The Value of the Energy Resilience that Solar Microgrids Can Provide to Puerto Rico

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Nana korobi, ya oki.

Fall seven, rise eight.

Japanese proverb

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Acronyms & abbreviations

BAU	Business as usual
BESS	Battery energy storage system
CAIDI	Customer average interruption duration index
CDF	Customer damage function
CIC	Customer interruption cost
CHOLES	Customer-hours of lost electrical service
C&I	Commercial & industrial
DER	Distributed energy resources
DG	Distributed generation
HOMER	Hybrid optimization of multiple energy resources
IRR	Internal rate of return
LCC	Life cycle cost
LCOE	levelized cost of electricity
NPC	Net present cost
NPV	Net present value
NREL	U.S. National Renewable Energy Laboratory
PREPA	Puerto Rico Electric Power Authority
PV	Photovoltaic
SAIDI	System average interruption duration index
SAIFI	System average interruption frequency index
T&D	Transmission & distribution
TOU	Time of use
WTA	Willingness to accept
VOLL	Value of lost load
WTP	Willingness to pay

Chapter 1: Introduction

Within the fields of science and engineering, it is often said that constraints promote innovation and creativity. The tighter one sets the boundaries for a given problem, the more forced one will be to come up with innovative solutions to address it. When it comes to an electrical grid, constraints couldn't be tighter than on an island. This is why islands are often referred to as "laboratories of the energy transition".

Because of the isolated nature of islands, fuel is usually imported to run transportation infrastructure, but also to generate electricity. Given its scale and isolation, island grids that rely on imported fuel tend to be economically expensive, energetically inefficient, environmentally polluting, and inherently fragile.

Until now, power systems have grown according to economies of scale that favor large, remote generating facilities. These legacy decisions have evolved the grid into what Rocky Mountain Institute [1] describes as a one-way value chain starting from large-scale generations that pump electrons into high-voltage transmission lines, then to low-voltage distribution lines, to be delivered finally to end-users who end up paying for all this infrastructure.

The dangers built in this one-way value chain have persisted ever since its inception: any disruption to any link of this chain can result in power interruptions. For the majority of its history, methods to protect from these dangers have mostly focused on “hardening” each link of the value chain against disruption; e.g., prioritizing security of supply to fuel delivery, investing in redundant generation capacity, and reinforce transmission and distribution infrastructure [1].

With 21st-century technology already available, this needs not be the case: the cost of distributed energy resources (DERs), particularly solar, wind, and energy efficiency, has plummeted in the past two decades, already making them competitive with or cheaper than legacy fossil fuel infrastructure. Similarly, energy storage technologies (e.g., lithium-ion and flow batteries) have shown similar learning curves to the one PV has been experiencing for the better part of this century. These technological tendencies are part of the current energy transition, namely the trend of energy infrastructure towards "3DER"; this is ***decarbonization, decentralization, digitization, electrification, & resilience*** [2].

Ultimately, this narrative plays out within a much broader one; that of anthropogenic global warming, the climate crisis and environmental degradation, of which island communities are positioned to endure a disproportionate share of its impacts [3]. Research shows that, although small island developing states (SIDS) contribute to a small fraction of anthropogenic climate change, they are and will continue to be some of the most vulnerable regions to its impacts. Small island developing states (SIDS) in the Caribbean, for example, are expected to lose 10% of their total GDP by 2050 due to inaction to adapt to climate change. By 2100, this number is expected to rise to 22% of their total GDP [4]. The escalating scale of the climate crisis make evident the need to improve, among other sectors, the resilience and reliability of islands’ energy systems.

As recently shown by Hurricanes Maria in 2017, and Dorian in 2019, islands in the Caribbean are simply not prepared for the volatile weather systems of the Anthropocene. Particularly Puerto Rico, an island country in the Caribbean with a (declining) population of 2.86 million as of 2020; officially an unincorporated territory of the United States, Puerto Rico has already had to endure the effects of natural disasters amplified by climate change.

Hurricane Maria was a Category 5 hurricane that devastated Dominica, Saint Croix and Puerto Rico in September 2017. Although it had diminished to Category 4 by the time it made landfall in Puerto Rico, it ranks as the third-costliest tropical cyclone to hit a U.S. territory, with losses estimated at 95 billion USD [5]. The humanitarian crisis in Puerto Rico following Hurricane Maria was the combination of a "once in a lifetime" storm with a decrepit electricity grid that had been deprived of maintenance and care for years. These conditions resulted in the longest blackout ever experienced in a US territory, and the second longest in the world [6], where more than 3 million people were left without power for months, with its last user not being able to turn on their lights until almost a year after the hurricane made landfall [7]. The New England Journal of Medicine estimates that up to 4,600 deaths can be directly linked to the storm and its effects on healthcare, electricity, water supply, and other critical services, approximately 0.14% of the total population [8].

1.1 Research motivation & objective

Two encompassing narratives motivate this thesis; the seizable opportunity to improve the energy infrastructure of islands through DERs, and the need to increase the resilience of islands facing natural disasters amplified by climate change, with Puerto Rico serving as a lesson of what could've been prevented, but wasn't, and what can be done now to prevent it from happening again.

1.2 Problem statement

In 2017, Hurricane Maria proved how fragile Puerto Rico's grid is to natural disasters. The consequence of this fragility was the longest power blackout in the history of the U.S., which affected 3.3 million people, lasted for 3.4 billion customer-hours, and resulted in economic losses estimated in 95 billion USD [5].

The solution, then, is **energy resilience, defined here as the overall ability of an electricity system to prevent, mitigate, and recover from wide-area, long-duration outages** [1].

But energy resilience itself is a term that is loosely understood and is even more ambiguously quantified. Previous studies have thoroughly delved into the disparities in grid restoration time depending on geography [9], and even provided plans to rebuild the electricity infrastructure [10], but none so far have attempted to assign a value to energy resilience in Puerto Rico. Being such a nebulous concept, many answers have been proposed to achieve energy resilience: fortifying the grid or burying its power lines altogether, securing several days' worth of fuel on site, increasing redundant generation capacity, or prioritizing distributed energy resources (DERs) instead. This last concept, DERs, is the main focus of this study.

Research done throughout the grid restoration process in the aftermath of Hurricane Maria has made clear that the main bulk of the damage done to electricity infrastructure was not at the generation level, but rather at the transmission and distribution level; e.g., only 15% of the power lines could withstand forces caused by a Category 4 hurricane, over 847 transmission structures fell due to Maria, 74% of the nearly 350 substations experienced some damage, and approximately 50,000 overhead distribution poles were damaged [11].

While not fully exempt from hurricane damage [11], distributed generation does provide an alternative path to energy resilience compared to traditional centralized generation, and its decentralized nature allows it to circumvent the vulnerabilities inherent in a top-down, one-way value chain, where a failure of any component of the grid can disrupt service to end-users. Accordingly, **the aim of this study is to quantify the value of the energy resilience that solar microgrids can provide to electricity users in Puerto Rico**.

1.3 Research question

In order to reach the previous objectives, the main research question this work aims to answer is:

> What is the value of the energy resilience that solar microgrids can provide to users in Puerto Rico?

To answer it, though, it is necessary to first understand the following:

1. The influence, frequency and magnitude of severe weather events on Puerto Rico's grid
2. How much economic value is lost due to an outage
3. The economic and energy savings that can be expected by installing a PV system *before* accounting for resilience
4. The impact of accounting for resilience when sizing a PV + storage system

Accordingly, sub-questions within this study are:

1. How many hours of lost electrical service do Puerto Rico's users experience because of extreme weather events?
2. What is the value of lost load for Puerto Rico's electricity user segments?
3. What is the net present cost of a PV + storage system sized to optimize savings and how does it compare to the net present cost of not deploying one?
4. How does valuing resilience when sizing a PV + storage system impacts its capacity, components and net present cost?

1.4 Scientific contribution

This research builds upon work previously developed by multiple groups, particularly the US National Renewable Energy Laboratory, Lawrence Berkeley National Laboratory, and the University of Puerto Rico – Mayagüez, who contributed to scientific knowledge by (among other things):

- evaluating the impact of valuing resilience on cost-optimal PV + BESS systems in commercial buildings [12],
- developing a methodology to estimate the value of electrical reliability [13] and the cost of an outage depending on econometric variables [14]
- describing the damage caused by Hurricane Maria on Puerto Rico's electricity grid [11], and, more importantly,
- analyzing the duration of the outage and its unequal distribution throughout the island [9]

One important step in the field of energy resilience on islands, following the previous works by NREL, LBNL and UPR – Mayagüez, is **the study of the value on resilience for an island where severe weather events happen on a recurring basis, which is the purpose of this study**. It aims to fill this knowledge gap by assigning a value to the cost of a long-duration outage in Puerto Rico and incorporate that value into a reframing of NREL's framework previously aimed for commercial buildings in the mainland [12], thus adapting it to Puerto Rico's context as an island heavily reliant on fossil fuel imports [15], dependent on a brittle electricity system [11], and vulnerable to severe weather events [9].

The main scientific contribution of this work are the proposed scenarios that serve as points of comparison to evaluate different levels of energy resilience, their estimated costs and value when accounting for the likelihood and impact of severe weather events. The main policy contribution, on the other hand, is a metric (the value of resilience) that can help policymakers make better decisions regarding investments in energy infrastructure. Lastly, that same metric also serves as a contribution to the solar industry, which the author hopes can help understand the value of decentralized energy resources.

1.5 Research scope and boundaries

This study focuses solely on Puerto Rico, including its electricity rates, tariff structure, policy mechanisms, and level of resilience. Load profiles and reliability indexes used in the model are from Puerto Rico's Integrated Resource Planning 2018-2019 [15], developed by Siemens for the Puerto Rico Energy Bureau, or from the U.S. Department of Energy [16].

Furthermore, while there are plenty of reports that elaborate on the importance of strengthening the Puerto Rican grid and make it more robust, **this study focuses on Puerto Rico's distributed generation from a bottom-up approach, instead of the traditional top-down view on its overall energy infrastructure**.

Regarding the scope of the cases analyzed, boundaries are drawn outside the electricity consumption of single-building consumers (whether a residential unit, commercial office building, or industrial factory), primarily because this marks the "building block" of larger micrograms, and yet still provides sufficient granularity (i.e., a distinct load profile) to be able to design an individual microgrid for that specific building. These types of systems can also be referred to as "multimode PV systems", which can work both in parallel to the grid and in standalone mode, but **this study will refer to them as microgrids**, since multimode PV systems are not necessarily able to perform load management, while microgrids by definition do.

Finally, while there are several definitions of a microgrid, there are four common denominators found among them [17]:

- A microgrid is an integration platform for local energy generation, storage and demand, all placed within a local distribution grid
- A microgrid should be able to work both in grid-connected mode, and emergency (islanded) mode
- Microgrids enable an active operation of the distribution network
- Microgrids may operate in multiple scales; a small-scale microgrid could typically be a house with PV panels, power converters and loads, medium-scale microgrid could be a factory, while a large-scale microgrid can be a university campus, or a neighborhood.

Based on this definition, **the main focus of this work is on microgrids at a building-level**, split into Puerto Rico's two largest groups of electrical users: residential and commercial.

1.6 Resilience & reliability

A clear distinction should be made between energy resilience and energy reliability, concepts commonly interweaved and erroneously conflated.

Energy reliability is the ability to maintain the delivery of energy (in this case, electricity) services to customers in the face of routine uncertainty in operating conditions [18].

Resilience, on the other hand, is a term that's liberally used but frequently vague. The concept itself was brought up in physics and psychology, and has been traditionally used as a measure of stability that communicates the ability to survive shock or trauma and timely recover to a state of equilibrium [19]. It has generally meant the ability to cope with misfortune, disturbance [20] and unforeseen circumstances [21]. Following these insights, [22] understood **energy resilience** as the ability of a power system to withstand initial shock, rapidly recover from a disruptive event and apply adaptation measures for mitigation the impact of similar events in the future.

Energy resilience, then, is a more expansive concept than energy reliability and encompasses consequences to the electricity system and other critical infrastructure from high-impact external events, leading to the aforementioned definition of energy resilience as **the overall ability of the electricity system to prevent, mitigate, and recover from wide-area, long-duration outages** [1].

1.7 Research outline

This work consists of 8 chapters, of which this is the first. A brief overview of the rest is mentioned below.

Chapter 2 enlists the several types of literature that this work builds upon, going from previous work done on energy resilience, metrics used to measure energy resilience and reliability, energy resilience on islands in general, and Puerto Rico in particular. Chapter 3 describes the methodology and resilience metrics used throughout this work, as well as a conceptual description of each scenario considered.

Chapter 4 details the HOMER Pro model used to compare different resilience scenarios, as well as its objective function, constraints, and sensitivity variables. A justification for each assumption made in the model is also provided here. Chapter 5 showcases key results from the resilience modeling performed.

Chapter 6 relies on several sensitivity analyses to explore "what-if?" scenarios. Chapter 7 provides a discussion of the model's limitations and lists other alternatives to energy resilience to portray the study's results into context, and finally Chapter 8 concludes this report with key findings and suggestions for further research.

Chapter 2: Background

Three different blocks of literature review where performed for this thesis. The first block delves into the topic of energy resilience, the concepts it encompasses and the concepts it doesn't, the several approaches used to quantify it, and the ways it can be valued in economic terms. This leads to the second block, that explains the metrics used to measure energy resilience. Afterwards, the third block provides an overview of the work that's been done on energy resilience in islands. Finally, a fourth block elaborates on the energy resilience of Puerto Rico.

