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Designing off-grid renewable energy systems for reliable and resilient operation under stochastic power supply outages

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ABSTRACT

The power supply from solar and wind generators is not only inherently variable but also prone to failure due to rare-weather related events, i.e., hailstorms, icing. Current system sizing strategies often consider system reliability or resilience but rarely consider them simultaneously. Here, we proposed a sizing approach for an off-grid power system to supply a minimum power threshold (L_{th}) during power disruption events. The L_{th} concept ensures blackout avoidance and enough dispatchable stored energy during power outages. We developed several scenarios with 4- to 24-hour simulated outage events occurring multiple times per year. After sizing a system, designs are tested by simulating the systems' operation based on data containing stochastic outage events. The resulting lost load is recorded to assess system reliability and resilience. Results showed that, regardless of outage frequency, total annual stochastic outage durations up to 32 h did not affect the optimal capacities of system components while ensuring the same reliability level. However, system capacities increased by up to 90% when the annual outage duration increased to 144 h. Meanwhile, introducing a minimum power threshold, Lth = 0.97, further increased the renewables generation and storage capacity up to 50% and 7%, respectively. Systems' resilience tests showed an 80% chance of a system designed with the Lth approach to withstand the prolonged stochastic power disruptions, while this value is only 25% for the systems designed using the conventional approach.

1. Introduction

Due to substantial cost reductions and reduced environmental footprints, photovoltaics (PV), wind-power, and battery storage have made the installations of new carbon-fuel power plants increasingly scarce and expensive [1,2]. The fundamental transformation of energy systems is occurring due to the increasing share of electricity-based end uses like e-mobility and electricity accessibility to everyone, i.e., remote sites [3,4]. The evolving low-carbon and low-cost electricity technologies (i.e., PV and wind) are widely proposed for the electrification of remote areas like islands and isolated villages to make electricity accessible to almost 1 billion people still living without this basic necessity of modern life [5,6]. However, these decentralized renewable energy (RE) solutions are more complex to design due to less flexibility to reduce net load variability (demand–supply gap) and, sometimes, no availability of power generation (hereafter called power outage) from these variable RE sources, i.e., extreme events such as resource drought and component failures [7–9].

The resilience of RE-based power systems has been a research topic of growing interest in recent years due to the rise in power outages caused by frequent extreme weather events and their prolonged durations [10–14]. For instance, blackouts due to extreme weather have an annual economic impact of $20 to $55 billion in the United States, and patterns of such incidents indicate that the frequency of such blackouts has increased over the last 30 years, with a sharp increase in the 2000 s [15–17]. Similar causes of power outages have been stated by the European Network of Transmission System Operators report that the most significant cause of power outages is severe weather events [18]. In the future, climate change will increase the likelihood of rare-weather-related events impacting RE-based power systems [19], whose reliability characteristics are already susceptible to the inherent intermittency of RE sources. Using historical data, studies have quantified that

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the duration of solar/wind droughts can prolong up to several hours/days or even weeks and occur several times during a year [20–22]. A recent study by Rinaldi et al. quantified the probability of solar and wind resource drought occurrence over California and Western Interconnect using 39 years of historical data [23]. The study showed that the chances of occurrence of wind and solar droughts were 1.5 and 15 fold, respectively, increased when California was treated as an island, meaning power outage occurrence probability for off-grid renewable energy systems (RES) is substantially higher than the regionally interconnected RES.

The definition of resilience from the energy systems research point of view is vast and covers the economic, technical, social, and policy perspectives. However, the merits of interdependency between these areas have not yet been well established and are still ongoing research. In this study, we considered resilience from the perspective of RES operation (i.e., technical), which is a critical part of resilience [24]. Although the exact words of the definition of reliability and resilience vary among research institutions, their typical properties are the same [25–28]. In power systems, reliability means an uninterrupted and sufficient power supply in the conditions for which the electrical system was designed. For instance, the average load-shedding likelihood is no more than 1% of the total annual electricity demand. However, particularly in recent decades, microgrids often face non-nominal operating conditions such as floods, extreme temperatures, and physical/cyber-attacks. The ability of microgrids to withstand, respond to, and recover from these rare, high-impact extreme events efficiently defines the resilience of power systems [29]. Overall, reliability is an outcome (uninterrupted power supply), whereas resilience is a system characteristic that empowers the microgrid to meet that outcome.

Climate change increases both the severity of rare-weather-related events and their frequency and poses a challenge to the resilience and reliability of RES [30–32]. Rare weather-related events often impact more the residents of the small-to-medium scale RES and experience environmental and social disadvantages, as those power systems are utterly dependent on meteorological conditions like irradiance and wind speed. For instance, Texas 2021 winter power outage caused billions of dollars in infrastructure loss and several hundred deaths, mainly deaths caused due to load shading [33]. In Ref [34], the authors assessed the renewables variability of Texas's different regions and suggested that a combination of different types and location-based RE cannot only enhance the low-carbon power penetration but would also ensure a reliable and resilient Texas power system. In another study, authors proposed three mechanisms to scale the demand flexibility and avoid load shedding during extreme weather events: residential load rationing, interruptible load, and incentive-based demand response [35]. The study simulated the mechanisms for the Texas grid model along with power outage data, demonstrating that no individual mechanism can completely avoid prolonged power outages. Instead, a portfolio of different mechanisms can substantially avoid blackouts. Though the authors address the power outage issue of the energy system, this study is mainly related to the large scale/regional power system and didn't comprehensively assess the energy storage's role in response to potential power outages that may occur with diverse duration and frequency. Various studies experimentally investigated the relationship between snow-related events and energy loss under the diverse solar panel architecture and tilt angle scenarios [36–38]. The studies revealed that the impact of severe weather events could be reduced with increased tilt angles. Similarly, many other studies also evaluated the extreme weather impacts on the distributed and off-grid energy systems like extreme weather impact on the voltage regulation [39], resilience assessment of power systems in extreme weather conditions[40], coordination of multi-energy systems to improve system resilience [41], and reducing the extreme weather impacts by predicting the power outages [42].

Stanley et al. optimized the physical layout and designed a resilient solar-wind-storage hybrid system to satisfy the minimum power threshold requirement throughout the year [24]. This study systematically increased the outage duration from 0 to 48 h and assessed its impact on the cost of energy (COE) and component sizing. However, this study only assumed one outage event and did not consider the effect of outage events frequency that can occur several times during a year, as assessed by Rinaldi et al. using 39 years of historical data [23]. A study by National Renewable Energy Laboratory (NREL) proposed a resilient hybrid RES by leveraging the solar-wind complementarity and concluded that diverse generation sources could provide resilience value to these systems [29]. Similar to the previous, this study's scope was limited to the resilience perspective. Nelson et al. contrasted the diesel generator-based microgrid with the hybrid microgrid to quantify the survivability of both systems during an islanding event lasting seven days [7]. The study inferred that a hybrid system provides 99.7% survivability during an islanding event; however, this study also quantified the resilience considering only one event. Often literature studies introduce the resilience aspect from a specific perspective, such as a model for power system survivability from storms [43], the relationship between increasing RES capacity and its autonomy [44], the relation between autonomy and survival time [45], and historical performance of bulk power systems during blackout [46].

Although the aforementioned studies added new information to the growing resilience research field, they did not statistically describe how varying outage event duration and frequency affect the RES optimal capacity sizing; and the performance of a designed resilient microgrid during random outage events. Moreover, rare studies considered the concurrent reliability and resilience aspects to design RES, the underlying relationship between them, diverse power outage conditions and how optimal sizing is affected by varying the reliability parameter for systematically designed outage events. This study sets out to answer the following questions:

- How does a power outage of varying duration and frequency affect optimal microgrid component capacities? Specifically, what are the relationships between storage capacity and its charging/discharging duration to increasing/decreasing total annual outage duration?
- To what extent can a microgrid withstand prolonged stochastic power disruptions if it is designed considering both reliability and resilience aspects? Particularly, do microgrids designed with resiliency in mind using minimum load-met threshold concept performed as intended during the simulation testing?
- How does the resilience of RES change when varying the minimum load-met threshold value? Explicitly, to what extent is system COE sensitive to an increase in RES resilience compared to the increase in reliability levels for a given power outage scenario?

We proposed a storage operation algorithm where storage is used based on a minimum load-met threshold to ensure enough dispatchable stored energy is available each time before the occurrence of an outage event, as nelson et al. found that storage state-of-charge (SOC) must be higher than 70% before the event occurrence to ensure the critical load is met during outage event [7]. We studied a wide range of scenarios by stepwise varying the demand threshold value (1 to 0.95), where one represents the conventional approach and drives the storage based on the actual load. We systematically constructed several cases of outage considering varying duration (0 to 24 h) and frequency (0 to 6) based on the Rinaldi et al. and Stanley et al. studies that showed the duration of often occurred random events is no more than one day, and their median occurrence is less than 6 [23,24]. Because we aspire to design a resilient and reliable hybrid power system, we optimized the microgrid design considering the aforementioned scenarios for various reliability levels by employing load loss constraint, which is stepwise changed from 0.5% to 0.3% (Table S1, S2). To address the concerns about the operational performance of the resilient microgrid that is optimized based on systematically designed outage events, we performed simulation testing of the designed RES with random outage events. These random events were generated based on the Monte Carlo approach and used as input data while ensuring a sufficient number of runs for satisfactory results, estimated based on the assumption that the confidence interval range should be less than 1% of the mean value (Fig. S4).

This study aims to demonstrate the design of a resilient microgrid that can withstand random prolonged power disruptions. In this paper, we developed outage events by modeling disruptions in RE power production. The cause of this power disruption could be extreme weather events, resource droughts, malicious attacks, human error, system failure or some other reason [47–49]. In this study, the exact cause is irrelevant; there is no power generation from solar or wind, and the only available power source during these events is storage. Findings and methods from this research can inform the design and operation of a reliable and resilient hybrid RES for off-grid operations or critical grid-connected loads.

Input data and analysis methods are described in Section 2, while Section 3 presents the results. Discussion on the key findings and the application of the proposed methodology is presented in Section 4, and concluding remarks are summarized in Section 5.

2. Methods

This section describes the input data and model formulation. Fig. 1 illustrates how power outages could affect the generation and distribution of power in solar-wind-battery (SWB) microgrids. Extreme weather events, lack of resources, malicious attacks, system failure or some other reason could cause these disruptions in SWB. The precise cause of the outage is irrelevant to this study; the lack of power generation for wind or solar is critical. Section 2.1 describes the systematically designed diverse power outage scenarios based on varying outage duration and frequency per year.

In section 2.2, the method for managing the off-grid system energy flow with the injection of minimum load-met threshold and designed outage-based input data is presented. The optimization framework to design a resilient RES is described in section 2.3.

