negligible    | Negligible 0–0.01         | Negligible 0–0.01                           | Negligible 0–0.01                                   |
| Cyberattack/IT fault   | Probability Low 0.05–0.3          | Controls override | Very low to low 0.01–0.2  | Negligible to very high 0–1                 | Negligible 0–0.01                                   |
|                        | Importance 1                     | PV damage     | Very low 0.01–0.05        | Negligible to low 0–0.2                     | Negligible to Low 0–0.2                             |
|                        |                                   | Turbine damage | Very low 0.01–0.05        | Negligible to low 0–0.2                     | Negligible to Low 0–0.2                             |
|                        |                                   | Generator damage | Very low 0.01–0.05        | Negligible to considerable 0–0.7            | Negligible to Considerable 0–0.7                    |
|                        |                                   | Storage damage | Very low 0.01–0.05        | Negligible to considerable 0–0.7            | Negligible to Considerable 0–0.7                    |
|                        |                                   | Distribution damage | Very low 0.01–0.05        | Negligible to very high 0–1                 | Negligible to Very High 0–1                         |
| Threat | Threat probability and importance | Vulnerability | Vulnerability probability | Impact on operational (% critical load losT) | Impact on infrastructure (effort of repairing system) |
|--------|----------------------------------|---------------|--------------------------|---------------------------------------------|--------------------------------------------------|
| Terrorism/sabotage/physical failure | **Probability**
Low 0.05–0.3
Importance 1 | PV damage | **Very low to Very high**
0.01–1 | **Negligible to low**
0–0.2 | **Negligible to Low**
0–0.2 |
| | Turbine damage | Very low to very high
0.01–1 | Negligible to low
0–0.2 | Negligible to Low
0–0.2 |
| | Generator damage | Very low to very high
0.01–1 | Negligible to considerable
0–0.7 | Negligible to Considerable
0–0.7 |
| | Storage damage | Very low to very high
0.01–1 | Negligible to considerable
0–0.7 | Negligible to Considerable
0–0.7 |
| | Distribution damage | Very low to very high
0.01–1 | Negligible to very high
0–1 | Negligible to Very High
0–1 |
non-negligible threats, meaning we assume that the constituents care equally about all threats that would be expected to occur in the region (i.e. concerned with hurricanes, not tsunamis).

We expect this New England microgrid would be exposed to a moderate to consider-able hurricane threat (experiencing a hurricane every 1 to 5 years). Regarding this threat, we identify a set of wind and water-induced vulnerabilities which include damage to solar PV, wind turbines, and distribution lines. We also identify a set of vulnerabilities resulting from the storage and natural gas generator exposure to coastal flooding. The likelihood of these weaknesses being exploited tends towards a lower degree of severity, given that hurricanes have typically diminished in strength by the time they reach New England. Nevertheless, all such vulnerabilities would be expected to induce considerable vulnerability impacts on operational and infrastructural resilience in a worst-case scenario where the utility grid has gone down. Regarding wind and water damages, distribution line loss is responsible for the largest individual impacts on resiliency because of the far-reaching impacts of this asset not being able to function at all. During flooding, damage to either storage or generators alone would notably impact resiliency (given the relative capacity of these technologies within the greater system). Note that we retain the possibility that no damage occurs, or that the grid is capable of serving critical loads, by setting the lower bound on resilience impacts to negligible. Moreover, we also recognize that reduced visibility and strong winds resulting from a hurricane are likely to lead to vulnerability impacts in the form of PV generation losses and, to a lesser extent, wind generation curtailment. In these cases, operational resilience would experience very low to low degradation, while infrastructural resilience impacts would be negligible.

The concerns posed by hurricanes largely overlap with those of severe winter storms (i.e. blizzards, nor’easters, etc.), which commonly occur in the North East. As such threats play out, we estimate conditions to commonly be reached that solar PV experiences power losses, but that it would be rarer that wind would need to be curtailed on account of high winds. Each of these vulnerabilities would in isolation have a very low to low vulnerability impacts on operational resilience (because of ample generator and storage capacity) and result in no significant vulnerability impact on infrastructural resilience. Moreover, both exposed solar PV panels and wind turbines have a low vulnerability to damage from a winter storm’s snow, ice, and wind. In these cases, both critical load losses and infrastructure damage would be negligible to moderate. In contrast to hurricanes, we assume no operational or infrastructural vulnerability impacts resulting from damage to storage or natural gas generators during winter storms.