2.1 Overview of energy resilience

Roege et al. [23] developed a matrix-based approach to generate energy resilience metrics, which can be used in energy planning, system design, and operations. To do this, the authors adapted Lietaer's sustainability vs. diversity/interconnectivity curve for ecosystem resilience [24], and adapted to energy resilience; as shown by Figure 1:

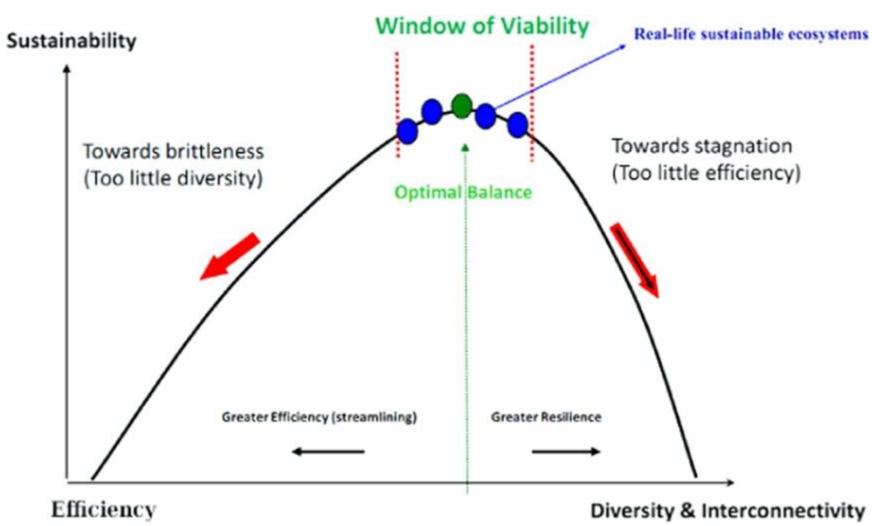


Figure 1. Resilience versus efficiency in ecosystems [23].

The authors point out that the curve shows an optimal "viability window" (i.e., the region where long-term system output sustainability is maximized), and that this window is skewed toward greater system resilience as opposed to greater system efficiency.

On that same topic, but from a utility's perspective, a team from Lawrence Berkeley National Laboratory provided insights on **value-based reliability planning**, which they define as **matching the level of reliability investments with the economic benefit from the reliability improvement** [25]. They also provide a similar correlation, this time between reliability and cost, particularly costs burdened by the utility, and costs burdened by customer interruptions, as shown by Figure 2:

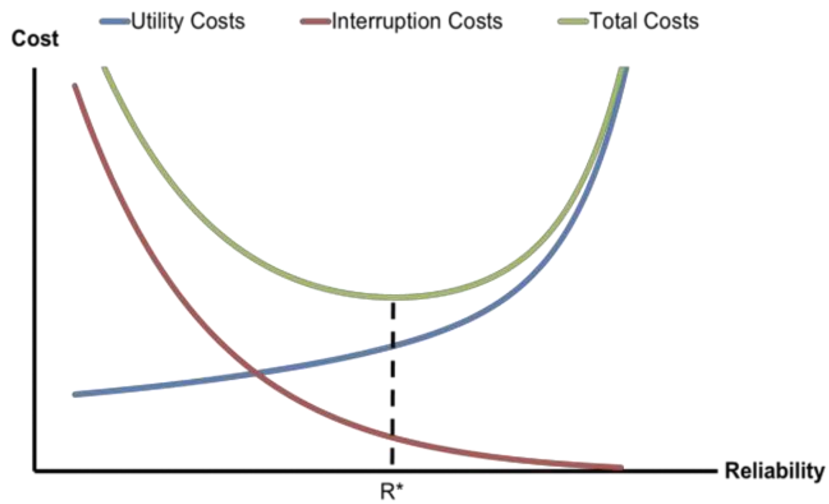


Figure 2. Components of the total costs of unreliability [25].

The reasoning behind the previous cost function is that a utility's investments in reliability (blue line) provide diminishing marginal returns on the other hand, the customer's interruption cost (red line) reflects the decreasing marginal cost of interruptions as reliability increases. The result is the total cost of reliability investments plus outage costs (green line), which has a minimum at R*, the point in which the marginal cost of investing in reliability equals the marginal benefit of reducing interruptions [25].

A report published by the National Academies of Sciences, Engineering, and Medicine delved into the many causes and consequences of grid failures [26]. Among other things, they classified the most common causes of outages, ranging from natural disasters, like droughts or volcanic events, to human-caused disasters, like cyber-attacks or physical attacks. These causes were ranked according to the amount of warning time before they occurred, and the time it takes to restore service after the event, as shown in Figure 3:

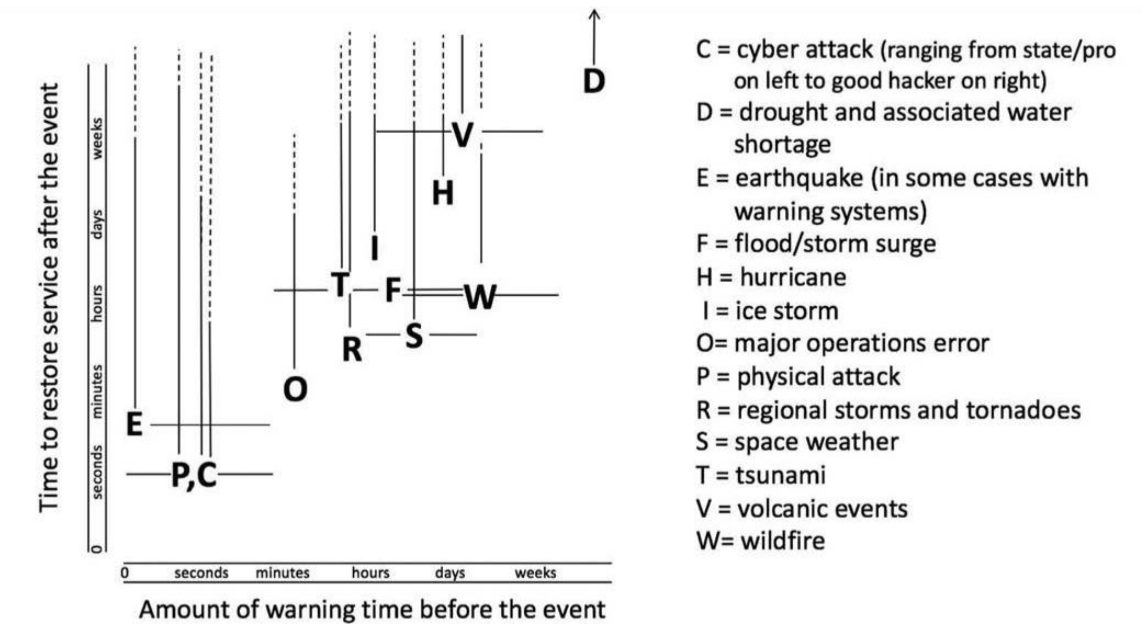


Figure 3. Mapping of events that can cause disruption of power systems [26].

On that same topic, the Rhodium Group keeps a database that shows that 9 out of the 10 longest blackouts in U.S. have been caused by hurricanes [6]:

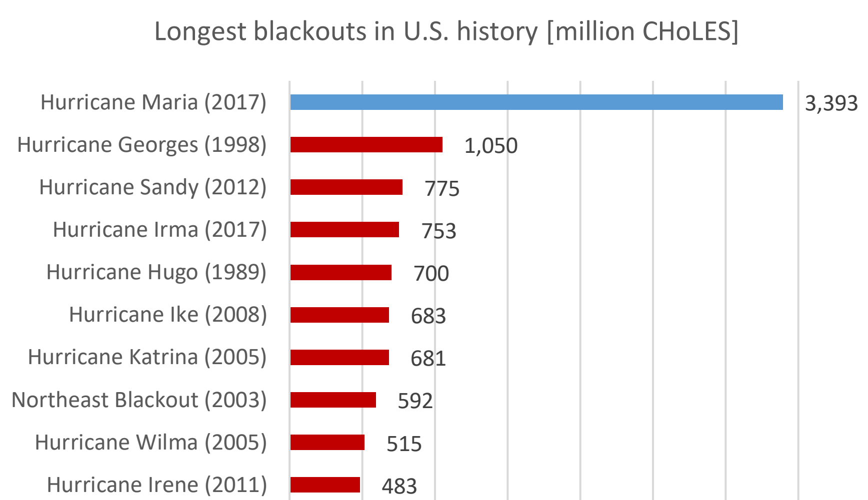


Figure 4. Longest blackouts in U.S. history, measured by customer-hours of lost electrical service [6].

2.2 Metrics used to measure energy reliability and energy resilience

Energy resilience and energy reliability, while distinct from each other, are closely intertwined concepts. Because of this, it's relevant to mention the metrics used to measure energy reliability, before moving on to the metrics that measure energy resilience.

2.3.1 Metrics used to measure energy reliability

Metrics for energy reliability are properly understood and widely agreed upon, and they are summarized below [27]:

SAIFI "System Average Interruption Frequency Index (Sustained Interruptions)—This is defined as the average number of times that a customer is interrupted during a specified time period. It is determined by dividing the total number of customers interrupted in a time period by the average number of customers served. The resulting unit is 'interruptions per customer'".

SAIDI "System Average Interruption Duration Index—This is defined as the average interruption duration for customers served during a specified time period. It is determined by summing the customer minutes off for each interruption during a specified time period and dividing the sum by the average number of customers served during that period. The unit is minutes or hours. This index enables the utility to report how much time customers would have been out of service if all customers were out at one time".

CAIDI "Customer Average Interruption Duration Index—This is defined as the average length of an interruption, weighted by the number of customers affected, for customers interrupted during a specific time period. It is calculated by summing the customer minutes off during each interruption in the time period and dividing this sum by the number of customers experiencing one or more sustained interruptions during the time period. The resulting unit is minutes or hours. The index enables utilities to report the average duration of a customer outage for those customers affected".

CAIFI "Customer Average Interruption Frequency Index—The average frequency of sustained interruptions for those customers experiencing sustained interruptions".
MAIFI "Momentary Average Interruption Frequency Index—Total number of momentary customer interruptions (usually less than five minutes) divided by the total number of customers served".

2.3.2 Metrics used to measure energy resilience

In 2015, Sandia National Laboratories published a conceptual framework for developing resilience metrics for the electricity, oil, and gas sectors in the U.S. [28]. One of the key tools of that framework is the Resilience Analysis Process (RAP), which can be used to assess baseline resilience and evaluate resilience improvements. In simple terms, it explains how to 'use' a resilience metric. The first six steps of the RAP give decision makers and stakeholders a method to assess the baseline performance of a system with respect to resilience. When all seven steps are followed, the focus of the RAP expands to identifying the improvements that will increase resilience. These improvements can be identified by analyzing or optimizing the characteristics of these proposals to identify the best improvement strategies. The RAP steps are depicted as a circle due to the iterative nature of resilience analysis. Periodic re-evaluation of system resilience is important for:

- Validating resilience analysis methodology
- Validating models against actual incident data, and
- Updating resilience assessments with current technology methods and improved threat characterization

Figure 5. The Resilience Analysis Process' steps move on counterclockwise starting from "define resilience goals" [28].

Each step shown in the previous figure is described below:

1. **Define resilience goals**

This step lays the foundation for all following steps. In this step, it is determined whether resilience is the main goal, or if other possible system improvements are the objective, with resilience serving as a side benefit of reaching the main objective. If evaluation improvements are part of the analysis, it's important to determine which changes will be within scope and which ones will not. Also, key stakeholders and possible conflicting goals should be identified.

2. **Define system and resilience metrics**

System definitions and resilience metrics are what determine the scope of the analysis. The scope can include geographic boundaries, relevant time periods, and/or system components. Metrics should be specific enough to enable decision-making, whether for operational or planning purposes.

3. **Characterize threats**

This step is critical to understand the system's capacity to absorb and adapt to different types of threats. It is necessary to obtain information about the probability and impact of each possible threat.

4. **Determine level of disruption**

Once the relevant threats have been understood, their attributes should be used to determine the amount of damage to the system (infrastructure, equipment, etc.) that is likely to result because of them.

5. **Define and apply system models**

The amount of damage calculated in the previous step is then used as input to system models, to estimate the output levels of the system after a given event. E.g., the anticipated damage from a hurricane on an electric grid serves as input into a model that correlates it to the load not served within a given period. Multiple system models (which can be dependent between each other) may be required to capture all of the relevant aspects of the full system.

6. **Calculate consequence**

When evaluation resilience, direct impacts to system output as a result of damage are not the only aspect that to be considered, but also indirect impacts.

7. **Evaluate resilience improvements**

After completing a baseline RAP through the previous six steps, the last step is to compare that baseline configuration with a modified scenario. This modification can be physical (e.g., a redundant power line), policy-based (e.g., incentivizing the use of microgrids), or procedural (e.g., turning off equipment in advance of a storm). Based on this analysis process, the Grid Modernization Laboratory Consortium (GMLC), a partnership between the U.S. Department of Energy and 13 national laboratories, summarized the multiple metrics used to measure resilience, by consequence category [18]:

Table 1. Examples of consequence categories for consideration in grid resilience metric development [18].