2.1. Designed input data

We used El Hierro Island, 1350 km from the Europe mainland, as a case study, irradiance data, wind speed, and demand for the 2021 year [50]. The ERA5 reanalysis hourly solar radiation and wind speed data were downloaded from Ref. [51]. Representative electrical load data for El Hierro island was obtained from Ref. [52]. In the case of electrical load, the average values of the previous and successive data points are used to fill in the missing values in the input data. The hourly solar and wind capacity factors were calculated using the Ref [23] method. The input data is shown in Fig. S8.

To design an outage-resilient microgrid, we constructed several scenarios of power generation disruption by varying the duration and frequency of these rare events during a year. In a recent study, Rinaldi et al. quantified the probabilistic occurrence of solar/wind droughts for California and Western Interconnect (WECC) using historical 39 years of data [23]. Authors found, on average, that the occurrence of outage events was up to 7 times per year, ranging from hours to days. However, the median occurrence value of long-duration events was negligible compared to the duration of the event of less than a day. Other literature studies have also shown similar findings that the most frequently occurring power outage event durations are not longer than 24 h [24,53,54]. Based on these studies, we systematically stepwise increased the number of outage events from 0 to 6 and outage duration from 0 to 24 h during a year to design several renewable power disruption scenarios such that a total annual power disruption duration may include different cases. For instance, a power disruption event of 48 h annually could happen with 2 T-24H, 3 T-16H, 4 T-12H, or 6 T-8H, where T is the frequency of the event during a year, and H represents the duration of the event. The frequency and duration of events can be described as:

Events frequency (T): The frequency of events describes the number of times during a year power disruption occurs in renewables' power supply. Here, we varied the number of events per year from two to six. In real-time scenarios, events frequency can be greatly varied from year-to-year, but here the scope of the study is to assess these outage events' impact on RES optimal sizing and their ability to withstand power disruptions during operation when it happens randomly rather than

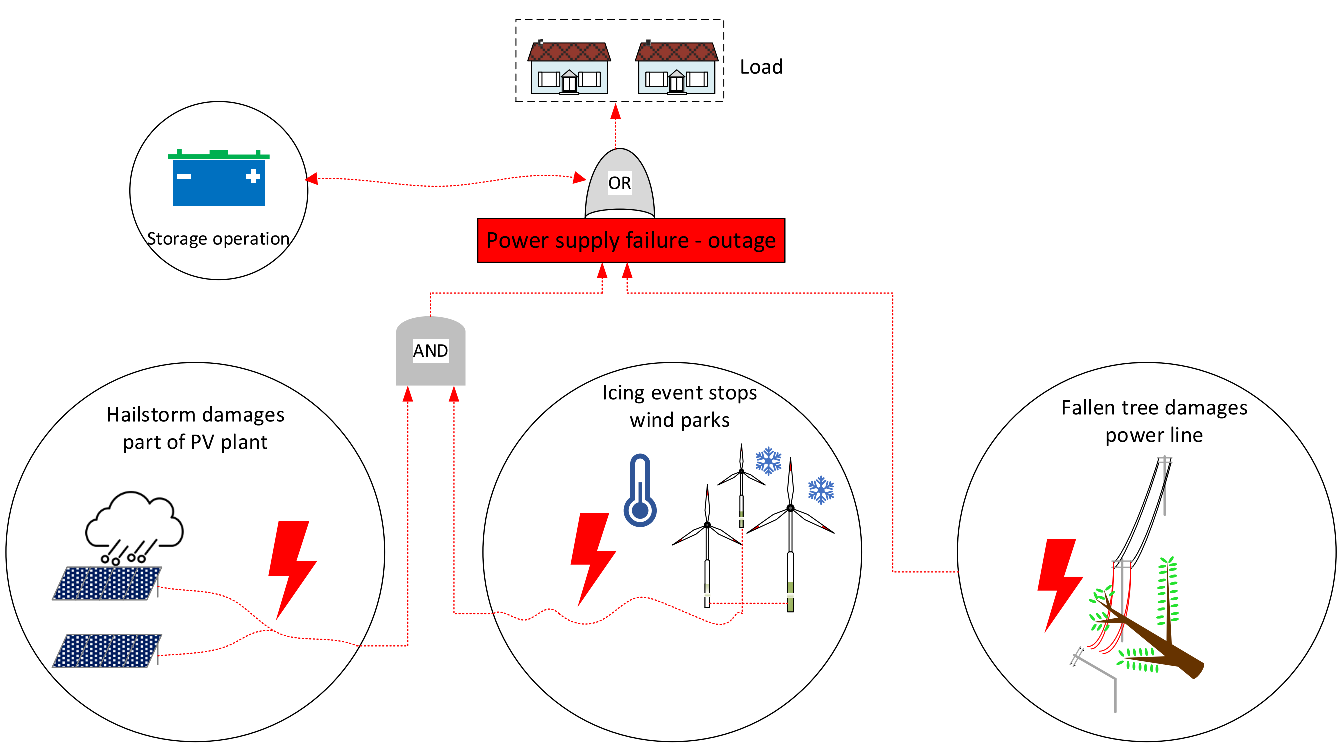

Fig. 1. Conceptual overview of how power outages could affect solar and wind powered microgrid.

systematically.

Events duration (h): It is the time series granularity that shows a block of consecutive time points within an event. Though event duration could sum up to several days/weeks but as discussed before, most occurred renewables power disruption events are less than a day. Therefore, we systematically increased the duration from zero to 24 h with a 4-hour time step for each value of T. For instance, 6 T-8 h denotes 6 events per year with 8 h duration; thus, the total annual renewables power disruption time would be 48 h (Table S1). It is worthwhile to note here that we applied these scenarios to solar/wind capacity factor values, which means these events did not consider those times when renewables are not generating power due to issues like irradiance not being available during night or wind turbine power curve – meaning we have simulated power plant outage due to some sort of failure.

Events start time: In real life, predicting when these rare outage events could occur during year is difficult. For instance, wind turbine generators may have faults at any time during the year, or solar inverter failure can occur during summer peak demand when solar power is most needed. Similar other reasons can cause random renewable power disruption, i.e., severe weather, natural disaster, or cyber event. We choose the event start times so that it spams over the year, and each event starts when the demand peaks during a certain month's block (see Fig. S7). For instance, the first event for 6 T scenarios always happened in February – starting from the 850th hour of the year – which is the peak load demand time between January and February. Fig. 2 shows the event start time for representative scenarios. All developed outage scenarios with varying frequency and duration are presented in Table S1.

The left figure of Fig. 2 illustrates how diverse outage scenarios can be made for the fixed annual power disruption hours like, here, 48 h of annual power disruption may occur with 2, 4, or 6 events per year, but their durations would vary accordingly. The right figure represents how annual power disruption hours vary with the same event frequency but different duration.

2.2. Model formulation

Model formulation starts with the outage-based input solar/wind data and load demand. The designed power outage events and how these are injected into the hourly capacity factor time series are described in the previous section. To ensure enough stored energy is available before random outage events, we introduced the minimum load-met threshold (Lth) variable to prioritize storage charging, meaning storage will be derived in charging mode if generated RE power is higher than threshold demand. We stepwise (0.01) varied the Lth value from 1 to 0.95 to assess its impact on the system reliability level during simulation testing with random outage events (Section 3.2). The Lth = 1 means the base case where both actual load and threshold demand are identical. In contrast, Lth = 0.95 means priority will be given to storage charging when the RE power generation is higher than the 95% of the demand (Eq. (1). If SOC is 100% or there is still power available after storage charging (due to charging rate or storage fully charged), that will be used to satisfy the remaining demand which otherwise would be considered as load loss (LL). The storage operation is entirely based on L_{th} rather than actual demand and is presented in Table 2.

$$L_{th}(t) = \alpha \times L(t) \forall t, \ \alpha = 1, 0.99, \ldots, 0.95 \tag{1}$$

All the developed power outage scenarios of varying frequency and duration are simulated with each L_{th} value, and the total cases for each power outage scenario are shown in Table S2. Besides, all cases are optimized with different reliability levels ranging from 99.5% to 99.7%, meaning yearly load shedding should not be more than 0.3% to 0.5% of total annual load demand. We evaluated the relation of reliability level (stepwise increasing its value) with demand threshold considering diverse power outage scenarios and assessed how much a designed RES for a certain reliability level is resilient during simulation testing with random events. More specifically, how changing the demand threshold value increases/decreases the system resilience at a given reliability level. The nomenclatures of the following model are shown in Table 1.

Cost calculations

Hourly generation and storage technologies cost (solar, wind, battery storage, inverter):

$$c^{g,v,s} = \frac{\gamma c^{g,v,s}_{capital} + c^{g,v,s}_{O\&M}}{H} \tag{2}$$

Capital recovery factor

$$\gamma = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{3}$$

Constraints

$$0 \leqslant D^g_t \leqslant C^g f^g \forall g, t \tag{4}$$

$$0 \leqslant D^v_t \leqslant C^v \forall v, t \tag{5}$$

$$0 \leqslant D^{to\ s}_t \leqslant \frac{C^s}{\tau^s} \forall t \tag{6}$$

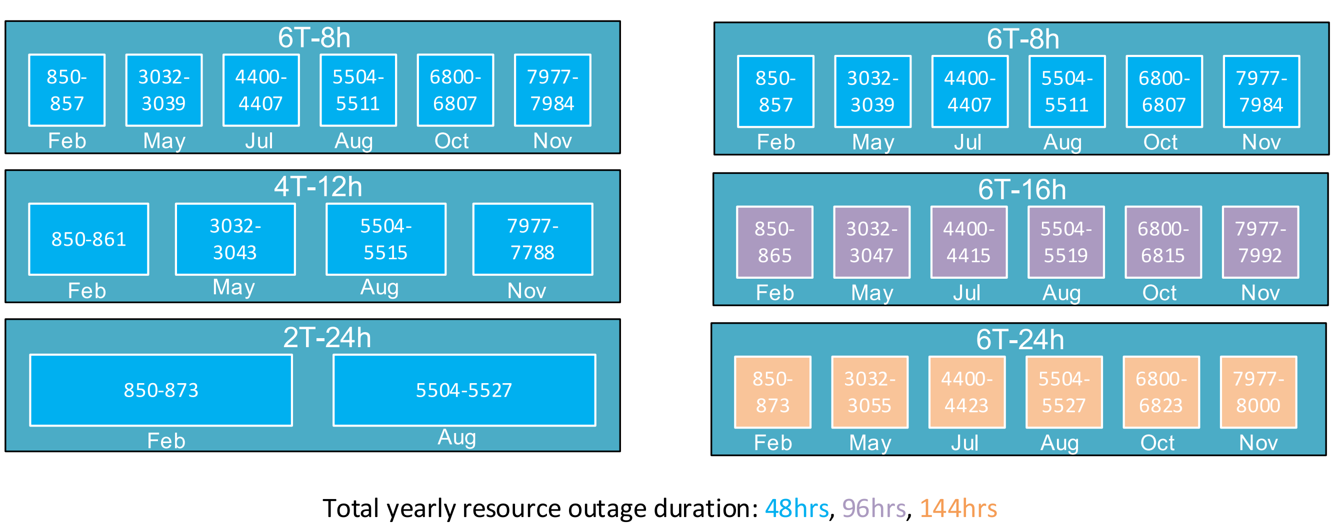

Fig. 2. Diagram shows how power outage durations, events frequency, and yearly outage duration are varied to construct diverse scenarios. See Table S1 for all outage scenarios considered in this study.