Our assessment of high winds and severe thunderstorm threats at this location also follows the reasoning described for hurricanes and severe winter storms. However, we generally expect thunderstorms to have more mild vulnerability impacts on operational and infrastructural resilience. Also, rare damage from lighting events does pose potentially high and moderate vulnerability impacts on operational resilience and infrastructural resilience, respectively. Damage from lighting may cause widespread outages but is expected to impact isolated components that are readily repaired or replaced.
Hail, too, is a high threat in New England. We expect hail in the region to rarely damage solar PV panels, with very low implications for operational and infrastructural resilience.

Situated coastally, the microgrid under study is also conceived to be exposed to low to moderate risk from flooding. During such events, solar PV panels, wind turbines, and distribution infrastructure would be expected to retain high operational and infrastructural resilience, while the natural gas generation and storage assets would experience a potentially moderate vulnerability to flooding. Thus, we would expect partial resilience losses even in worst-case scenarios.

A microgrid in New England would be at a high risk of experiencing an earthquake, though very rarely do quakes in this region result in physical damage. Accordingly, the vulnerability to physical damage from such threats is very low. Still, given the historic magnitudes of quakes in this region, considerable vulnerability impacts on operational and infrastructural resilience are possible. Similarly, tornados do occur in New England annually, such that the threat is high, but the vulnerability to anyone’s event is very low. New England tornados can cause severe property damage, and so we recognize potentially considerable vulnerability impacts on operational and infrastructural resilience.

This microgrid’s electronic components (i.e. control systems, inverters) would furthermore be vulnerable to damage from rare electromagnetic pulses (EMP). For the purposes of this classification and to avoid duplication of vulnerabilities, we consider just those EMP’s originating from solar weather, and exclude those originating from lightning or weapons in this grouping in Table 2. EMP’s, while rare, have the potential to cause complete outages by damaging electronic equipment which facilitates microgrid operations. Generation assets, however, are expected to stay largely undamaged such that they can come online soon after control systems are replaced. Accordingly, the infrastructural vulnerability impact is less serious than the impact on operational resiliency.

Furthermore, it is conceivable (though not necessarily likely) that this microgrid’s fossil-fuel-based generation assets would need to be curtailed due to economics in the event natural gas prices spike. While uncertainty exists, current prevailing trends suggest price spike threats are low and that few price spike events would make the microgrid vulnerable to generation curtailment. Vulnerability impacts could considerably reduce operational resilience in a worst-case scenario but have no impact on infrastructural resilience.

We do not consider wildfires, droughts, and tsunami’s to be capable of having more than negligible impacts on the operational and infrastructural resilience of a microgrid in this location. Moreover, due to its small size and a presumed lack of critical government infrastructure [24] in this example community, the threat of cyberattack and terrorism is assumed to be very low for a microgrid. All the same, we recognize two levels of cyberattack—a low probability controls override capability that does not damage the system but causes partial to complete outages, and the more rare and sophisticated attack that causes the microgrid to physically damage itself (i.e. overloading lines, overworking batteries). We also recognize that terrorism and sabotage (direct physical damage inflicted on system components) require less sophistication but potentially highly destructive to the
microgrid. Thus, within this classification the range of possible vulnerability likelihoods and vulnerability impacts is expansive.

4.2 Baseline resilience calculation

We compute the average operational and infrastructural residual risk for each threat across 1 million simulations, before averaging these results again into the cumulative residual risks shown in Fig. 3 below. These average resilience metrics provide a baseline for understanding the tendencies of risks at this site. Note that potentially severe individual risks may be obscured in such a calculation and that a holistic resilience assessment will consider residual risks not under a Monte Carlo approach but through a worst-case scenario approach. From Fig. 3 we see that variability in residual risk approximates a normal distribution, with operational residual risk (mean 0.0066, standard deviation 0.0013) being somewhat higher than infrastructural risk (mean 0.0053, standard deviation 0.0012). Taking the cubic root of mean operational and infrastructural residual risk (because the score is essentially derived from the product of three parameters given that level of importance is always 1) suggests that threats, vulnerabilities, and impacts tend towards a ‘low’ classification.