Consequence category	Resilience metric & units
Electrical service	Cumulative customer-hours of outages [user-hours]
	Cumulative customer energy demand not served [MW]
	Average number (or percentage) of customers experiencing an outage during a specified period [%]
Critical electrical service	Cumulative critical customer-hours of outages [user-hours]
	Critical customer energy demand not served [MW]
	Average number (or percentage) of critical loads that experience an outage [%]
Restoration	Time to recovery [hours] or [days]
	Cost of recovery [USD]
Monetary	Loss of utility revenue [USD]
	Cost of grid damages (e.g., repair or replace lines, transformers) [USD]
	Cost of recovery [USD]
	Avoided outage cost [USD]
Community function	Critical services without power (e.g., hospitals, fire stations, police stations) [N/A]
	Critical services without power for more than N hours (e.g., N > hours of backup fuel required) [N/A]
Monetary	Loss of assets and perishables [USD]
	Business interruption costs [USD]

	Impact on gross municipal product or gross regional product [USD]
Other critical assets	Key production facilities without power [N/A]
	Key military facilities without power [N/A]

2.3.3 Reliability metrics used in resilience analysis

As their names imply, both SAIDI and SAIFI are system-centric, they evaluate the grid's reliability as a whole. On the other hand, CAIDI and CAIFI approaches reliability from the end user's perspective, and relate to the average duration (or frequency) of a single outage. Depending on their priorities, policymakers or grid operators might focus on system-centric or user-centric indexes. **This study focuses on user-centric indexes**.

Resilience is a more encompassing concept than reliability, comprehending consequences to the electricity system and other critical infrastructure from high-impact, low-probability external events. Reliability metrics generally ignore extreme weather events like hurricanes or earthquakes when measuring a grid's performance, while resilience is often expressed as a quality that enhances the response to such events [29].

To distinguish between reliability and resilience, it's useful to imagine two hypothetical grids: grid A, with a near-perfect CAIDI of only 5 minutes per year, and grid B, with an undesirable CAIDI of 10 hours per year. If grid A suffers an earthquake and it takes five hours to restore power to all its users, it might be a reliable grid, but its resilience is clearly lacking. On the other hand, if grid B suffers a similar earthquake, but its users don't experience a power blackout, it's reliability could certainly improve, but its resilience is rock solid.

This being said, **reliability indicators can certainly be used as resilience metrics, as long as any grid disturbances after a given event are properly accounted for**, like in [30]. This is also one of the methods used in this study.

2.4 Methods used to estimate outage costs

Although a survey is the gold standard for estimating outage costs, there is a variety of methods to determine costs, including customer survey-based methods, market-based methods, regional economic modeling, and blackout case studies. Value-based reliability planning focuses on the impact of short duration outages. The 24-hour mark is the approximate point at which the literature makes the distinction between short-duration and long-duration outages [31]. Table 2 shows the strengths and weaknesses of each CIC estimation method [25]:

Table 2. Strengths and weaknesses of CIC estimation methods [25].

Method	Strengths	Weaknesses
Survey-based	• More accurate • Applicable to many geographical areas & interruption scenarios	• Costly • Responses are based on hypothetical scenarios • Unable to estimate costs for long duration, widespread interruptions
Market-based	• Less costly than surveys • Based on observed behavior	• Lack of available data to estimate full range of CICs
Regional economic modeling	• Inexpensive • Can model indirect costs & adaptive behavior for long duration, widespread interruptions	• Lack of granularity • Lack of data on firms' adaptive behavior during long duration outages • Further model development required
Blackout study	• Responses are based on actual interruptions • Can estimate costs for long duration, widespread interruptions	• Costly • Major blackouts not representative

2.5 Energy resilience & islands

In 2016, a group of researchers from US National Renewable Energy Laboratory (NREL) proposed a method to estimate the resilience that a PV + storage system can provide at any given location [30]. They presented an optimization model that can optimally size the system components to minimize the lifecycle cost of electricity to a given site, including costs incurred during grid outages. Their results showed that including the value of resilience during a feasibility study can lead to larger systems and increased resilience.

Two year later, another group from the same laboratory developed a **methodology that incorporates the value of resilience provided by a PV + BESS system into a techno-economic analysis for commercial buildings** [12]. They found that including the value of resilience when sizing a cost-optimal PV + BESS microgrid generally increases the capacities (in kW of PV and kWh of BESS) of the system, and in some cases makes a system economical where it was not before.

Their model focuses on weighing the electricity rates, load profile, critical loads and average outage time and cost of a given site, and the costs of PV + BESS systems. With these metrics as inputs, the life cycle costs and optimal system sizes for each scenario are determined using REopt, NREL's techno-economic, mixed-integer linear programming tool.

Bundhoo, Shah, & Surroop, on the other hand, proposed a framework, based on resilience theory, on how island energy infrastructures have been negatively impacted by extreme weather conditions, which also provides steps to identify the challenges involved in recovery, rebuilding and providing energy security [32]. They adapted, in turn, Biggs' seven principles for improving the resilience of ecosystems, and applied it to islands' energy infrastructure [33]:

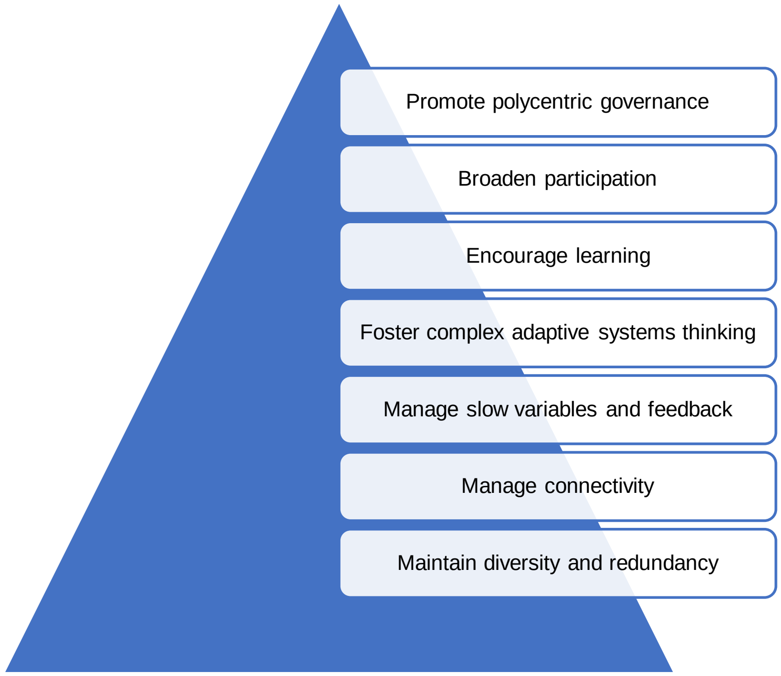


Figure 6. Seven principles for improving energy resilience of ecosystems (author's diagram based on the principles developed by Biggs et al., 2012).

2.6 On Puerto Rico's energy infrastructure and the 2017 hurricane season

Since Hurricane Maria is a relatively recent event, not enough time has passed to accurately assess its long-term impacts on the electricity grid, particularly when one considers that "long-term planning" in grid terms typically means decades. If there's one positive outcome of this disaster, it's that it catalyzed the urgency of Puerto Rico's energy transition.

Most of the literature review on Puerto Rico's energy infrastructure was written by Kwasinski, Castro-Sitiriche, & O'Neill-Carrillo [11], who summarized that, although Hurricane Maria's impact on Puerto Rico damaged to the conventional electric power generation infrastructure was relatively minor, both the transmission and distribution portions of the grid suffered much worse damage than that observed during other hurricanes that affected the US in the past decade. This extensive damage added to logistical limitations and the island orography were important factors that contributed to an extremely slow restoration process leading to a very low grid resilience.

The authors committed an entire scientific report to understand the impacts of Maria on Puerto Rico's power infrastructure, of which the key highlights are enlisted below:

- Only 15% of the power lines could withstand forces caused by a Category 4 hurricane (at its peak, Maria was a Cat 5, but it struck Puerto Rico as a Cat 4)
- 847 transmission structures fell due to Maria

- The most critical failures were observed in 230 kV structures
- None of the high-voltage towers showed signs that corrosion had been a contributing factor for their failures
- 74% of the nearly 350 substations experienced some damage. Yet, this damage seems to have been less severe than the one observed in transmission towers
- Approximately half a million poles were used to distribute power with overhead lines, 10% of which were damaged by Maria; this percentage is considerably higher than the typical 1-3% of poles that need replacements because of hurricane damage
- Renewable energy sources were not exempt from hurricane damage; of the two wind farms operating during the hurricane, one had all of its wind turbines damaged (the other farm was unscathed), while all of the five utility-scale solar farms had modules blown away by hurricane winds.

Finally, the authors studied the cumulative customer-hours of lost electrical service in the aftermath of Hurricane Maria, and concluded that the total outage time was 3,316 million customer-hours, evaluated over the first 196 days of available data. They also concluded that the length of this outage, translated into resilience as defined by [34], is equal to 0.045 on a scale of 0 to 1, where 0 is no resilience whatsoever, and 1 is full resilience. This extremely low value is explained by the fact that it took 192 days to restore service to 95% of PREPA's users, shown in Figure 7:

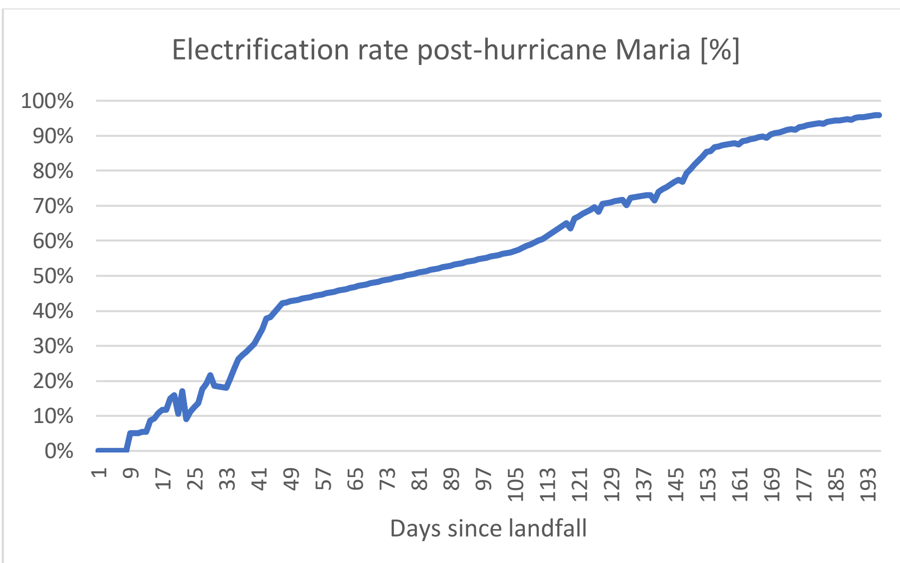


Figure 7. Electrification rate post-hurricane Maria, up until day 196 (author's work based on data from [11].

2.7 Conclusion on literature review

Looking at the existing literature, the following can be concluded:

- Puerto Rico is mostly vulnerable to hurricanes and, to a lesser extent, floods and earthquakes [11]. Of these, hurricanes have been shown to be orders of magnitude more destructive than the other two. Luckily, hurricanes are the easiest to foresee in advance, with modern meteorological services being able to anticipate them in a matter of days. However, the grid restoration time after a hurricane tends to be measured in weeks [26].

- There are multiple definitions of resilience and energy resilience. Accordingly, there are several methods and metrics to measure resilience in general and energy resilience in particular [27].
- Biggs' seven principles for improving the resilience of ecosystems can be adapted to improve the resilience of an island's energy system. The first principle, **maintaining diversity & redundancy**, motivates the reasoning behind this report's focus on DERs in general and solar in particular; as explained in chapter x, Puerto Rico's grid has always been overly dependent on centralized fossil fuel infrastructure, whose fragility and vulnerability to natural disasters is proven and well-documented [35] [36].
- The seven steps of Sandia National Lab's Resilience Analysis Process [28] provide the framework to develop the resilience metrics used in this report, as described in Chapter 4.
- As shown by [12], the optimal size of a microgrid tends to increase when valuing resilience, compared to the traditional method of sizing a microgrid, where the priority is to optimize for energy & demand savings.

Based on these conclusions, this study will next focus on explaining the methodology that builds upon these past findings; particularly those by Law's on optimal microgrid sizing for resilience, and Kwasinski's on the vulnerability of Puerto Rico's grid to natural disasters.

Chapter 3: Methodology

This chapter explains the methodology used in this study. It begins by describing the approach used to answer the main research question, enlisting the inputs required and the outputs considered. It explains what a scenario consists of, and how each scenario differs from one another. Following this, an explanation of how scenarios are compared between one another is given, as well as a description of the adjustment made to account for the likelihood of different weather events. Lastly, the chapter ends by defining the value of resilience and the method used to calculate return on investment between scenarios.

3.1 Approach

This study provides a bottom-up approach to valuing resilience, from the perspective of an energy user/prosumer, contrary to the traditional perspective of a utility/grid operator. At its core, its goal is to quantify the effect of valuing resilience on the cost-optimal system capacities of PV + BESS microgrids, the ultimate comparison being scenarios where resilience is valued and scenarios where it is not, each of them with different microgrid architectures and sizes.