Table 1
Model nomenclature.

Symbol	Unit	Description
L_{th}	MW	minimum demand-met threshold
L	MW	load demand
LL	MW	load loss/load shedding
t	hour	time step, starting from 1 and ending at H
g	label only	generation technology (solar, wind)
s	label only	energy storage technology (battery storage)
ν	label only	electricity conversion technology (inverter)
γ	1/year	capital recovery factor
n	years	asset lifetime
i	%	discount rate
H	hour/year	number of hours per year (8760)
$c_{capital}$	\$/kW; \$/kWh	(overnight) capital cost
$c_{O\&M}$	\$/kW; \$/kWh	operation and maintenance (O&M) cost
c_{rep}	\$/kWh	replacement cost
c_{rem}	\$	remaining components cost/salvage value
D_t	MW	dispatch at time step t
C	MW, MWh	components capacity (decision variable)
f	%	capacity factor (input time series for generation technologies)
to s	label only	charge to energy storage
from s	label only	discharge from energy storage
τ	hours	storage charging duration (decision variable)
S_t	MWh	remaining energy in storage at time t
S_0	MWh	initially assumed stored energy in storage (50% charge)
δ	1/hour	per hour energy loss as a fraction of stored energy
η	%	efficiency (storage round trip)
curt	MW	energy curtailed
losses	MW	dispatch losses
X	%	maximum allowed load loss during a year

Table 2
Battery storage operation algorithm based on the minimum load-met threshold.

Algorithm 1: Battery storage operation

Input:
C_{min}; C_{max}: battery minimum and maximum capacity
C(t): battery charge at time t
C_r: battery charge/discharge rate
$P_g(t)$: RE power generation at time t
L(t) & $L_{th}(t)$: load & minimum load-met threshold at time t
Output:
c(t+△t): new battery charge
$P_s(t)$: storage charge/discharge power at time
LL: load loss

if $P_g(t) > L_{th}(t)$ **then**
  if c(t) < C_{max} **then: charge the battery**
    $P_s(t) = \min[C_r; P_g(t)\text{-}L_{th}(t)]$
  else
    c(t+△t) = C_{max}
    $P_s(t) = 0$; **end**
net power = $P_g(t) - P_s(t)$
  if net power > L(t) **then**
    surplus power curtailed
  else
    LL; **end**
else if $P_g(t) < L_{th}(t)$ **then**
  if c(t) > C_{min} **then: discharge the battery**
    $P_s(t) = \min[C_r; L(t) - P_g(t)]$
  else
    c(t+△t) = C_{min}
    $P_s(t) = 0$; **end**
LL: if $(P_s(t) + P_g(t)) < L(t)$
else if $P_g(t) = L_{th}(t)$ **then**
c(t+△t) = c(t)
LL = L(t) – $L_{th}(t)$
end

$$0 \leqslant D_t^{\text{from } s} \leqslant \frac{C^s}{\tau^s} \forall t \tag{7}$$

$$0 \leqslant D_t^{\text{from } s} \leqslant S_t(1-\delta^s) \forall t \tag{8}$$

$$0 \leqslant C^{g,v,s} \forall g, v, s \tag{9}$$

Storage energy balance

$$S_1 = (1-\delta^s)S_0\Delta t + \eta^s D_1^{to\ s}\Delta t - D_1^{from\ s}\Delta t \tag{10}$$

$$S_{t+1} = (1-\delta^s)S_t\Delta t + \eta^s D_t^{tos}\Delta t - D_t^{from\ s}\Delta t t \in (1, \dots, H-1) \tag{11}$$

$$S_H = S_0 \ (\text{No free energy}) \tag{12}$$

System energy balance

$$\sum_g D_t^g \Delta t + D_t^{from\ s}\Delta t + LL_t\Delta t = L_t + D_t^{to\ s}\Delta t + D_t^{curt}\Delta t + D_t^{losses}\Delta t \forall \mathrm{t} \tag{13}$$

Objective function

$$\text{minimize system cost} = \sum_g c^g C^g + \sum c^s C^s + \sum c^s_{rep} C^s - \sum c^{g,s}_{rem} \tag{14}$$

such that:

$$\sum_1^H L - \sum_1^H LL \geqslant (1-X) \times \sum_1^H L \tag{15}$$

$$L_{th}(t) \geqslant \alpha \times L(t) \forall t, \alpha \tag{16}$$

2.3. Optimization framework

RES optimal capacity sizing framework to design a renewable power outage resilient microgrid is shown in Fig. 3. All input and output details of the proposed model are illustrated in the figure. The solar/wind capacity factor (CF) time series is employed with each power outage scenario, having varying events frequency and duration, and defined demand threshold values to optimize the RES seeing the given reliability criteria. Thus, several RES optimal capacity-sizing cases are simulated with systematically designed power outage scenarios, demand threshold values and LL (Table S2). A well-known population-based particle swarm optimizer (PSO) is used for the RES components' capacity sizing [55].

PSO is a population-based heuristic algorithm where each particle represents a solution set with a vector array of decision variable values. Particles-based population explore and exploit the entire search space, which is the lower and upper bound of variables, based on information exchange with nearby particles. Four elements of particle movement ensure particles should either move towards global best or stay at the same position (decision variable values did not change) during each iteration, thus providing a stable solution compared to other evolutionary algorithms. These elements are current direction, personal best position, velocity, and neighbor's best position. Furthermore, after each iteration, the velocity of particles is defined by three parameters: inertial weight constant, social component, and momentum component (see Table S4). The detailed mathematical formulation and working principle of PSO is presented in the authors' previous study [56].

This optimizer has been comprehensively used for energy systems optimal sizing due to its stability in repeated executions, good exploration behavior compared to other stochastic algorithms, rapid/high convergence rate and less chance to stuck in local solution due to its stochastic behavior [57–59]. The PSO parameter values for this study are carefully defined and presented in supplemental Table S4. In PSO, the proposed RES objective function can be modeled as:

$$\begin{aligned} &\text{Objective}(c^g, c^s) : \Gamma \rightarrow R^j = \text{minimize cost} \\ &\quad \forall \text{ outage scenarios } (\mathrm{T},\ \mathrm{h}),\ \alpha,\ \mathrm{X} \end{aligned} \tag{17}$$

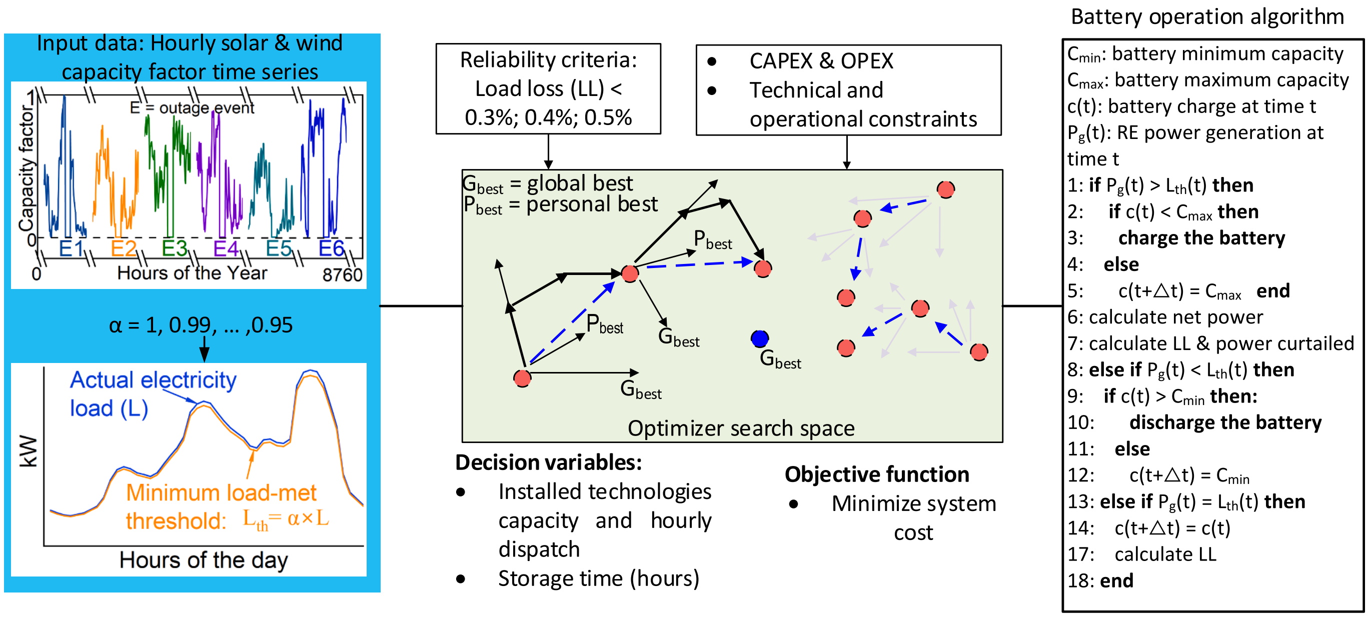

Fig. 3. Conceptual visualization of RES optimal capacity sizing framework with power outage events and minimum load-met threshold. The figure also shows the input techno-economic variables to the optimizer.

where $\Gamma \rightarrow R^j$ illustrates the feasible exploration region for the optimizer. Fig. 4 shows the overall structure of the proposed design strategy for a reliable and resilient off-grid RES.

3. Results

In this section, we discussed the obtained optimal microgrid designs using the method described in the previous section. We also assessed their operational performance during simulation testing with generated random outage events and compared the resilience of the designed system under varying annual power outage duration. Of the infinite power outage scenarios (with varying events frequency and duration) we could have examined, we explored scenarios with a total number of events of less than seven and each event duration of not more than a day (Table S1, S2). The proposed methodology is applied to design a power outage resilient RES for El Hierro Island, one of the Spain Canary Islands. El Hierro Island selection obeys the principle of the presence of a real-world RES application being in operation since 2015, and it is well-align with the clean energy mission. RES components techno-economic figures used for this study are shown in Table S3.