When equally weighted and aggregated into a final resilience metric, we yield the distribution shown in Fig. 4. Resilience values at the New England site range from 0.989 to 0.997 (mean 0.994, standard deviation 0.0008).
4.3 Resilience interventions

We next explore how the resilience baseline can be used to compare the relative effectiveness of interventions at the site on resiliency. First, we explore the impact of moving all distribution lines underground. This intervention is expected to render obsolete vulnerability of distribution lines to hurricanes, severe winter storms, severe thunderstorms, and high winds. Moreover, this would also cap the vulnerability of terrorism at low, given that the lines would be less readily exposed to attack. Furthermore, this intervention would introduce new resilience impacts to flooding and earthquakes.

For comparison, we also examine the physical hardening of generator and storage assets such that they are immune from hurricanes, tornados, earthquakes, and flooding threats (negligible operational and infrastructural impacts). Moreover, these improvements would be expected to reduce vulnerability and resilience impacts resulting from terrorist attacks on storage and generator assets to moderate.

The proposed distribution system intervention reduces the average operational residual risk from 0.0066 to 0.0053 and infrastructural resilience from 0.0053 to 0.0038. Respectively, these reductions represent 20% and 28% reductions in resilience impacts. Overall resilience improves marginally from 0.9938 to 0.9954. Comparatively, the physical hardening of generator and storage assets would be expected to improve operational resilience to 0.0058 (12% reduction), infrastructural resilience to 0.0043 (19% reduction), and overall resilience to 0.9949. Thus, while the interventions are both largely effective relative to baseline conditions, the distribution line enhancements are estimated to more effectively enhance overall resilience. Note this analysis does not answer which intervention is more cost-effective and a more extensive analysis of intervention costs and externalities would be necessary for comprehensive resilience planning.

5 Summary and outlook

Microgrids offer a host of benefits for expediting the decarbonization of the power grid including integration of distributed renewable energy resources, the ability to generate revenue streams for end-users, and at the same time support power systems resilience. For a microgrid to serve its purpose of being a resilience resource for the utility grid, it is paramount to ensure that the microgrid itself is resilient enough to absorb, restore, and adapt to the changing circumstances when a low-probability high-impact event occurs. Building resilience within microgrid requires assessment and analysis for the determination of the high-risk threats and their potential negative impacts on microgrid’s infrastructure and operations—accounting for microgrid’s vulnerabilities. There are technical, economic, and social aspects involved in arriving at an optimal microgrid design that has a desired level of resilience.

This endeavor of determining an optimal microgrid design can be approached in qualitative and quantitative ways. Both the approaches have their pros and cons. However, for the purpose of making economic decisions regarding the deployment of resilience interventions within microgrids, the quantitative approach is more
effective. Nonetheless, the availability and burden of obtaining detailed data (i.e. microgrid layout, critical load, dispatch profiles, capital, and operational costs) for each new microgrid in the planning phase prevent one from engaging at a more detailed level of quantitative resilience analysis. Generally, resiliency practitioners find themselves in a similar situation where critical data does not exist or is overly burdensome to obtain. The benefit of the framework laid out in this research work is that it provides a methodology for estimating the range and tendency of resilience outcomes.

Through Monte Carlo simulation refined to reasonable ranges, we expect to come close to approximating the true resilience of a site, though it is not evident that it will occur towards the upper or lower bound of observed resilience rankings. As better empirical or modeled data become available, these ‘placeholder’ distributions can be supplemented or replaced to yield more accurate resilience rankings. Moreover, having established a baseline range of resilience outcomes through this framework, interventions can be quantitatively compared to identify those that have the highest impact on improving the resilience of the microgrid. Therefore, this work, in essence, lays out a solid foundation for conducting resilience analysis during the planning phase.

The main limitation of this work is that it does not weigh into the economic aspects of resilience interventions’ deployment. Cost justification is standard practice for making a business case for building a needed resilience intervention into a microgrid’s physical or cyber infrastructure. So, the future research directions include a detailed line-of-inquiry into quantifying the benefits in monetary terms, that is cost–benefit analysis. This future analysis will be the third and final leg of a resilient microgrid design’s effective decision-making process. The prior two legs being qualitative and quantitative approaches (considering threats, vulnerabilities, and impacts) to quantifying the degree of resilience a microgrid possesses.

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