These scenarios are:

1. A base scenario, where no DERs are deployed
2. A least-cost scenario, where DERs are deployed with the purpose of minimizing energy costs
3. A resilient scenario, where DERs are deployed with the purpose of providing energy resilience during and following a severe weather event

3.1.1 Base scenario

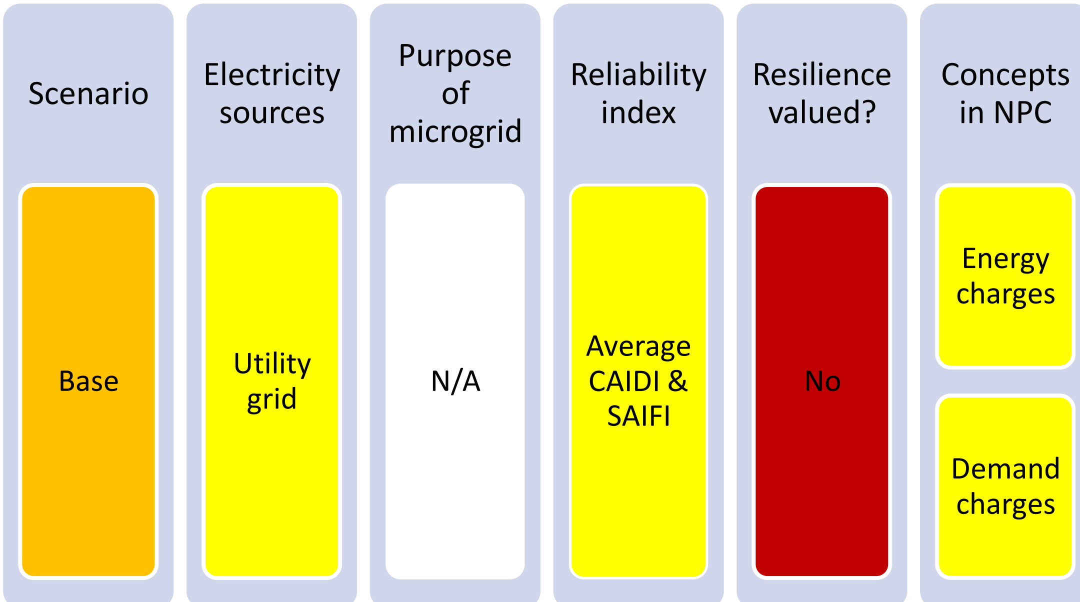


Figure 8. Components, characteristics, and costs included in the base scenario.

The base scenario assumes no deployment of DERs, and does not place a value on resilience. The only electricity source is the power grid. Accordingly, the only concepts considered within the NPC are energy charges and demand charges, depending on the utility rate.

3.1.2 Least-cost scenario

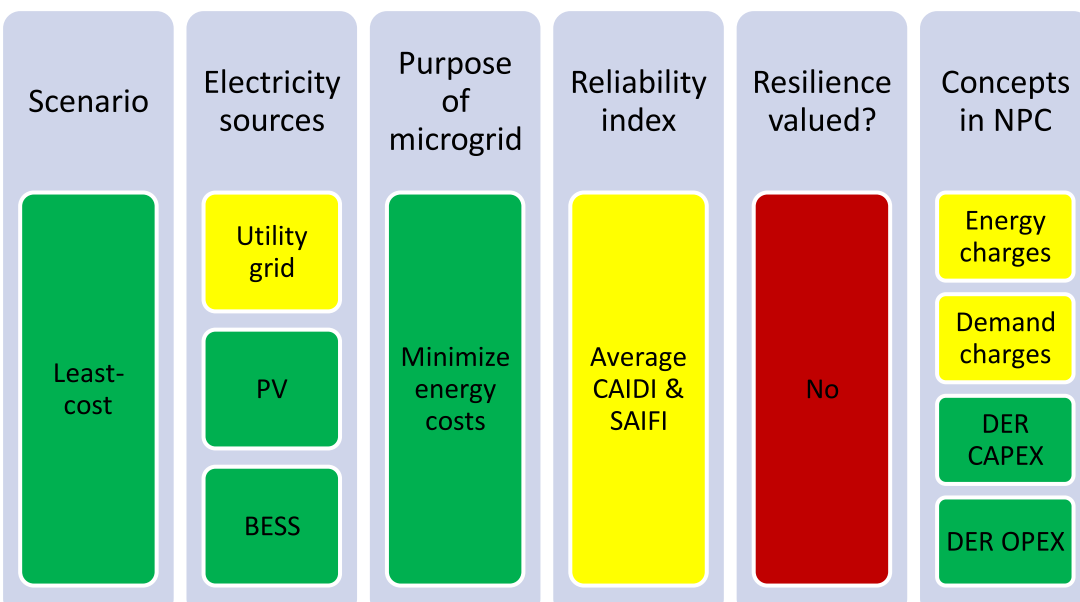


Figure 9. Components, characteristics, and costs included in the renewable scenario.

This scenario considers the deployment of a PV + BESS microgrid, whose purpose is to minimize energy costs. Since resilience is not valued, the only concepts included in the NPC are utility rates and the capital and operating expenditures of the microgrid.

3.1.3 Resilient scenario

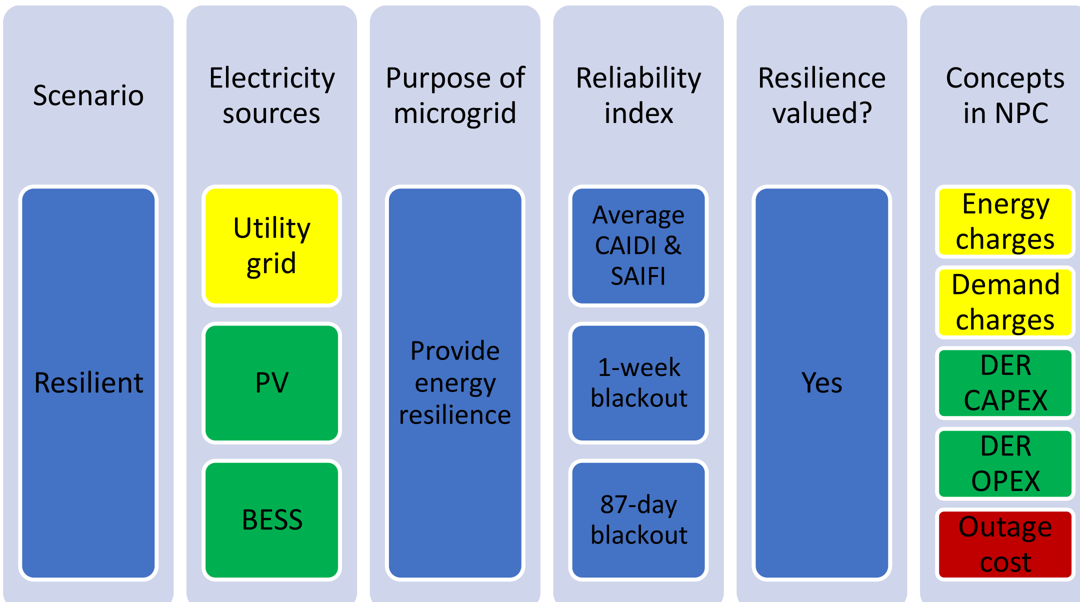


Figure 10. Components, characteristics, and costs included in the resilient scenario.

Lastly, the microgrid in this last scenario is meant to provide energy resilience during grid blackouts, and assigns a value to this resilience. The characteristics of these blackouts are explained in "Section 3.4 Hurricane probability adjustment". This scenario stands out from the previous two by adding one more concept to the NPC, the cost of an outage.

The concepts included in the NPC of each scenario can be visually understood through Figure 11, which shows how the resilient NPC encompasses the concepts of the least-cost scenario, plus the outage costs. The least-cost NPC, in turn, encompasses the concepts of the base NPC, plus the costs of deploying and operating the microgrid:

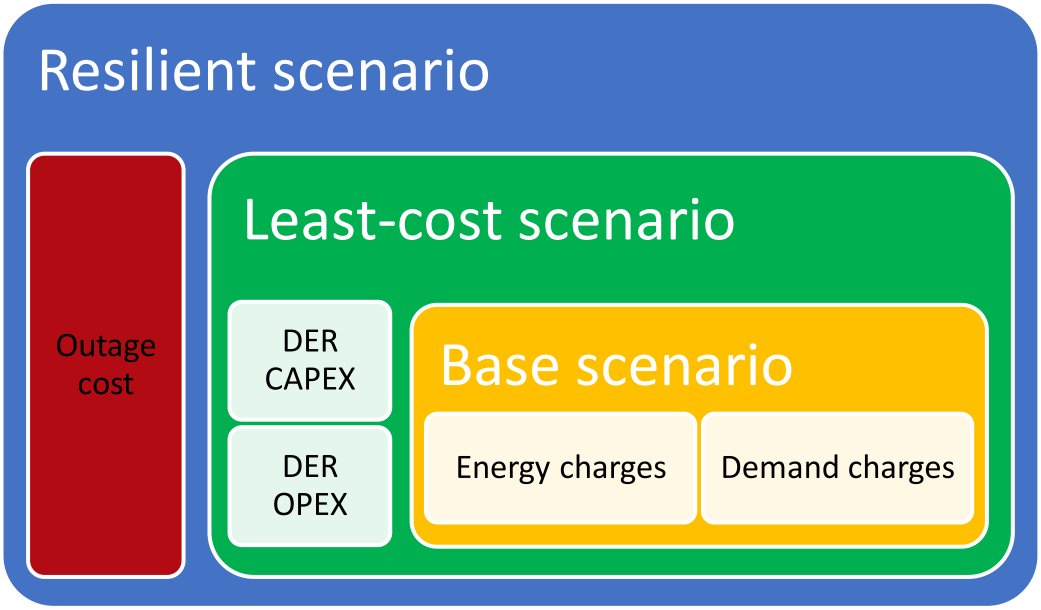


Figure 11. Concepts considered in the net present cost of each scenario.

3.2 Microgrid modeling

The aim of the model is to minimize NPC. **The key difference, however, are the concepts considered in each scenario when modeling it**.

Both microgrids are sized using REopt Lite™, an energy system integration & optimization platform developed by NREL. REopt is a techno-economic decision support model used to optimize energy systems for buildings, campuses, communities, and microgrids. A key modeling assumption is that decisions made by the model do not influence energy markets; i.e., the model is always assumed to be a price-taker, not a price-setter. This assumption aligns with unit commitment and dispatch models where pricing is ultimately a decision variable. REopt solves a single-year optimization to determine N-year cash flows, assuming constant production and consumption over all N years of the given planning horizon.

The REopt model is further described in Chapter Chapter 4: Microgrid models.

3.2.1 Least-cost microgrid

First, REopt is used to evaluate the economic viability of grid-connected PV and battery storage systems at a site, given the following data:

1. Location
2. Electricity rate
3. Load profile
4. Discount rate
5. Cost of solar
6. Cost of storage

Using this information, REopt solves a deterministic optimization problem to determine the optimal technology mix and size of a microgrid so that electrical loads are met at every time step at the minimum life cycle cost [37]. Figure 12 provides an overview of the inputs and outputs of the REopt mode, while the form of the objective function REopt optimizes is:

$$\min (LCC) = \min (E + D + CapEx + OpEx)$$

Equation 1. Form of the objective function that optimizes energy savings.

Where

LCC	is the microgrid's life cycle cost
E	is the total energy charges paid to the electric utility
D	is the total demand charges paid to the electric utility
$CapEx$	is the total capital expenditures of the microgrid
$OpEx$	is the total operating expenditures of the microgrid

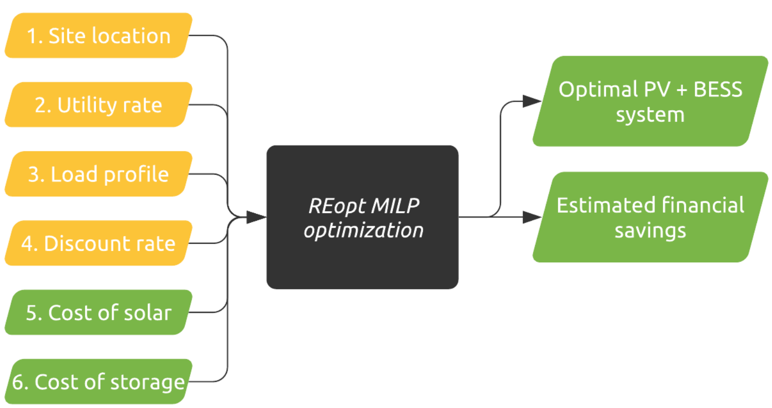


Figure 12. Step process of the least-cost scenario.

3.2.1.1 Description of inputs

- **Site location**: knowing where a solar microgrid will be deployed is the first step in the process of sizing one, mainly to understand the solar resource availability and temperature data for the given site. **This location, San Juan, is the same for all cases analyzed in this study.**
- **Utility rate scheme**: it's indispensable to have electricity rate data and tariff structures to compare the competitiveness of distributed resources.
- **Building load profile**: analyzing load data is the second step in the process of sizing a PV system and/or microgrid. Particularly for a microgrid, it is critical to understand how energy demand shifts over the span of minutes, hours, days and months, so that the microgrid can be sized accordingly.