3.1. Effect of the power outage on optimal capacity sizing

This section discusses the RES optimal capacity sizing for different power outage scenarios with varying RES reliability levels. Fig. 5 shows the impact of total annual outage durations on system cost and components capacity, while Fig. 6 shows the sensitivity of storage duration time, optimal RE mix, and system cost to outage events frequency. Bellow, each aspect is discussed independently.

3.1.1. Total outage duration impact

This section observes the optimal storage capacity for both varying threshold demand and LL cases. We found a non-monotonic relation between storage capacity and total annual outage duration, highlighting the importance of not only considering these rare events in the input data but also how accurately or precisely these events have been quantified using historical solar/wind data. Fig. 5a & 5d show the variation in storage capacity when the total annual power outage duration increased from 8 h to 144 h. Regardless of events frequency (represented with small circles) and reliability level, storage capacity did not change up to an annual outage duration of 32 h with the base case (L_{th} = 1), while this value reduced to 24 h when the demand threshold varied (Fig. 5d). Indeed, optimal storage capacity is a function of both total outage duration and events frequency. It is evident from Fig. 5A & 5D that optimal storage capacity did not linearly increase with the total outage duration due to the varying event duration, meaning if both events frequency and total outage duration rise, it did not necessarily increase the storage capacity as the highlighted representative case with the black box. This box shows the first increase in the storage capacity with total outage duration (from 24 to 60 h), but it decreased when the duration jumped from 60 h to 64 h. The included reason is that first the event's duration linearly increased up to 24 h, then decreased to 16 h when the event's frequency increased from 2 to 4 (see Table S1 for power outage scenarios). Though net total outage duration increased from 60 to 64 h, total storage capacity decreased from 111 to 96 MWh for 0.4% LL case. However, to meet the reliability constraint, 3 MW RE capacity was added to ensure enough dispatchable stored energy was available during outage events (5C). A similar trend can be observed in optimal storage capacity for both varying threshold demand and LL cases.

The cost of designing a resilient RES (i.e., ensuring the minimum demand threshold is met during prolonged outage events) could be higher than designing a system to ensure only uninterruptable power supply when random power outage scenarios are not happening. RES components' optimal capacities are substantially affected by outage events frequency, total annual outage duration, single event outage duration and demand threshold value. Deviating from the base case, demand threshold value changes further increase the pivotal role of energy storage. Although there is an increasing trend in storage capacity regardless of the demand threshold value, the average storage capacity rate increase is 5% to 13% high when the threshold value stepwise changed from 1 to 0.96 (Fig. 5a & 5d: slope of yellow line). While this increase to enhance system reliability level (i.e., decrease in LL from 0.5% to 0.3%) at a given demand threshold is not more than 11% (supplemental file 2). Similarly, following the storage trend, the average increase in system cost concerning the demand threshold is 9% to 20% (Fig. 5e), while its range concerning different reliability levels is 4% to 10% (Fig. 5b). The included reason for higher storage capacity increase with demand threshold value is to ensure having enough energy storage capacity (eventually stored energy) to continuously supply minimum

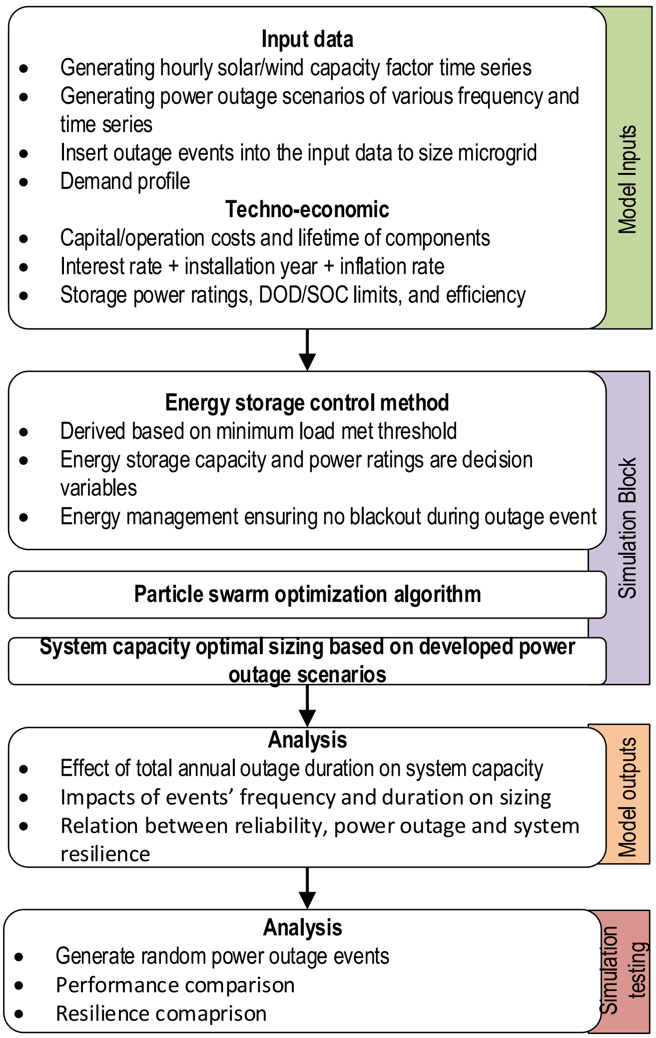

Fig. 4. The flowchart showing the proposed strategy for a reliable and resilient microgrid.

power threshold (i.e., minimum power requirement) during random outage times to meet the reliability criteria. The effect of the reliability level (0.5% to 0.3% – loss of load probability) increase on the COE is less compared to the demand threshold, which shows the cost of designing a resilient RES could be higher.

For a given reliability level or demand threshold value, variation in RE generation capacity is lower compared to the storage with the increase in total outage duration (Fig. 5c & 5f). Furthermore, the role of storage becomes more pivotal to ensuring minimum demand-met criteria when rare outage events are considered. Average variation in RE capacity due to varying LL value range between 17% and 18% (Fig. 5c). This change due to varying L_{th} values is up to 23% (Fig. 5f, S1). On the other hand, variation among storage optimal capacities is up to 70% when L_{th} changed from 1 to 0.96 with varying total outage duration. However, the solar-wind ratio substantially reduced as the total outage duration increased, showing that solar/wind penetration should not only be optimized based on their capacity factor but also the rare power outage events based on historical data. Moreover, we noticed the higher sensitivity of optimal RE capacities to varying total outage durations at a given demand threshold value compared to a given LL value, i.e., a higher percent increase in RE capacity with the increase in outage duration at a given L_{th} value compared to a given LL value. Though the increase in RE capacities is marginal, it ensures enough charge is available all the time to meet reliability criteria and ensure minimum demand is met during prolonged power disruption events. For instance, RE capacity only increased by 1 MW (3%) compared to a 61 MWh (69%) increase in storage capacity when the total outage duration increased from 24 to 144 h with the base case (**supplemental file 2**).

3.1.2. *Impact of events frequency and duration*

The single event duration analysis can help assess the impact of certain durations on the RE generators and energy storage sizing. For instance, our optimal capacity sizing analysis reveals that shorter outage durations could be adjusted with the marginal increase in RE generation capacities (which may slightly increase the curtailment, Fig. S2). Meanwhile, to satisfy the same demand, it is inevitable to substantially increase the storage capacity for prolonged power disruption events (greater than12 h). Fig. 6 shows the effect of events frequency and duration on optimal capacity sizing and cost. Though deviating L_{th} value from one increases the RES withstand capability during rare outage events, it also further increases the capital cost of off-grid RES, which already is a major hindrance in the widespread of these zero-carbon systems. Because system cost is susceptible to the L_{th} values, as discussed in the previous section, here, we showed the results for L_{th} values 1 and 0.98 only with LL values 0.5% and 0.4% (Fig. S2). Results with varying L_{th} up to 0.95 with LL value ranging 0.5% – 0.3% are presented in **Supplemental file 2**.

Indeed, storage duration time and solar-wind (s/w) ratio are the functions of event duration (consecutive time points in an event) rather than events frequency (Fig. 6a-b, 6d-e). For instance, regardless of L_{th}, LL and event frequency values, the optimal storage duration time range remained between 6 and 8 h when event duration systematically increased to 12 h (Fig. 6a, 6d, Fig. S2). While after 12 h, both storage capacity and duration time substantially increased with the frequency of the event, illustrating smaller events duration (less than12 h) would not affect much the systems' withstand ability regardless of their frequency. Furthermore, up to 12 h events duration, to meet the reliability constraint, there is a marginal increase in RE capacity with the increase in events frequency to ensure enough dispatchable stored energy is available each time before outage event occurrence. However, for higher event durations (greater than12 h), RES reliability is ensured with the exponential increase in storage optimal capacity as the events frequency upsurge, which causes to decrease, contrary to shorter outage durations, the total optimal RE capacity (Fig. 6a-b, 6d-e).

€There is a direct relation of event outage duration with storage duration time while having an inverse relation with the S/W ratio, meaning one value increases with event duration increase while the other decreases (Fig. 6a-b). The reduction in the S/W ratio reflects that an appropriate mix of variable RE technologies is critical to reducing the power outage impacts in 100% RE scenarios. Since the starting time of the outage event would be uncertain in real-time, an appropriate RE technologies mix would ensure high storage charge seeing the available resource density. For instance, if the wind capacity factor was higher than the solar before the outage event, but its proportion was not enough to enable the storage to be charged for power outage hours; eventually, it will lead to a system blackout. Similarly, higher storage duration time means having the liberty of providing the power to meet minimum demand threshold requirements during prolonged power disruption times and thus to meet system reliability level.