- **Discount rate**: a discount rate is the interest rate used to determine the present value of future cash flows in a discounted cash flow analysis. This helps determine if the future cash flows from a project or investment will be worth more than the capital outlay needed to fund the project in the present.
- **Cost of distributed energy resources**: accurate cost data is essential to understand the required investment to deploy a PV system or microgrid.

Other possible inputs outside the scope of this study

- **Roof/land area**: while information regarding available space is compulsory when sizing a PV system and/or microgrid, it is not considered in this study. Instead, any building case studied here is assumed to have enough roof and/or ground space for the PV system/microgrid proposed in each scenario.

3.2.2 Resilient microgrid

This scenario requires that a given fraction of the total load be met for a defined grid outage duration using on-site energy resources; e.g., solar, storage, backup diesel generators. REopt can determine the amount of resilience provided by a given technology mix and the cost of this resilience provided by it. Because of the explicit modeling of the grid within REopt, the model can simulate grid outages by turning off the grid for certain time steps. Moreover, the load profile can also be modified during these same time steps to simulate a critical load, typically represented as a percentage of the original load profile. This allows REopt to evaluate all technologies in the model, both during grid-interactive mode (most of the time) and isolated mode (whenever the grid is unavailable and local generation must power the critical loads). **This ability to stack value is inherent of renewable technologies** given that they can generate value during grid-interactive mode and support critical loads during outages, while traditional backup generators only provide value during outages.

This scenario requires two additional inputs, the duration of an outage and the value of lost load:

- **Outage duration**: the duration of an expected outage gives insight into the amount of resilience that the microgrid will be expected to provide; a microgrid that's only able to provide power for several minutes does not have the same resilience as one that is able to supply loads for days or weeks.
- **The value of lost load (VoLL)**: this is the estimated amount that customers receiving electricity with firm contracts would be willing to pay to avoid a disruption in their electricity service [38].

The additional consideration of an outage duration forces the REopt model to propose a microgrid that is able to supply electricity to critical loads for an entire period of 87 days when the grid is assumed to be unavailable. It is important to point out that this microgrid is likely to be much oversized when compared to a financially-optimized microgrid, since it first aims to size a microgrid that will survive the outage, then reduce costs.

However, while this approach allows to size a resilient microgrid, **it does not yet assign a value to the energy resilience it provides**. For this, it is first necessary to model the original, base scenario under the same conditions assumed in the resilient scenario (i.e., a blackout that lasts 87 days) *while assigning a value to the load not served during a blackout*. One decisive metric that is notoriously left out of REopt Lite's resilience optimization is the avoided outage cost, which is why HOMER is chosen as the modeling tool to measure the value of resilience, since it allows the value of lost load to serve as an input in the form of a capacity shortage penalty.

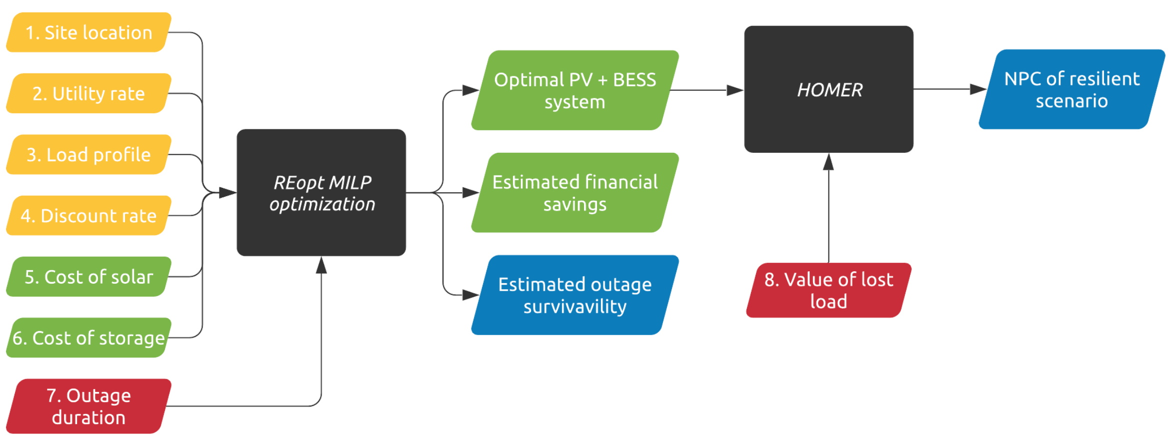


Figure 13. Step process of the resilient scenario.

In this sense, the objective function to be solved when considering resilience is:

$$\min\,(LCC) = \min\,(E + D + CapEx + OpEx\; + C_{outage})$$

Equation 2. Form of the objective function that optimizes energy savings while accounting for outage costs.

Where

C_{outage} is the cost of an outage

The cost of an outage is simply:

$$C_{outage} = VoLL \times \bar{L} \times t_{outage}$$

Equation 3. Cost of an outage.

Where

$VoLL$ is the value of lost load, in USD/kWh
$\bar{L}$ is the annual mean load, in kW

t_{outage} is the total outage duration, in hours

Conversely, the value of resilience is given by:

$$VoR = VoLL \times \bar{L} \times H_R$$

Equation 4. Value of resilience in terms of outage survivability.

Where

H_R is the amount of time in which the microgrid provides power to the critical loads during an outage, in hours

If the microgrid is able to power the critical loads for the entire duration of the outage, then $t_{outage} = H_R$.

3.2.2.1 Outage duration

For this study, the duration of the assumed outage is based on the average outage time experienced after Hurricane Maria, shown in Figure 14:

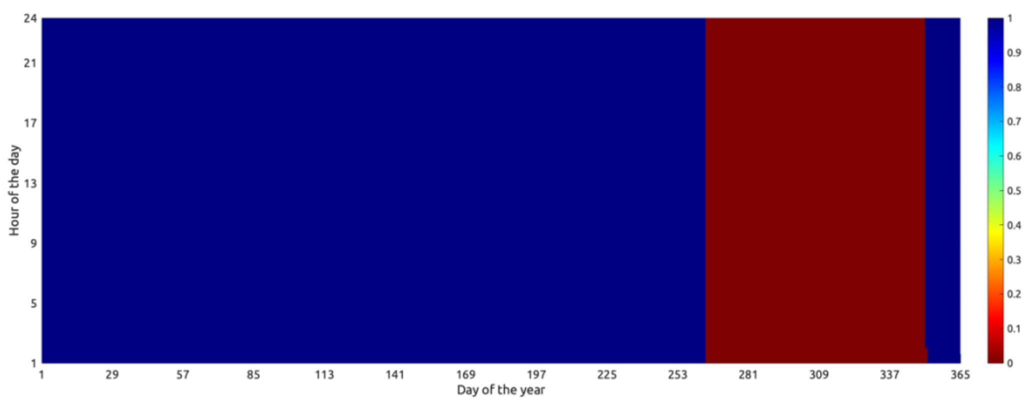


Figure 14. Average grid availability after Hurricane Maria. Blue represents that the grid is available, red represents that it's not. Average outage duration totaled 2,089 hours (author's work based on data from [16]).

3.2.2.2 Value of lost load

This section introduces the concept of the value of lost load; what it measures, how it's calculated, and its values for Puerto Rico's user segments.

As mentioned before, **the value of lost load (VoLL) is the estimated amount that customers receiving electricity with firm contracts would be willing to pay to avoid a disruption in their electricity service** [38]. To find Puerto Rico's VoLL, this study relies on a methodology developed by Michael Sullivan at the Lawrence Berkeley National Laboratory (LBNL) [13], which has been shown to be of use when valuing resilience, like in [1] and [12].

Sullivan performed a meta-analysis of 28 studies of customer interruption costs for the U.S. and analyzed the resulting data to develop customer damage functions useful for evaluating the economic benefits of electric system reliability reinforcements. The customer damage function (CDF) takes the general form proposed by Keane & Sullivan in 1995 [14], and can be used to predict interruption cost values from a number of variables that have been shown in interruption cost surveys to influence customer interruption costs. The general form of this CDF is:

$$Loss = f\{interruption\ attributes, customer\ characteristics, environmental\ conditions\}$$

Where the interruption cost (loss) is expressed in dollars per event, per customer. The factors on which interruption costs depend are:

- **Interruption attributes** are factors such as interruption duration, season, time of day, and day of the week during which the interruption occurs
- **Customer characteristics** include factors such as customer type, customer size, business hours, household family structure, presence of interruption-sensitive equipment, and presence of backup equipment
- **Environmental conditions** include temperature humidity, storm frequency, and other external/climate conditions

Sullivan and his team at LBNL used regression analysis techniques to study alternative specifications of CDFs for commercial and residential users, and ultimately to summarize the impacts of interruption attributes, costumer characteristics, and environmental conditions on the economic losses that customers said would occur as a result of electric interruptions in numerous studies [13]. Instead of relying on a multiple regression based on an ordinary-least squares (OLS) approach, they used a two-part regression model to estimate the customer damage functions. The steps followed are:

- A limited dependent model is used to predict the probability that a particular customer will report a value of zero versus any positive value for a particular interruption scenario, based on a set of independent variables which describe the nature of the interruption as well as customer characteristics. The predicted probabilities from tis first stage are retained.
- Interruption costs for only those customers who reported positive costs are related to a set of independent variables (which may or may not be the same as the independent variables used in the first stage). Predictions are made from this model for all customers, including those whore reported zero interruption costs.
- Finally, the predicted probabilities from the first step are multiplied by the estimated interruption costs from the second step to generate the final interruption cost predictions.

A simple way to define the customer damage function given the above constraints is to estimate the mean interruption cost, which is linked to the predictor variables through a logarithmic function. The values of the parameters in the two-part model cannot be directly interpreted in terms of their influence on interruption costs because of the relationships are among the variables in their logs. However, the estimated model produces a predicted interruption cost, given the values of variables in the models. To analyze the magnitude of the impact of variables in the CDF on interruption cost, it is necessary to compare the predictions made by the function under varying assumptions. E.g., it is possible to observe the effects of outage duration on interruptions costs by holding the other variables constant at their sample means. In this way, one can predict average customer interruption costs of varying durations holding other factors constant.

These customer damage functions provide estimates of the costs of interruptions of varying durations, occurring at different times of day, days of week, and season. They also provide estimates of interruption costs for customers of different size; and in the case of business customers, by business type (e.g., retail, construction, services, etc.). It is possible to estimate costs for planned as opposed to unannounced interruptions and for customers with and without backup generation. Thus, by inserting reasonable assumptions about the interruption characteristics and customers into the customer damage functions, it is possible to use them to estimate the cost of a wide range of interruptions for a wide range of customers. This econometric models were subsequently integrated into the Interruption Cost Estimate (ICE) Calculator, a modeling tool designed to estimate interruption costs and/or the benefits associated with reliability improvements. In 2015, the same team at LBNL updated their database and re-estimated their underlying econometric models to enable the ICE Calculator to estimate costs for interruptions lasting longer than 8 hours. At the time of writing, the meta-dataset now includes 34 different datasets from surveys fielded by 10 different utility companies between 1989 and 2012, totaling more than 105,000 observations, divided as follows:

- 34,212 observations for residential users
- 27,751 observations for small C&I users
- 44,328 observations for medium and large C&I users

The parameters used to estimate Puerto Rico’s VoLL, including their sources, are shown Table 3:

Table 3. Parameters used to estimate Puerto Rico's value of lost load.

Parameter	Description	Units	Value
Reliability indexes	SAIDI	Minute/year-customer	1920
	SAIFI	Events/year-customer	2
	CAIDI	Minutes/event-customer	960[1]
Annual usage per customer [15]	Residential	MWh/customer	4.87
	Small C&I	MWh/customer	70.5
	Medium & large C&I	MWh/customer	192
Number of customers [15]	Residential	#	1,335,643
	Small C&I	#	116,094

[1] *The ICE Calculator allows for a maximum SAIDI of 32 hours, and a maximum CAIDI of 16 hours, orders of magnitude lower than the indexes experienced after Hurricane Maria.*

	Medium & large C&I	#	11,707
Industry composition [15]	Construction	%	5%
	Manufacturing	%	9%
	Other industries	%	86%
Household income [39]	Average	USD	20,166
Power interruption distribution	Outages from 5:00 to 17:00	%	50%
	Outages during summer	%	50%
Customers with backup generation [15]	Small C&I	%	30%
	Medium & large C&I	%	46%
U.S. state	U.S. state	N/A	Hawaii[2]

By integrating the data shown above into Sullivan's customer damage functions from [25], Puerto Rico's VoLL's for its three customer segments can be calculated, and are shown in Figure 15:

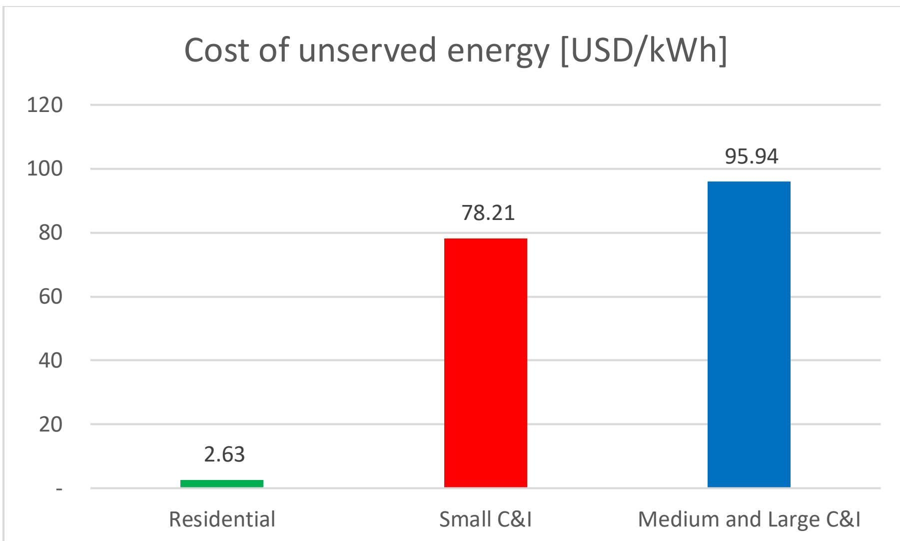


Figure 15. Value of lost load for Puerto Rico's three customer segments.