Like storage size, the system cost is less sensitive to events frequency up to event durations of fewer than 12 h. Fig. 6c & 6f show, regardless of L_{th} value, COE marginally increases with the frequency of the event up to 12 h duration, but it becomes highly sensitive to the number of events when simulated events duration surpasses 12 h. For instance, the COE increase is not more than 11% with 12 h, but it surged to 21 % with 24 h when the power outage frequency increased from 2 T to 6 T. Besides, for longer outage durations, the percent increase in COE is higher at low-frequency events when the allowed LL value is reduced from 0.5% to 0.3% (size of small circles in Fig. 6C, 6f). The included reason is storage size (Fig. 6 versus Fig. S2). For instance, in 2 T, storage size increased up to 30 MW when LL reduced from 0.5% to 0.4%. However, this change for

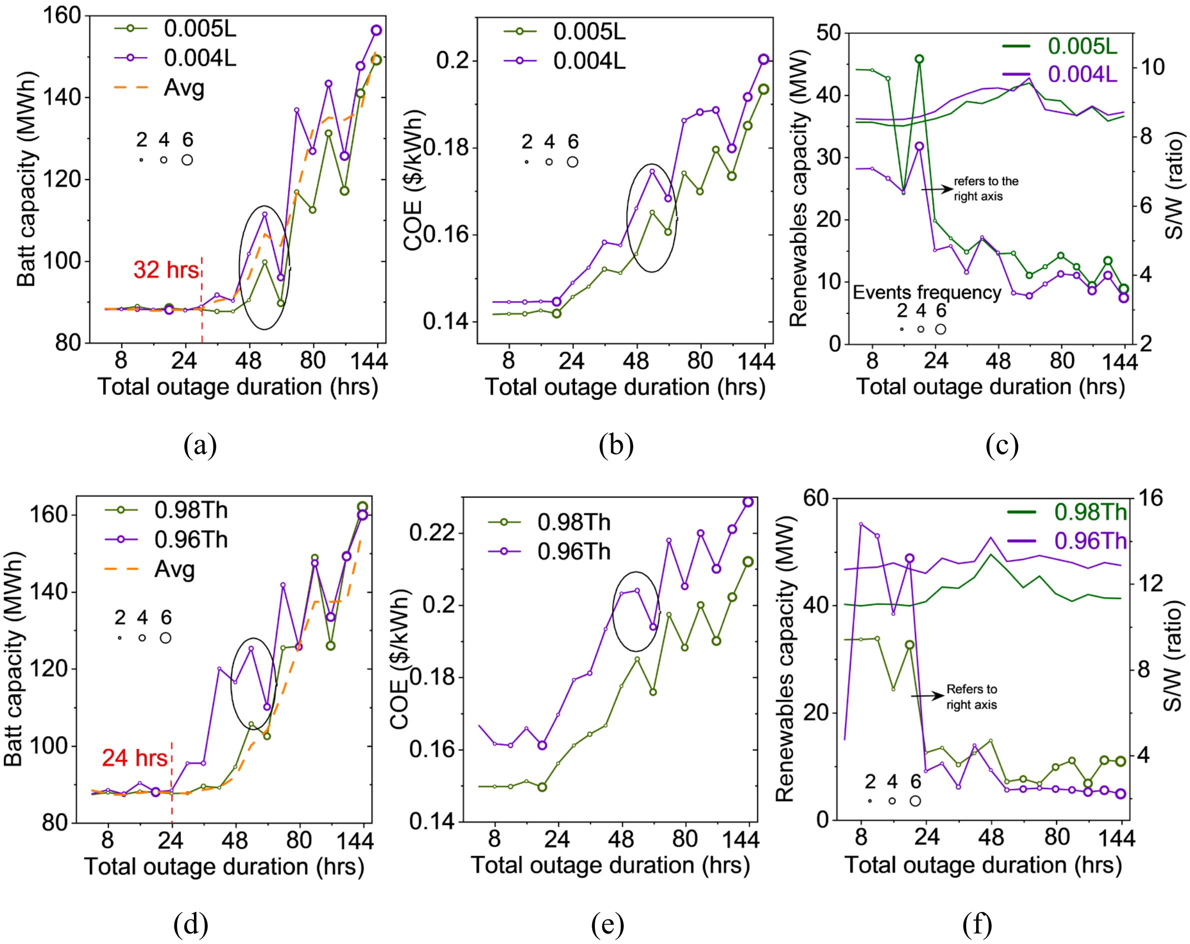

Fig. 5. Variation in RES components optimal capacity and system cost under diverse reliability (1st row with base case $L_{th} = 1$) and demand threshold (2nd row) values. Figures exhibit the optimal capacities variation as a function of varying event duration, its frequency, and total yearly outage duration (x-axis). The horizontal axis shows the total outage hours in a year, while the size of the circles represents the total number of events during a year. (a-c) SWB optimized with the base case ($L_{th} = 1$) for the maximum allowed load loss (LL) of 0.5% (0.005L) and 0.4%. (d-f) SWB optimized with the L_{th} values of 0.98 (0.98Th) and 0.96 for the maximum allowed LL of 0.5%. For LL = 0.4% with L_{th} values of 0.98 and 0.96, see supplemental figure.

6 T was only 19 MW due to storage already having a larger size at 0.5% LL (**see supplemental file 2**). It means RES configurations optimized considering larger outage event durations are highly likely to cover even longer power disruption events than the durations at which they are designed.

The sensitivity of curtailment to event frequency is marginal for smaller event durations. For example, events frequency has almost no impact on curtailed energy with 4 h duration; however, its value starts to decrease with events frequency increase in 24 h case (Fig. S2). Curtailment analysis revealed the apparent increasing trend when L_{th} value changed from 1 (base case) to 0.95 and LL value stepwise decreased, i.e., higher reliability (Fig S2). However, the curtailment percent increase is higher for smaller event duration cases (less than12 h) because, as stated previously, a higher increase in RE generation capacity compared to the storage capacity. Moreover, curtailed energy is comparatively more sensitive to varying demand threshold values than LL. For instance, curtailment increased to 113% when Lth decreased from 1 to 0.96 while this increase was 75% when LL decreased to 0.3% at a given L_{th} value (**supplemental file 2**).

3.1.3. *Effect of reliability levels and demand threshold on capacity sizing*

Fig. 7 illustrates the impact of varying L_{th}/LL values on components' optimal capacity sizing and cost for a given power disruption scenario. Storage size is more sensitive to varying L_{th} values, while varying LL values considerably impact the RE generation capacity, as reflected from 144 h (6 T-24 h) and 72 h (6 T-12 h) power outage scenarios (Fig. 7, Fig. S3). For the 144 h power outage scenario, the median increase in storage capacity is 17 MW when L_{th} varied from 1 to 0.95, while this median value for varying LL (from 0.5% to 0.3%) is 10 MW. Moreover, the storage capacity spread due to varying L_{th} value at a higher reliability level (LL = 0.3%) is more compared to a lower reliability level, unveiling a basic relationship between L_{th} and LL to design a resilient microgrid considering power outage events (variation in blue boxes length in Fig. 7). The storage capacity spread increased up to 31% when LL shifted from 0.5% to 0.3%. It means the storage capacity requirement would increase exponentially compared to the RE generators (length of green boxes) to meet the final 0.2% reliability level with resilient RES criteria (see discussion section 4).

€Compared to the storage capacity, RE generation capacity variations are more sensitive toward LL value (Fig. 7, Fig S3). Overall, system costs tend to increase at a given power outage scenario regardless of whether the L_{th} value changed from the base case or the LL value decreased. The median RE generators capacity increased by 15% when LL varied from 0.5% to 0.3% in a given power outage scenario. Meanwhile, the variation in RE capacity spread was marginal (less than4 MW) due to varying L_{th} value when LL decreased from 0.5% to 0.3% (variation in green boxes length in Fig. 7). The included reasons are satisfying the minimum demand-met threshold criteria and large curtailments. This analysis of varying L_{th} and LL values to design a resilient microgrid at a given outage scenario reveals that variations in storage capacity are

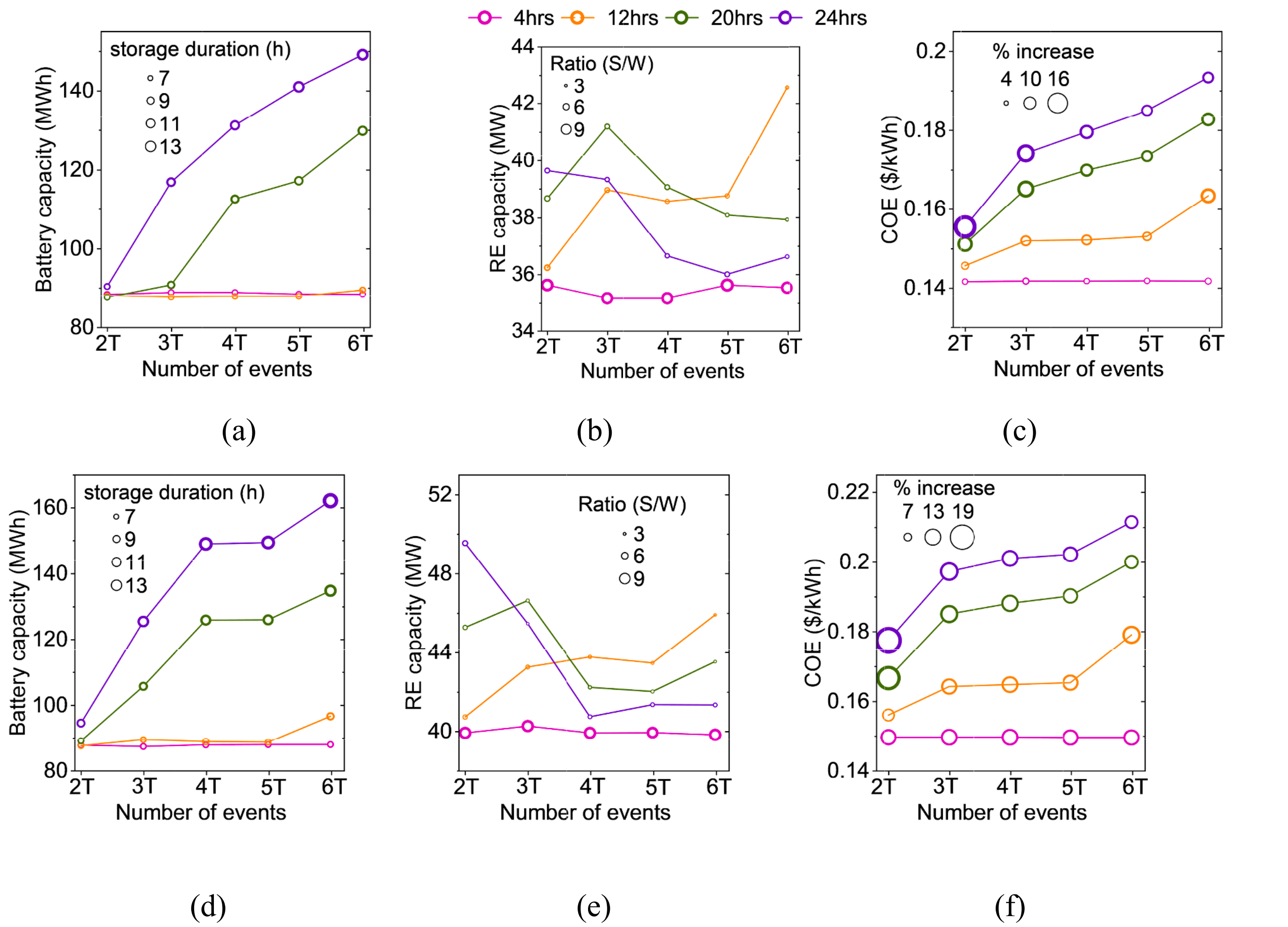

Fig. 6. Effect of outage events frequency as a function of outage durations on components capacity sizing and system cost. The maximum allowed load loss is 0.5%, while the 0.4% case is presented in the supplemental file (Fig. S2). (a) & (d) shows the change in battery storage optimal capacity with the minimum load-met threshold (L_{th}) = 1 & 0.98, while the size of circles exhibits the optimal storage duration time in hours. (b) & (e) shows the change in RE capacity with L_{th} = 1 & 0.98, while the circle size illustrates the change in optimal solar-wind ratio. (c) & (f) exhibits the variation in COE value with L_{th} = 1 & 0.98, while circle size shows the percent increase in COE value when the maximum allowed loss load is decreased from 0.5% to 0.3%. S/W: solar/wind.

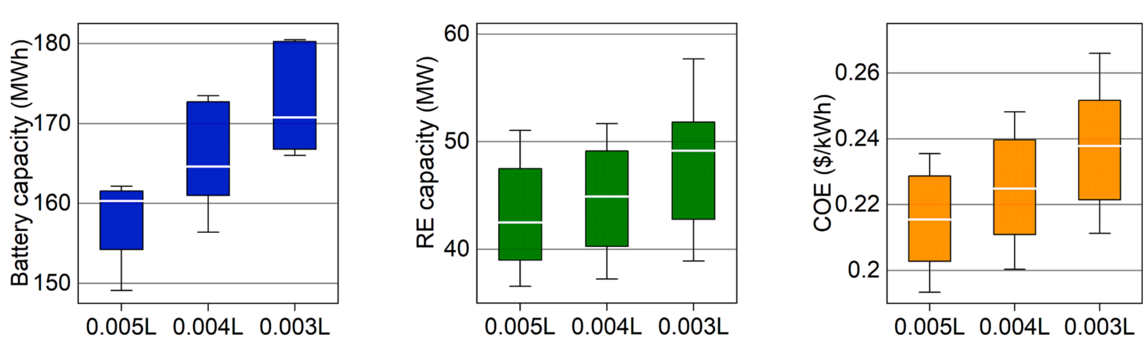

Fig. 7. Variation in optimal RES component capacities and cost at various allowed load loss (LL) values when demand threshold stepwise changed from 1 (base case) to 0.95. The body of the boxes exhibits the 5%-95% values, while whiskers show the minimum and maximum values. The horizontal axis represents the maximum allowed LL for optimal capacity sizing (i.e., 0.005L = 0.5% of the demand). The figures show the results for a yearly 144 h outage duration (6 events with each 24-hour duration). The results with 72 h of outage duration are presented in the supplemental file (Figure S3).

directly linked to user-defined demand threshold criteria, while RE generators' capacity would be sensitive to defined reliability levels. However, meeting the final 0.2% reliability levels would substantially affect storage size rather than RE capacity and eventually increase the system cost. The median increase in system cost due to varying LL values is 10%, while this median increase was 24% when L_{th} changed from 1 to 0.95 for the 144 h scenario.

3.2. Simulation testing of designed RES with randomly generated outage events

We tested the RES that was designed considering systematically generated outage events, with randomly generated outage events of the corresponding scenarios, making sure the total yearly outage duration should be equal to the designed duration, thus evaluating these RES withstand ability to random prolonged power disruptions. For instance, the RES designed with a 6 T-24 h scenario (total duration: 144 h) would be tested for a similar scenario by generating random start times for these events that were systematically selected during optimal sizing. Thus, all six events could happen during the year's first half or be equally distributed throughout the year. However, we made sure that the event start time should not overlap, i.e., the start of a new event while the previous event was happening.

Moreover, a constraint was set for the random event start time to ensure no event starts during the night, i.e., when solar is unavailable. We also compared these designed RES performances with the optimally designed RES without the power outage and demand threshold criteria (conventional approach). We used the Monte Carlo approach to generate random outage events, and a set of constraints was applied to satisfy the above criteria [60]. To find the number of runs for satisfactory results, we estimated them by trial and error method (Fig. S4). We assessed the confidence interval range with the increase in the number of runs and selected the number where this range was less than 1% of the mean value, which was 1000 runs. It means we have assumed a confidence interval (CI) range of less than 1% of the mean value, i.e., if the average value is 100, CI will start at 99 and end at 101.

3.2.1. Performance comparison

We analyzed the designed RES withstand ability in two ways during simulation testing. How well performed the RES during random outage events only (Fig. 8a), and what is the mean percent decrease in overall LL compared to the system designed with the conventional approach (Fig. 8b). As Fig. 8a illustrates, regardless of the power outage scenario, the RES designed with the demand threshold values comparatively performed better than the base case ($L_{th} = 1$) since the base cases have comparatively high outage load loss to outage load ratios (OLL/OL). For instance, this average ratio for 1Th-6 T-24 h is 12%, meaning 12% of the load during the random event was not met, which was reduced to 8% and 5% when the load threshold changed to 0.98 and 0.96. This illustrates the significance of demand threshold integration in designing a resilient system. However, the system cost is highly sensitive to the demand threshold values (Fig. 5, Fig. 7), and RES designers would see the tradeoff between these two objectives (Fig. 8c). Fig. 8c shows the tradeoff between the demand threshold and COE. Deviation from $L_{th} = 1$ decreases the OLL/OL ratio but also increases the system cost. For the 144 h outage scenario, a 0.98 value of L_{th} would be appropriate, as OLL is less than 1% of OL while COE only increased by 10%.

Fig. 8b shows the mean percent decrease in the yearly LL during simulation testing of the RES designed considering outage scenarios compared to the RES designed without any power outage scenario, i.e., the conventional sizing approach. Indeed, RES designed considering power disruption events have, on average, up to 75% lower LL than the system designed with a conventional approach during simulation testing. Moreover, regardless of power disruption duration, the reliability of the conventionally designed RES worsens with the increase in event frequency. The results showed that when the outage duration is higher than 12 h, RES designed without the power disruption events consideration might withstand smaller events frequency but eventually would have blackouts with the increase in events frequency, mainly, i.e., 12 h duration events almost have a similar impact as 20 h, 24 h have at 6 T (Fig. 8b).

3.2.2. €Resilience comparison

We further tested the systems' ability to withstand random outage events during 1000 runs of simulation testing. For instance, if a designed RES meets the designed reliability criteria – LL should be less than 0.3% of load – during 1000 test runs, it would be considered a 100% resilient system. Meanwhile, if RES meets the reliability criteria only 250 times during 1000 runs, there is a 25% probability of meeting the designed reliability level when a supposed random outage event occurs. Furthermore, we comparatively assessed the accumulated resilience levels of designed RES for the given load loss levels, which unveils that though RES can be designed considering historical outage data, it would still be challenging to design a 100% resilient microgrid due to the reasons, including RE level of availability or density during the final hours before a random outage occurs and available dispatch options during outage times, i.e., storage, firm generation source etc.

Fig. 9 shows the levels of resilience at given load loss values for RES designed considering events durations from 12 h to 24 h with frequency from 3 to 6 for two demand threshold cases ($L_{th} = 1, 0.97$). The figures show the performance of RES during outage events. These systems were optimally sized with the reliability constraint of 0.03L, meaning LL should be less than 0.3% of load demand. Though both cases were optimized considering systematically designed outage scenarios, the RES designed with a 0.97 demand threshold performed better than the $L_{th} = 1$ case (Fig. 9). Regardless of the outage event scenario, there was 80% of the time during simulation testing when at least 73% of demand was met during outage events for RES designed with $L_{th} = 1$. Meanwhile, this reliability level further increased to 80% for the same resilience level (i.e., 80%) when L_{th} changed to 0.97, as no blue color is below the red dotted line. Moreover, we performed similar testing for the RES that was designed without any outage event consideration (conventional approach), which showed there were only 25% times when LL was less than 30% of the total load during outage times (not shown here).

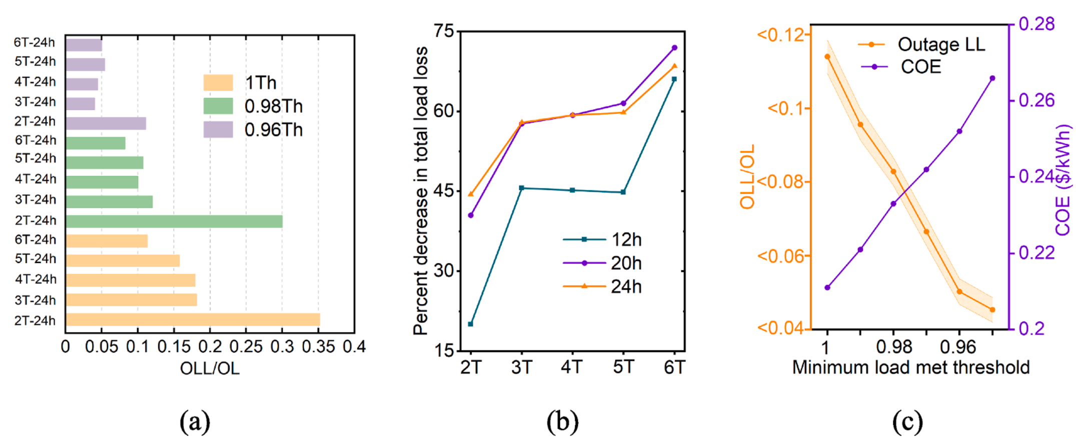

Fig. 8. Reliability evaluation of RES designed considering diverse outage scenarios when simulated with randomly generated outage events. (a) The ratio of load loss during outage hours to total load during outage durations (OLL/OL). Vertical axis represents the optimally designed RES under diverse outage scenarios. Graph shows the mean values when simulated 1000 times. (b) Mean percent decrease in total RES load loss during testing compared to the RES designed using the conventional approach. (c) Change in mean load loss during outage durations for varying demand threshold values (L_{th}) with a 95% confidence interval when simulated with random outage events. This figure shows the 6 T-24 h scenario, while the 6 T-12 h scenario is presented in Fig. S5. Outage LL: load loss during outage events.

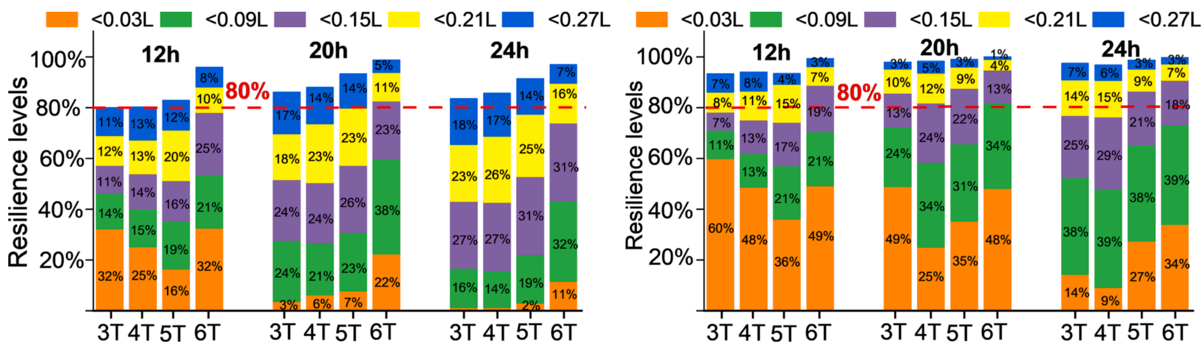

Fig. 9. Resilience level during simulation testing with generated random outage events. Random outage events are generated according to the designed scenarios. For instance, if RES is designed with a 6 T-12 h scenario (72 h total outage duration), random events during simulation testing are generated accordingly but with the random starting time of each event during a year. Legends represent the reliability level, i.e., 0.03L means load loss is 3% of demand. The red line shows at which reliability level RES was proved 80% resilient during simulation testing for diverse outage scenarios. The length of different bar colors represents the resilience level concerning different reliability levels (color type) for any given outage scenario during simulation testing.