The values from Figure 15 serve as input variables in the HOMER model, as "capacity shortage penalties". The capacity shortage penalty is a cost penalty applied to the system for any capacity shortage that occurs during the year. Applying the values shown above to the average load and outage time experienced by their respective fraction of electricity users provides total cost of the outage caused by Hurricane Maria in 2017.

[2] Puerto Rico is not a state, but rather a commonwealth of the U.S., and therefore is not included within the ICE Calculator database. However, the similarities between the Puerto Rican grid and the Hawaiian grid are large enough for the latter to serve as a proxy for the former. This is also one of the assumptions done by [15] when calculating their own VoLL values.

3.3 Comparison between scenarios

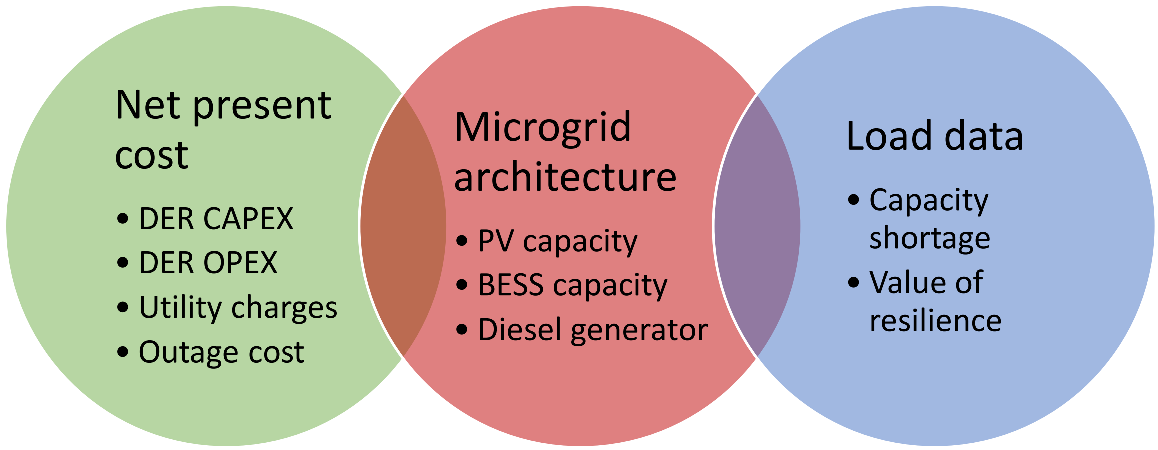


Figure 16. Model outputs.

The outputs, on the other hand, are net present cost, microgrid architecture, and load data, with its respective components (CAPEX, PV capacity, LCOE, etc.). In this way, a scenario consists of:

- A residential or commercial building load profile, including its respective utility rate scheme
- A microgrid architecture (PV / PV+BESS / PV+BESS+generator and their respective capacities) or lack thereof
- A VoLL, which is zero in scenarios that do not value resilience
- CAIDI and SAIFI values that either consider severe weather events or disregard them
- The performance and cost of microgrid components (PV/BESS/generator)

3.3.1 Explanation of output choices

Net present cost can be broken down into four components:

- **DER CAPEX**: distributed energy resources are known for requiring large upfront capital expenditures for their deployment, regardless of whether the system is paid for by the end user or financed by a third-party.
- **DER OPEX**: on the other hand, operating expenditures are traditionally lower for PV + BESS, although this is not the case when they're paired with a diesel generator that continuously burns fuel to generate electricity.
- **Utility charges**: utility charges are considered before and after the deployment of a microgrid; although possible, the purpose of a microgrid is not necessarily to drive utility

charges down to zero, and they can even be negative if the value of the energy supplied by the microgrid to the grid is greater than the value of the energy supplied in the opposite direction; i.e., the value of one kWh sold to the grid is not the same as the value of one kWh bought by the grid, due to Puerto Rico's particular net metering rules (described in section 4.3.4).

- **Outage costs**: lastly, outage costs are present in scenarios where resilience is valued, and can also be present even after deploying a microgrid, if the size of the optimal microgrid is not enough to supply power during a given outage.

A microgrid's architecture, similarly, can be described by its:

- **PV capacity**: this is the nameplate (nominal) capacity of the PV system proposed for the microgrid, in kWp (kilowatt-peak).
- **BESS capacity**: this is the nameplate capacity of the battery energy storage system of the microgrid, in kWh, and its accompanying power rating in kW. Both capacity and power rating are modeled separately.
- **Diesel generator**: this component is only considered in one scenario

Load data

- **Total capacity shortage**: the total capacity shortage (or annual capacity shortage) is the total amount of capacity shortage that occurs throughout the year. A capacity shortage is a shortfall that occurs between the required operating capacity and the actual amount of operating capacity the system can provide. This metric is useful to understand if a microgrid is under or oversized, and to analyze the time periods in which a capacity shortage can be expected (e.g., at night if the batteries are depleted, or during wintertime when solar resource is scarcer).

The least-cost scenario and the resilient scenario are framed according to SNL's resilience analysis process [28]:

Table 4. SNL's resilience analysis process applied to this study.

Step	Least-cost scenario	Resilient scenario
Define resilience goals	Resilience is not the goal of a microgrid, but it may be a side benefit	Resilience is the goal of a microgrid, savings are a side benefit
Define system	Average residential and commercial load profiles	
Define resilience metrics	N/A	Electricity served during an outage
Characterize threats	N/A	Severe weather events
Determine level of disruption	Average reliability indexes	87-day outage
Define and apply system models	Described in Chapter 4	
Calculate consequence	Net present cost	
Evaluate resilience improvements	Comparison between microgrid sizes, costs, and topologies	

3.4 Hurricane probability adjustment

Until now, the resilient scenario assumes continuous hurricanes striking the island on a yearly basis, at exactly the same day, with an ensuing blackout always lasting the same amount of time. For a more realistic outlook, this scenario's cash flows are adjusted to account for the likelihood of a hurricane impacting the island on a given year. The purpose of this adjustment is to avoid overly inflated outage losses in the scenarios' cash flows, in order to calculate more accurate NPCs.

Archived data from NOAA shows that Puerto Rico is affected, brushed or hit by a tropical storm or hurricane every 3.4 years, and is directly struck by one once ever 12.3 years [40]. On the other hand, Kossin [3] recently estimated that the probability of a major hurricane forming in the North Atlantic (including the Caribbean) has increased at a rate of almost 50% per decade over the last four decades, compared to the global average increase of 8% per decade. Between 1979 and 1997, there were 777 tropical cyclones in the North Atlantic, 136 of which were categorized as major (Category 3 or greater). On the other hand, the period of 1998-2017 experienced 1,572 tropical cyclones, 529 of which were Cat 3 or greater [3].

Following this trend, Puerto Rico instead might expect to be affected by a low-category hurricane every 2.3 years instead of every 4.6 years, and be directly struck by a high-category hurricane once every 8.2 years instead of every 31.9. To account for this, the idealized cash flows where a hurricane hits the island every year are instead replaced with cash flows that expect either:

- No severe weather event on a given year, with the reliability index being equal to the average in Puerto Rico, reported by [15]; i.e., **a CAIDI of 2.5 hours per customer-year, and a SAIFI of 3.8 events per customer-year**.
- A relatively low-impact weather event occurring every 2.3 years, where the outage for that respective year lasts for **one continuous week**

- A high-impact weather event occurring every 8.2 years, where the outage for that respective year lasts **exactly the same as the 2017 average blackout (2,089 hours or 87 days)**

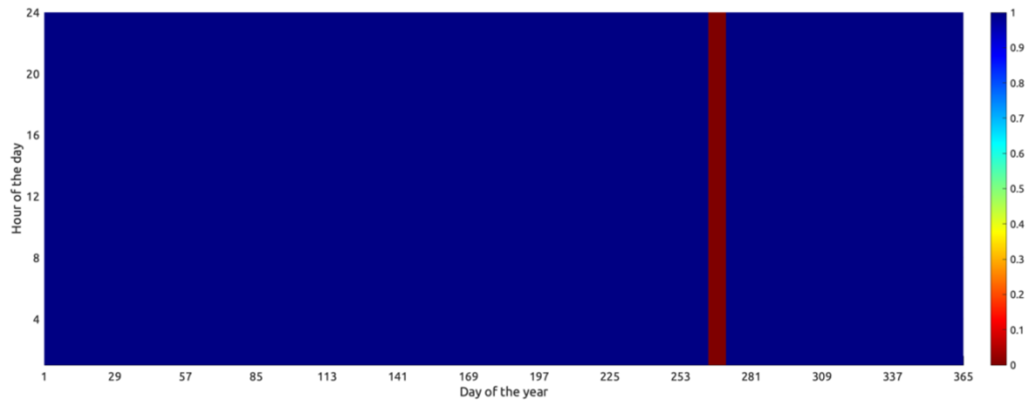


Figure 17. Grid availability after a low-magnitude hurricane. Blue represents that the grid is available, red represents that it's not. Total outage duration is 168 hours (one full week) after hurricane landfall.

The net present outage cost, then, is the weighted average of outage costs of different length, multiplied times their probability of occurring in the next decades, given the increase in frequency and magnitude of hurricane activity in the North Atlantic, and particularly the Caribbean:

$$NPC_{OutageCost} = p_1 * NPC_{base} + p_2 * NPC_{SmallHurricane} + p_3 * NPC_{LargeHurricane}$$

Equation 5. Net present outage cost weighted to account for the likelihood of weather events of different magnitude.

Where:

p_1	is the probability of no hurricane striking the island on a given year
p_2	is the probability of a low-impact weather event occurring on a given year
p_3	is the probability of a high-impact weather event occurring on a given year
$NPC_{SmallHurricane}$	is the net present cost of experiencing a one-week blackout every year for 30 years
$NPC_{LargeHurricane}$	is the net present cost of experiencing an 87-day blackout every year for 30 years

In other words, the average outage cost on a given year is:

$$C_{Outage,avg} = p_1 * C_{Outage,base} + p_2 * C_{Outage,SmallHurricane} + p_3 * C_{Outage,LargeHurricane}$$

Equation 6. Average annual outage cost weighted to account for the likelihood of weather events of different magnitude.

3.5 Net present value

The net present value (NPV) of any other scenario is the difference between its real LCC and the real LCC of the base case, which may be positive, negative, or zero depending on the objective. Future costs and/or revenues are appropriately discounted for NPV calculations:

$$NPV_{scenario} = LCC_{base} - LCC_{scenario}$$

Equation 7. Net present value.

3.6 Return on investment

To following equation is used to calculate the return on investment (ROI) [41]:

$$ROI = \frac{\sum_{i=0}^{R_{proj}} C_{i,ref} - C_i}{R_{proj}\left(C_{cap} - C_{cap,ref}\right)}$$

Equation 8. Return on investment.

Where:

$C_{i,ref}$	is the nominal annual cash flow for the reference system
C_i	is the nominal annual cash flow for the current system
R_{proj}	is the project lifetime in years
C_{cap}	is the capital cost of the current system
$C_{cap,ref}$	is the capital cost of the reference system

So, **the ROI is the average yearly difference in nominal cash flows over the project lifetime, divided by the difference in capital cost**.

3.7 Value of resilience

The amount of resilience that a microgrid can provide is measured in terms of the load the microgrid can meet during an outage. Following this, the value of resilience is defined as:

$$VoR = VoLL \times \left(Load_{Unmet,base} - Load_{Unmet,resilient}\right)$$

Equation 9. Value of resilience relative to base scenario.

Where $Load_{Unmet,base}$ is the total amount of unmet load that occurs throughout the year in the base scenario, while $Load_{Unmet,resilient}$ is the total amount of unmet load that occurs throughout the year in the resilient scenario. It's important to note that, during a blackout, the only load supplied by the microgrid (and accounted for when calculating the total VoLL), is the critical load.

Chapter 4: Microgrid models

Both REopt and HOMER have the capacity to model microgrids according to several constraints, like the ones listed in Chapter 3. However, most of HOMER's optimization and sensitivity analysis algorithms are proprietary, while the parameters, variables and equations of REopt Lite's model are openly available. For this reason, **REopt was chosen to validate the simulations in this study, particularly when it comes to optimizing for financial savings**. **HOMER, on the other hand, allows the implementation of a capacity shortage penalty that serves as a proxy for the value of lost load, and is used to evaluate the cost of an outage and, analogously, the value of resilience**.

This chapter explains the REopt and HOMER models used to evaluate and compare the life cycle costs of the different scenarios previously described, and their accompanying microgrid components or lack thereof. First, a thorough description of REopt's objective function, constraints, parameters, and decision variables is given, followed by HOMER's relevant calculations for net present cost and outage costs. Lastly, the chapter lists and elaborates on this study's assumptions regarding discount rates, planning horizon, costs of DERs, utility rates, net metering, resource availability, and load profiles.

4.1 REopt Lite™

REopt is a techno-economic decision support model used to optimize energy systems for buildings, campuses, communities, and microgrids. A key modeling assumption is that decisions made by the model do not influence energy markets; i.e., the model is always assumed to be a price-taker, not a price-setter. This assumption aligns with unit commitment and dispatch models where pricing is ultimately a decision variable. REopt solves a single-year optimization to determine N-year cash flows, assuming constant production and consumption over all N years of the given planning horizon.

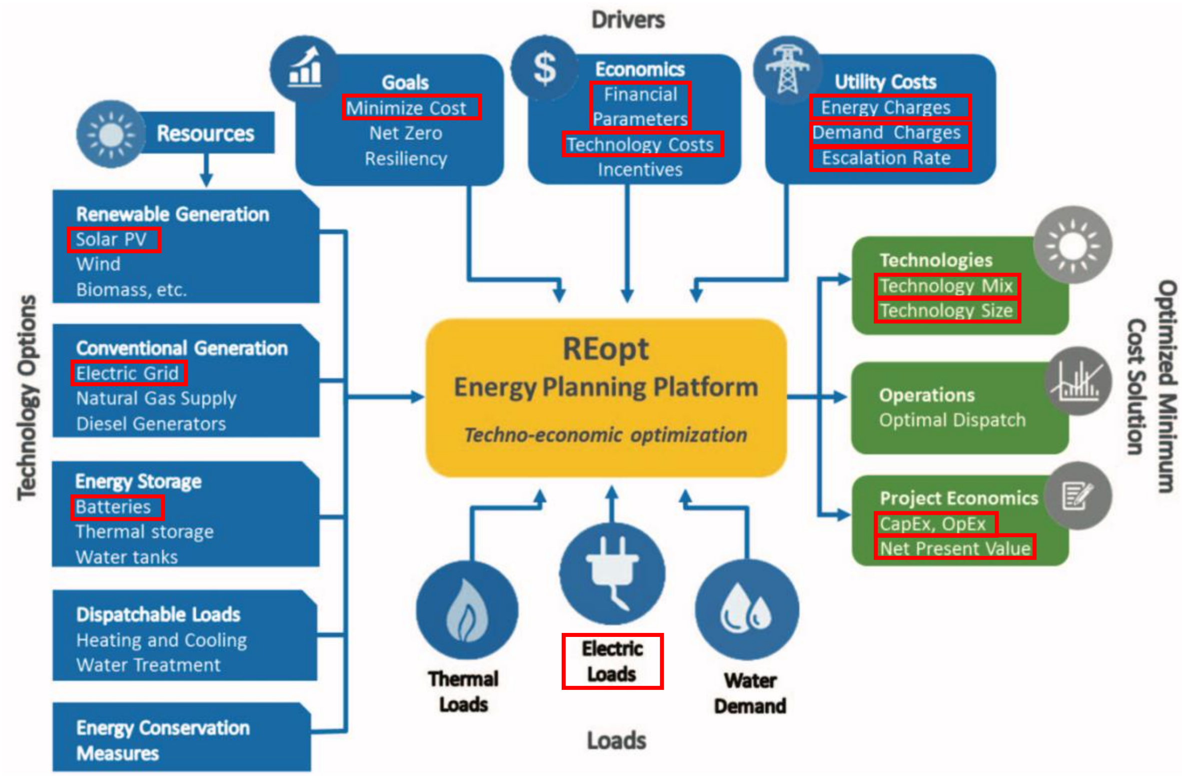


Figure 18. Inputs and outputs of REopt model [37]. Concepts marked in red are within the scope of this study.

4.1.1 PV model

REopt uses NREL's PVWatts application to determine the electricity production of solar PV systems. By default, the model assumes fixed-tilt arrays oriented due south with a tilt angle equal to the latitude of the site's location. The amount of electricity produced by the PV system at each time step is proportional to the hourly capacity factor at the site. Since the production of PV systems tends to decline over their lifespan yet the model only optimizes for Year 1, the model calculates an annual production profile that has an economic equivalent production profile with 0.5%/year degradation over the analysis period. This calculation is done by applying the ratio of geometric series present worth factor, with degradation included, and uniform series present worth factor to calculate the economic equivalent profile, as given by Equation 10:

$$pwf = \sum_{n=1}^{Y} \frac{(1+g)^n}{(1+d)^n}$$

Equation 10. Present worth factor used to calculate annual solar production throughout the lifetime of a PV system.

Where:

Y is the planning horizon

g is the electricity escalation rate

d is the real discount rate

4.1.1.1 Resource data

Hourly solar irradiance values are sourced from TMY2 data from the 1991-2005 National Solar Radiation Database [42]. Site location is mapped to the closest available station. For all cases modeled in both REopt and HOMER, the chosen location is San Juan, Puerto Rico. Figure 20 provides a visual representation of the solar resource available in Puerto Rico [43]:

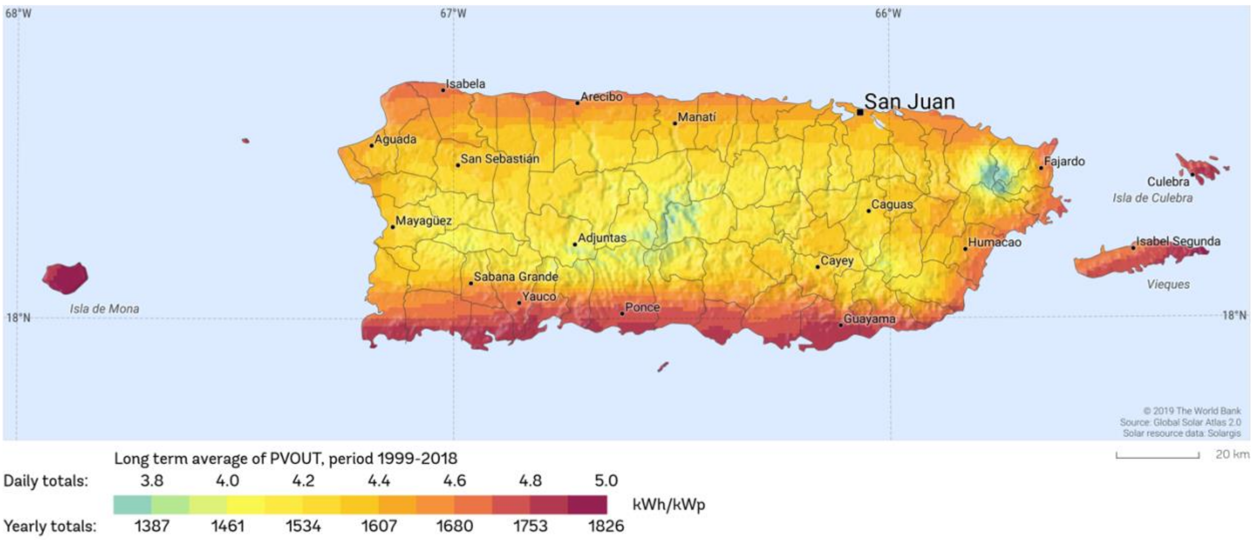


Figure 19. Solar resource map of Puerto Rico.

4.1.1.2 Assumptions

The assumptions made for the PV system are summarized by Table 4:

Table 5. PV data sources and assumptions.

Resource data source	TMY2
System losses	14% (soiling, wiring losses, availability, mismatch)
Inverter efficiency	96%
Annual performance degradation	0.5%
Space requirements	N/A (out of scope)
Useful life	30 years
Array tilt/azimuth	Equal to site's latitude, facing the Equator

4.1.2 Energy storage model

Energy storage (i.e., BESS), is modeled as a "reservoir" in REopt; energy produced during one time step can be consumed during another. Battery chemistry is not explicitly modeled, but rather heuristic constraints are imposed that are designed to ensure the battery operates within the manufacturer's specifications. A round-trip efficiency is assumed, and limits are imposed on the minimum state of charge, charging and discharging rates, and the number of cycles per day. The model is able to select and size both the energy capacity of the battery in kWh, and its power capacity in kW. Because of net metering and the federal ITC regulations, only solar PV is allowed to charge the battery. BESS are modeled to capture revenue from multiple value streams: performing energy arbitrage, time-shifting excess renewable energy production, selling ancillary services to the grid, participating in demand response programs, deferring T&D upgrades, reducing demand charges (also known as "peak shaving") and increasing the energy resilience of a site.

4.1.2.1 Assumptions

Table 6. BESS technical assumptions.

Minimum SoC	10%
Maximum E-rate	3
Rectifier efficiency	96%
Round-trip efficiency	97.5%
Inverter efficiency	96%
Total AC-AC round-trip efficiency	90%
Initial SoC	100%

4.1.3 Utility grid model

REopt models the utility grid as an ideal source capable of supplying an unlimited amount of electricity. Because it already exists, the model does not incur any capital or O&M costs for using the grid. Energy from the grid incurs only the costs specified by the relevant utility rate tariff.

The costs to acquire electricity from the grid are divided into usage costs (USD/kWh) and demand charges (USD/kW). The model pays for each kWh of electricity consumed at a rate specified by the utility tariff, whereas demand charges are accrued based on the largest grid purchase within specific hours of particular demand ratchets.

4.1.4 Optimization results

4.1.4.1 Recommended solar installation size

This is the size of the PV system, measured in nameplate capacity, that minimizes the life cycle cost of energy at the site, given the set of inputs used in the analysis. This optimized size may not be commercially available. In this case, the closest commercial option would have to be procured (e.g., REopt might suggest a 10 kW PV system, but local suppliers might only have 350 W modules. The closest system configuration using these modules would be 10.5 kW), but this is beyond the scope of this study.

If a resilience requirement is specified, PV may be recommended to meet it even if it does not reduce the LCC.

4.1.4.2 Recommended battery power and capacity

This BESS size minimizes the LCC of energy at the site, given the set of inputs used in the analysis. Battery power (in kW) and capacity (in kWh) are independently optimized for economic performance (and resilience if required); a power:energy ratio is not predefined. As in the case of PV, the optimal BESS configuration might not be commercially available.

4.1.4.3 Potential life cycle savings

This is the NPV of the savings (or costs if negative) realized by the project based on the difference between the LCC of energy of the base scenario compared to the optimal case.

4.1.4.4 Resilience

If resilience is chosen as a goal, this ensures that the recommended system sustains the critical load specified for the outage period specified.

Also provided is the percentage of outages of the same duration that the recommended system would sustain out of all potential outage start hours through the entire year (e.g., if the outage specified as an input starts on March 1 at 9:00 and lasts ten hours, REopt also studies how many 10-hour outages the system would survive if they start on any other hour of the year, given load demand, renewable resources, and energy storage).

Additionally, the **average resilience** is provided. This is the average amount of time that the system can sustain the critical load, based on 8,760 outage simulations (where the same outage starts on each hour of the year). The average resilience is calculated as the average time survived during the simulated outages.

Lastly, the **minimum resilience** is the minimum amount of time that the system can sustain the critical load, based on the 8,760 simulations previously mentioned.

4.1.5 Mixed integer linear program formulation

REopt solves a mixed-integer linear program (MILP), the general form of which is given by [44]:

$$\min \sum_{j=1}^{n} c_j x_j$$

Subject to:

$$\sum_{j=1}^{n} a_{ij}x_j = b_i; \quad i = 1,2,\dots,m$$

$$x_j \geq 0; \quad j = 1,2,\dots,n$$

$$x_j \in \mathcal{N}; \text{ for all or some } j = 1,2,\dots,n$$

Where $\mathcal{N}$ is the set $\{1,2,\dots\}$.

The objective function in the REopt model minimizes total LCC, comprised of a set of possible revenues and expenses, over the analysis period subject to a variety of integer and non-integer constraints to ensure that thermal and electrical loads are met at every time step by some combination of candidate technologies.

4.1.5.1 Objective function

The objection function of the MILP is to minimize the present value of all energy costs (i.e., the LCC) over the analysis period. These costs can be broken down into (1) capital costs, (2) variable O&M costs (based on energy produced), (3) demand costs, (4) battery costs, (5) increased electric costs, (6) fixed O&M costs (based on system size), (7) fixed costs, and (8) fuel costs, minus (9) production incentives. The objective function can be found in Appendix 1.

Costs considered include:

- **Capital expenditures**: investments made to deploy new energy technologies, including generation technologies like wind and solar, storage technologies like BESS, and other auxiliary equipment
- **Operating expenditures**: fixed and variable costs related to operation and maintenance (O&M), equipment replacement, fuel, utility purchases, and financial losses incurred due to grid outages
- **Operating revenues**: namely net metering income and wholesale electricity sales
- **Incentives and tax benefits**: federal, state, and utility incentives, accelerated depreciation schedules

4.1.5.2 Constraints

The constraints that bound the technology mixes that REopt models can be broken down into the following categories:

- **Load constrains**. Electrical loads must be fully met by some combination of local energy generation (either renewable or fossil-based), local energy storage, and the utility grid during every time step modeled.