Besides, Fig. 9 also illustrates the impact of events frequency and duration on the resilience levels to satisfy given reliability criteria. For instance, regardless of event frequency, RES performed well for the smaller events duration. Like, for $L_{th} = 1$, RES was up to 32% resilient to meet the 3% LL criteria for 12 h duration events, while this value for 24 h cases dropped to 11% (and even zero; brown colors). The same trend is reflected with $L_{th} = 0.97$, where resilience level ranged between 36% and 60% for varying events frequency with 12 h duration, while this range for 24 h duration cases is decreased to 9%-34% but still higher than RES that was designed with $L_{th} = 1$. This analysis shows the critical role of rare power outage events in designing resilient and reliable microgrids. However, even though resilient RES can be designed based on the historical power outage data but it would still be challenging for those systems since it is difficult to predict those rare events' occurrence time, duration and frequency, i.e., summer could have higher rare events frequency due to extreme weather conditions while having the peak load demand at the same time. On the other hand, there is also a possibility of having zero events during consecutive months, thus

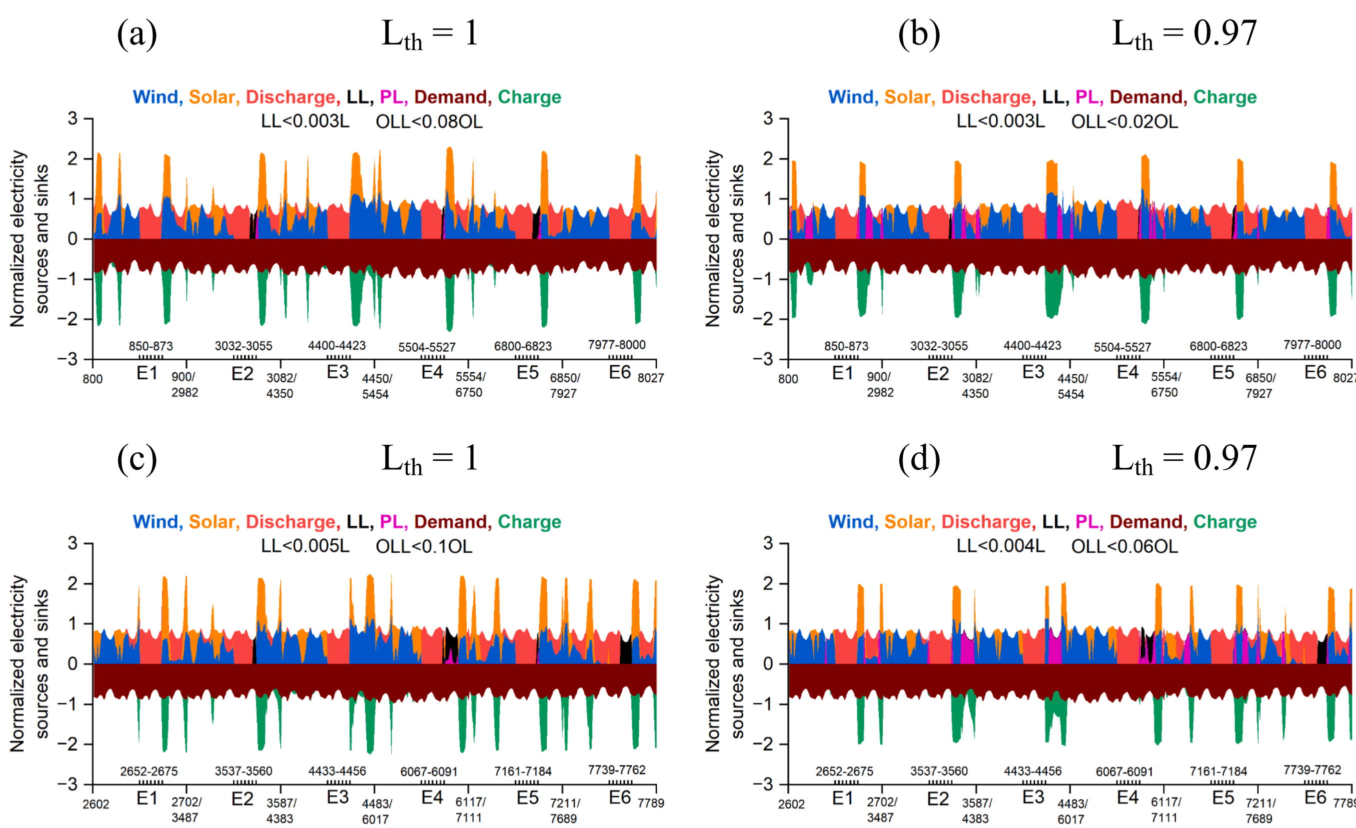

Fig. 10. Hourly balanced electricity sources and sinks of each outage event during a year. Energy flow of 100 h duration (+-50 h from event start time) is shown. The horizontal axis represents the year's hours with outage events duration on the upside of the horizontal line. Figures (a) & (b) show the energy flow when input data with systematically designed outage events is used while (c)&(d) show the energy flow when designed RES is simulated with outage events generated randomly (see horizontal axis for the random events happening time during a year). The left figures represent the base case with $L_{th} = 1$, while the right figures show the case with $L_{th} = 0.97$. The simulated RES is designed for a maximum allowed load loss of less than 0.3%. Similar cases with the RES optimally sized with the conventional approach are shown in Fig. S6. Indeed, RES designed considering outage events can meet the demand during rare events 90% more reliably than the RES designed with the conventional approach. LL: total load loss; OLL: load loss during outage events; L: total demand; OL: demand during outage events; PL: load partially met.

leading to a lower usage factor of the system components [6].

Fig. 10 shows the optimized RES energy sources and sinks during power outages. Two cases with demand thresholds 1 and 0.97 are shown with the input data having systematically designed power outage events (1st row) and data with the random starting time of events. It can be seen that, regardless of the L_{th} value, RES effectively managed to keep the LL less than 0.3% when simulated with the systematically designed outage events input data. Meanwhile, when RES designed considering the conventional approach (without outage events consideration) simulated, LL values were higher (1.1%-1.5%) than the designed LL (less than0.3%) value despite the fact that we also integrated the demand threshold approach (Fig. S6). Furthermore, we simulated the same RES cases with the random outage events (Fig. 10c-d; Fig S6). With random outage events, total LL marginally increased from the designed LL, but still, RES designed with $L_{th} = 0.97$ has a lower yearly LL (0.4%) than the $L_{th} = 1$ case (0.5%). Among six random outage events, the system was able to completely satisfy the minimum demand threshold requirement four times with $L_{th} = 0.97$, while this value for the $L_{th} = 1$ case is 2. As can be seen, OLL is 66% increased when L_{th} changed from 0.97 to 1. On the other hand, there was not only one event when the conventional approach RES was able to satisfy the outage load demand completely (Fig. S6). Therefore, these systems only met 30% of the demand during outage events despite being designed with an LL constraint of 0.3%.

4. Discussion

In this section, we briefly discuss the overall key findings when viewing this study as a whole, the application of the proposed approach in designing resilient systems, and the limitations of this study.

4.1. Assumptions and limitations

In this study, the minimum demand met threshold is used to charge the storage so that there would be enough dispatchable stored energy available each time when rare outage event occurs. It could be possible to drive storage to permanently satisfy only threshold demand while the remaining load (1- L_{th}) can be met by seeing the available RE generation power. However, it could certainly affect the reliability of the RES, which is already highly sensitive to variable generation and load; thus, we did not capture this scenario. It means storage is discharged whenever generation is less than Lth to meet the 100% load during that period. If the generation is higher than L_{th}, it is used to charge the storage and the remaining load (1-L_{th}) either be satisfied with the surplus available power (i.e., storage fully charged or charging power constraint) or considered as LL (Fig. 11). Second, optimal energy system results could be highly sensitive to the input parameters (i.e., optimal RE mix due to solar/wind capacity factors), and problem formulation could be varied, like deciding whether the L_{th} parameter should be applied for both modes or charging mode only. This study is intended to understand general relationships and patterns in designing a resilient and reliable low-carbon power microgrid; thus, we modeled an idealized system. However, to design an actual plant, it is imperative to perfectly model the system considering the resource and market where the power system will operate. The final sizing of system components will also be sensitive to the assumptions made.

We did not consider the varying duration of events in one case. For instance, 6 T-8H means each event duration is fixed to 8 h, which in real-time scenarios could vary. This study assumed that power from both solar and wind sources is not available during power outages, which may not be the case in real-time scenarios like it is possible that solar modules are installed very near to the demand area, and the probability of having outage events due to solar could be less than the wind turbines that are installed very far, i.e., transmission/components failure or maintenance time lags. The purpose of considering the shutdown of both sources is to analyze the worst power outage scenarios and their impact on microgrid capacity sizing and performance. These points could be potential future research topics for designing a resilient RES. We vary the reliability levels within 1% of the electric load because satisfying the last percent of load using variable RE is challenging, as it significantly increases system costs [61–63]. Similarly, storage size is highly sensitive to varying demand threshold values (Fig. 7); thus, we stepwise changed up to 0.95. The resilient design approach of this study is not intended to be used directly to plan/design microgrids. Instead, the general observations of this idealized study may motivate researchers to assess further the potential benefits and challenges of incorporating the resilient perspective in designing zero-carbon energy systems.

4.2. Discussion on key findings

RES components optimal capacities are substantially affected by outage events frequency, outage duration, defined reliability level, and demand threshold value. We found that storage capacity is not necessarily linearly increasing with the increase in total annual outage durations; instead, it is highly sensitive to the event duration (consecutive time points within the event) and becomes the function of events frequency for large events durations (Fig. 5). Furthermore, the analysis revealed that the cost of designing a resilient microgrid could be higher than designing a system ensuring uninterruptible power supply only when rare outage events are not happening. This finding aligns with the Rinaldi et al. study that a decrease in power outage occurrence could reduce the system cost by up to 16% [23].

The shorter events duration did not affect much the system's optimal

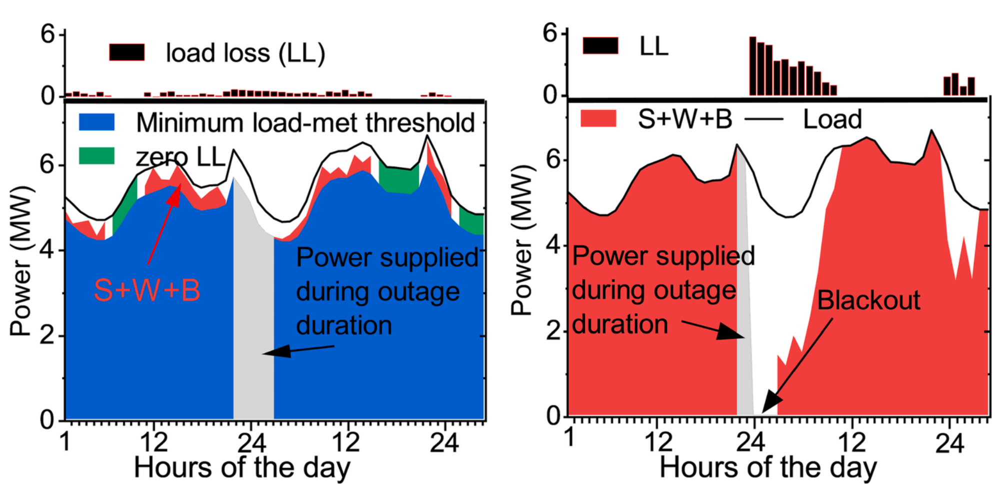

Fig. 11. Power flow during random power outage event. S: solar; W: wind; B: battery storage.

sizing. It could be adjusted with the marginal increase in RE generator capacity, while power disruption events greater than 12 h substantially increase the storage capacity, which further increases as the events frequency surges. We noted that optimal storage size is more sensitive to varying L_{th} value while varying LL value affects more the RE generator size (Fig. 7). The possible reasons are minimum demand met threshold criteria and large curtailments when RE capacity increase with the varying L_{th} (Fig. S2). Performance comparison revealed that the RES designed without considering power disruption events might withstand smaller events but eventually will have blackouts with increased event duration and frequency. We show the optimal RE mix (solar to wind ratio) substantially reduced with the increase in outage durations that illustrates each RE source penetration should not be optimized only based on their capacity factors. The comparative performance of the proposed minimum demand-met threshold approach with the conventional sizing approach is shown in Table 3. The proposed approach performed well regarding increased reliability and resilience, which is particularly important for off-grid systems with no backup source. Meanwhile, these benefits come up with the simultaneous marginal increase in cost and curtailment.

This study is in agreement with Stanley et al. that observed to meet the minimum power requirement, there is a substantial increase in storage size and system cost as the outage duration surpasses 18 h [24]. Similar to these findings, we find that regardless of outage frequency and reliability levels, storage capacity did not change much up to 24–32 h, depending on the defined minimum demand met threshold (Fig. 5). The similar findings between our study and previous study provide confidence to the developed method herein. Our use of varying minimum demand threshold concept is one primary difference from the previous studies where either a similar demand pattern is used or analysis is made for a constant minimum power requirement. The proposed minimum load-met threshold strategy offers a balance between the resilience and economics of off-grid power systems.

While power outages are unavoidable, the proposed strategy highlights that their impact can be minimized via smart energy management, particularly when microgrid relies on variable RE resources. By simultaneously integrating the proposed minimum load-met threshold approach with other demand flexibility mechanisms, the microgrids' reliability and resilience can be robustly enhanced not only in unprecedented weather conditions but also overcoming location-specific challenges. Having more than one mechanism to cope with power outage challenges in a microgrid may actually lead the power system to more cost-effective blackout avoidance. The outcomes of this study may help system operators to understand the power system operation under extreme conditions and develop a more intelligent and insightful mechanism to fully avoid the impacts of power outages to satisfy the demand during these unusual periods. One of the authors' future work would be integrating the proposed mechanism with diverse demand flexibility portfolios and assessing the power system performance under different extreme weather events.

Table 3
Key findings of this study.

	Proposed minimum demand-met threshold approach	**Conventional approach**
Cost	(—) 4–24% higher	(+) Less
Resilience	(+) 80% of the outage events demand met during 80±% of the simulation testing time.	(—) 73% of the outage events demand met during 80±% of the simulation testing time.
Reliability	(+) RES effectively managed to keep the load loss to less than 0.3% during one-year simulation	(—) Load loss 0.8–1.2% higher than the level for which RES designed.
Curtailment	(—) 30%-110%	(+) 30%-80%

4.3. Application of proposed resilient design approach

In our study of idealized outage scenario-based modeling, the power outage events consideration with the input data allows the microgrid to ensure the minimum load threshold is met during the random events throughout the year, particularly during peak load times and thereby increasing not only the system withstand ability with prolonged power disruptions but reliability as well. This analysis provides a flexibility enhancement complement to the demand response program (DRP) studies that showed adding certain DRP (i.e., load shifting) can reduce the storage capacity required to meet the same load demand with a cost saving of up to 50% [64]. The characteristics of peak load can be changed using DRP, and if integrated with the proposed approach, the reliability of resilient systems can be 100%, which we did not consider here. For instance, it would be impossible for a RES to be designed using Lth = 0.98 to ensure 100% load is met throughout the year, as 2% of demand would always depend on whether storage is fully charged or surplus power is higher than the storage charging rate. However, DRP integration can satisfy the final 2% of the demand without an increase in system cost. Many literature studies have evaluated the viability of DRP for RES, including changes in consumption patterns, firm power backup source, and time-based pricing [65–68]. This would be the authors' future research topic as well.

If the proposed resilient design approach is applied at the macro scale, DRP can still play a role in meeting the 100% load met criteria. According to the U.S. Energy Information Administration, electric utilities with the DRP successfully reduced their peak electric loads by ~ 1%-2% of the mean annual electric loads each year since 2013 [69]. Moreover, peak load values for macro scale systems could be 150% to 180% of the mean load, which can significantly increase the storage requirement when designing a resilient system with a minimum demand threshold [66]. This suggests that designers need to precisely plan future low-carbon energy systems by incorporating the outage events, DRP, and weather influence. Having access to the exact hours when DRP is substantially reducing electric load could help to charge storage during those times, thus ensuring 100% load met during other times since storage would be charged enough and available power higher than the demand threshold would be used to meet the remaining electric demand.

Another scenario applying the proposed resilient design approach could be based on fixed and flexible loads, particularly at the macro scale. Load profiles are significantly evolving due to the enhanced electrification of various sectors like electric vehicle charging [70]. Based on the electric load (fixed and flexible) grouping, whether the minimum load-met threshold should be set based on total load (fixed + flexible) or just flexible load only during a given time can be decided. As fixed load is usually considered critical baseline demand that should be 100% satisfied each time, the charging preference of dispatchable stored energy (i.e., L_{th}) could be set based on flexible electric load only. Alternatively, the electricity system operator can directly control this operation, like DRP, seeing the event occurrence probability, the current state of dispatchable stored energy and the ratio of fixed to flexible load over a given time. Furthermore, it is worth mentioning that as load profiles evolve, the proportion of flexible load would also increase (i.e., smart appliances); thus, the viability of designing resilient future low-carbon energy systems would also be higher.

The results shown here may be applicable at a broader scale as U.S. Department of Energy Office of Efficiency and Renewable energy statistics reveal that power outage events of less than 100 h often occur [71]. Based on such data, probabilistic models for outage events can be designed and integrated for the optimal capacity sizing of future zero-carbon energy systems. However, it is worth noting that these outage data are rarely available and are based on several assumptions. The precision of future planning targets for renewables-based electricity systems can be improved with the availability of more consistent and predictable outage event data. Though it is possible to design resilient and reliable future low-carbon energy systems using historical weather, outages, and load data, changes in long-term trends in RE profiles (i.e., solar/wind) over time due to climate change may still be challenging for these systems.

5. Conclusions

With the continued growth of renewable energy, interest in the topic of resilience has increased. Often, resilience is seen from an operation point of view as the ability of a power system to withstand and recover from random disruptive events. Although this alone is not enough, it is an important part of resilience. This study employed an idealized approach to study a resilient microgrid and used simulated outage events as an input with the solar/wind data. A storage operation algorithm is proposed based on the demand threshold value where preference is given to charge the storage whenever available power is higher than the demand threshold value.

As illustrated in this study, optimizing the system to be resilient can ensure power availability throughout the year, even during prolonged power disruption events, while using variable renewables as a microgrid base source. We showed that, regardless of the frequency of outage events, short outage events (less than12 h) and having a total annual duration of less than 32 h negligibly affected the systems' cost and reliability criteria, which can be met by a marginal increase in generation capacity. The further increase in outage durations significantly increased the storage capacity while decreasing the high proportion of solar capacity in the optimal energy mix, fully exploiting the solar/wind complementary effect. This study showed that optimal storage capacity is more sensitive to the demand threshold values than the reliability values (i.e., load loss), which, when varied, affects the generation capacity more. The median increase in system cost was up to 10% with the varying load loss values (0.3% − 0.5%), while this increase for varying minimum demand met threshold values (0.95%-1%) was up to 24%.

Following our proposed model and optimization framework, we compared the resilience levels during the performance evaluation of microgrids, considering the proposed approach with the energy system designed using the conventional approach. We showed that there is an 80% chance of the systems designed with outage event scenarios to withstand prolonged power disruptions. In comparison, this value is 25% for the systems designed with the conventional approach.

There are two central contributions of this study. First, we introduced the storage operation algorithm to prioritize storage charging based on the minimum demand met threshold, ensuring enough dispatchable stored energy available each time before an outage event. Second, we presented an idea of integrating the outage event data as an input, thus including both resilience and reliability perspectives in the design phase of a hybrid power system. Although this work provides insights to design a reliable and resilient hybrid power plant, it is only the start of an understanding of fully leveraging zero-carbon renewables while ensuring critical resilience levels. More finely resolved outage data in the future could help to integrate the resilience perspective and to alleviate the common assumption about variable renewables changing the common characteristic of electricity systems. For instance, with local demand and hazard data, the hybrid power plant could be sized to satisfy actual load during disruptive and nominal conditions instead of being unable to meet demand during outage events.

CRediT authorship contribution statement

Muhammad Shahzad Javed: Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Visualization, Writing – original draft. **Jakub Jurasz:** Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Visualization, Writing – review & editing. **Tyler H. Ruggles:** Writing – review & editing. **Irfan Khan:** Writing – review & editing. **Tao Ma:** Conceptualization, Methodology, Resources, Funding acquisition.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary material

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