- **Resource constraints**. The amount of energy that variable renewable energy technologies can generate is limited by the amount of renewable resource available on site or by the size of the storage systems, whereas the utility grid is assumed to be able to provide unlimited amounts of energy (except on time steps that simulate an outage by turning the grid off).
- **Operating constraints**. Dispatchable technologies like BESS and fossil generators may have minimum ramp-up or ramp-down limits that prevent them from operating at partial loads less than a specified level. Other operating constraints may limit the number of times a dispatchable technology can cycle on and off on a daily basis, or impose minimum and/or maximum state of charge (SoC) on battery technologies.
- **Sizing constraints**. Sites may have limited land and/or roof area available for renewable energy systems, which may restrict the size of technologies like solar PV. The user may also specify minimum and maximum technology sizes as model inputs.
- **Policy constraints**. Utilities commonly impose limits on the cumulative amount of renewable generation a site can install while still qualify for a net metering contract. Similarly, interconnection limits may restrict the total amount of renewable energy systems that may be connected to the grid. Other policy constraints may limit the size of a variable renewable energy technology in order for it to be eligible for a production incentive.

REopt is also able to consider emissions constrains (to limit GHG emissions) and scenario constraints (e.g., to comply with renewable energy portfolio standards or net zero goals), but neither are considered in this study. Lastly, the model also considers other constraints related to combined heat and power (CHP), solar water heating (SWH), and domestic hot water (DHW), but since those technologies are not considered within this study's scenarios, their constraints are not relevant and therefore exempt from this study.

4.1.5.3 Temporal resolution

The optimization model assumes that energy generation and consumption are constant throughout the planning horizon; i.e., the energy balance in one year is the same as the balance from the next year and the one after that. Accordingly, the model only takes into account the energy balance of year 1. Each time steps simulates one hour of the year, for a total of 8,760 time steps in a N-year analysis. This approach makes possible to capture seasonal variation in load and resource availability.

4.2 HOMER Pro®

HOMER (Hybrid Optimization of Multiple Electric Renewables) is a microgrid software that evaluates both grid-connected and off-grid power systems. It optimizes the configuration and size of each component for a given microgrid, according to user-determined constraints and objectives. It also allows the review of sensitivity analysis that help understand the cost and benefits of different system configurations. HOMER simulates the operation of a system by making energy balances in each time step of a given year. For every time step, HOMER compares the electrical demand to the energy that the system can supply in that moment and calculates the flow of energy to and from each system component. For systems with BESS and/or diesel generators, the software also determines how to operate the generators and whether to charge or discharge the BESS.

HOMER performs energy balances for all system configurations considered. It then determines whether a configuration is feasible (i.e., whether it can meet the electricity demand under the specified conditions) and estimates the cost of installing and operating the system over its lifetime. Costs included in the analysis are capital, replacement, O&M, fuel, and interest costs.

4.2.1 Optimization

HOMER has two different optimization algorithms:

- A grid search algorithm that simulates all of the feasible system configurations defined by the search space
- A derivative-free algorithm to search for the least-costly system

Unlike REopt, these algorithms are proprietary and their objective functions, constraints and parameters are given as a "black box" model, where inputs are given and outputs are received without a transparent disclosure of the logic behind the algorithms. Because of this, **the microgrid optimization is left to REopt, and HOMER is only used to estimate the avoided outage cost and its corresponding value of resilience**. This is done by:

- Running a scenario with an 87-day outage where no microgrid is deployed (base scenario), while assigning a capacity shortage penalty equal to the VoLL
- Running a scenario with an 87-day outage with REopt's optimal microgrid size and configuration (resilient scenario), while assigning a capacity shortage penalty equal to the VoLL

Following this, a comparison is made between the outage losses incurred in the base scenario, versus the losses incurred in the resilient scenario.

4.2.2 Objective function

The objective function of HOMER is the minimization of the total net present cost (NPC). However, since this study strictly adheres to the resilient microgrid modeled in REopt, HOMER is not primarily used to perform an optimization on its own, but rather accepts an already given size of solar and storage to model. However, HOMER's optimization tool is used later on (see chapter 6), namely to validate the results obtained from REopt, and check whether HOMER suggests an alternative microgrid of a different size and configuration.

NPC is the present value of all of the costs the system incurs (including costs for installation and operation of all components) over its lifetime, minus the present value of all the revenue it earns over its lifetime. Costs include capital costs, replacement costs, operation and maintenance (O&M) costs, fuel costs, and the costs of buying power from the grid. Revenues include salvage value and grid sales revenue. The objective function is mathematically expressed by Equation 11 [45]:

$$\min(C_{NPC}) = \sum_{all\ elements} [-R_{0,i} + \sum_{t=0}^{T} \frac{R_{t,i}}{(1+x)^t}]$$

Equation 11. Form of the objective function optimized by HOMER.

Where:

C_{NPC}	is the net present cost [USD]
$P_{load,t}$	is the load in time step t [kW]
$r_{load,t}$	is the operating reserve as a percentage of annual peak load [%]
$R_{0,i}$	is the initial investment [USD]
$R_{t,i}$	is the net cash flow for component i at time step t [USD]
x	is the real discount rate [%]
t	is a given time step [hour]
T	is the planning horizon [years]

Regarding the cost for each element, the Equation 12 applies for the entire planning horizon:

$$C_{element,i} = \sum C_{O\&M,i} + C_{variable,i} + C_{replacement,i}$$

Equation 12. Cost function of each element considered in HOMER.

Where:

$C_{element,i}$	is the cost associated with element i over the planning horizon [USD]
$C_{variable,i}$	is the variable cost of element i (fuel, payments to utility) [USD/liter, USD/kWh, etc.]
$C_{O\&M,i}$	is the fixed O&M cost of element i [USD]
$C_{replacement,i}$	is the replacement cost of element i [USD]

4.2.3 Sensitivity Analysis

HOMER repeats the optimization process for every specified sensitivity variable; e.g., if the cost per watt of PV systems is defined as a sensitivity variable, HOMER simulates system configurations for the different costs per watt specified. Sensitivity analyses for this study can be found in Chapter 6.

4.2.4 Outage analysis in HOMER

The same outage specified within REopt is specified in HOMER. For the latter, outages are modeled as one or more time steps in which no electricity can be purchased from or sold to the grid. This is done by importing a time series with a single-column, 8,760-row file of ones and zeros (each row corresponding to one hour of the year); ones indicating that the grid is operational during that corresponding time step, and zero indicating the grid is unavailable and no energy imports nor exports are allowed during that time step.

As previously mentioned, the particular outage modeled in REopt and in HOMER takes the form of the average outage experienced after Hurricane Maria. Within HOMER, the time series has ones for most of the year, except for randomized zeroes representing the average reliability values of Puerto Rico, but shows zeroes starting on hour 6,313 (midnight of September 21), until hour 8,402 (1:00 of December 15), a full 2,089 hours after the outage started, as shown in Figure 21:

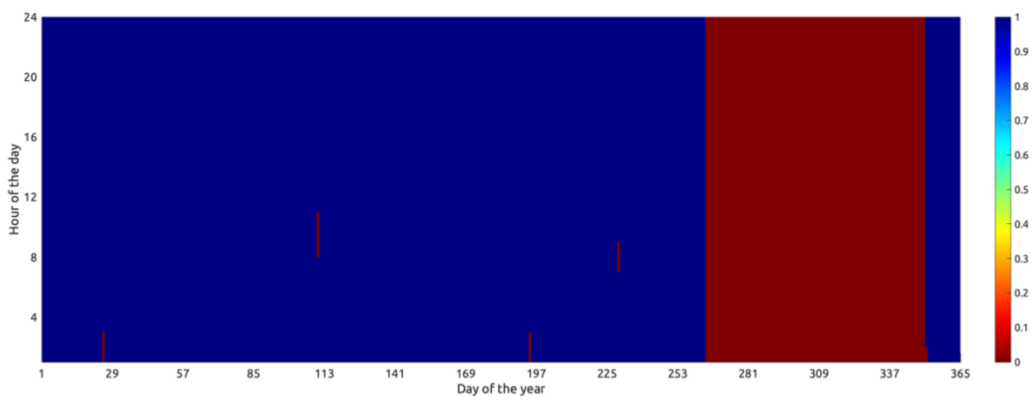


Figure 20. Puerto Rico's average grid availability on a year where a severe weather event takes place. Blue represents that the grid is available, red represents that it's not. Based on data from [16].

As for calculating outage costs, HOMER relies on capacity shortage penalties, which are applied every time there is a shortfall between the required operating capacity and the actual amount of operating capacity the system can provide. E.g., if a given time step has a required load of 20 kW served by a 15 kW PV system plus the grid (with infinite capacity), no capacity shortage nor its accompanying penalty will occur. If, however, an outage occurs in the next time step, the 15 kW PV system will not be enough to supply the 20 kW load, so the capacity shortage would be 5 kW. If the value of lost load is 100 USD/kWh, that particular time step would incur an outage cost of 500 USD. HOMER adds the outage costs of all time steps for a given year to calculate the total outage cost.

4.3 Technical and economic assumptions used in the models

4.3.1 Topology of modeled microgrids

If either REopt or HOMER determine that the optimal solution for a given scenario is not a microgrid but a traditional, grid-interactive PV system, the system's components modeled would be the PV array itself, and its accompanying converter, as shown by Figure 22:

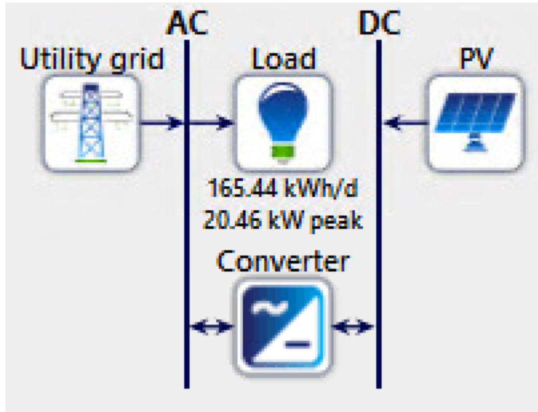


Figure 21. Example of a grid-interactive PV system modeled in HOMER. The PV array is modeled as being connected to the inverter (converter) through a DC bus, with the inverter connected to the load and the utility grid through an AC bus. This AC bus usually takes the form of the site's main electrical service panel.

If, on the other hand, the optimal solution for a scenario is a full microgrid with solar, a converter, battery storage and separate critical and non-critical loads, the microgrid would have the following topology:

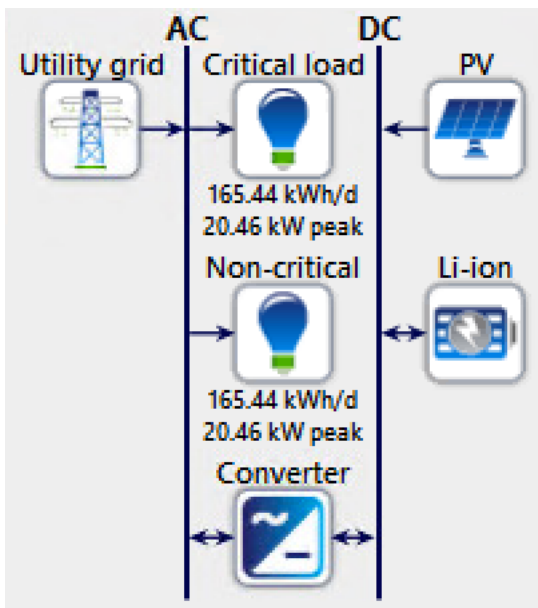


Figure 22. Example of a complete microgrid supplying power to the loads in parallel to the utility grid. In this case, the battery storage system is DC-coupled, and the site's loads are segregated between critical and non-critical. In case the utility grid experiences an outage, the non-critical load would not be energized, and the microgrid would supply electricity solely to the critical load.

4.3.2 Planning horizon and temporal resolution

The microgrids reviewed in this study are assumed to have a lifetime of 30 years, aligned with industry observations and trends, considering modern PV modules have increased their projected lifetimes from 21.5 years in 2007, to 32.5 years in 2019 [46] [47].

The temporal resolution of load profiles is defined for one-hour intervals, e.g., a load is assumed to draw the same amount of power for one full hour, before increasing, decreasing, or staying the same in the next interval. The same applies for the resolution of an outage, PV generation, and battery charging/discharging.

4.3.3 Economic assumptions

4.3.3.1 Discount rate, inflation rate, and escalation rate

The discount rate is assumed to be 10%, while the inflation rate is assumed to be equal to 2%, the average inflation rate in Puerto Rico from 2003 until 2020 [48]. As for electricity tariff escalation, this study assumes a rate of 0%; i.e., electricity tariffs are the same every year for the entire planning horizon (a conservative assumption, given the volatility in Puerto Rico's electricity rates).

4.3.3.2 Cost of solar

The cost of a PV system in Puerto Rico is assumed to be 2.70 USD/W, consistent with average market prices observed as of August 2020 [49]. **However, after taking into account an investment tax credit of 26%** [50], **this cost decreases to 2.00 USD/W, which is the value used in this study**. This value encompasses the cost of PV modules, power conditioning units (inverters/charge controllers), mounting systems, wiring, and other balance of system (BOS) components, as well as installation costs. Rocky Mountain Institute's Solar Under Storm II report estimates that, in general, solar projects tend to incur an increase of approximately 5% in engineering, procurement, and construction (EPC) costs when best practices to increase resilience are implemented, compared to the standard solar PV installations rated to withstand Category 3 or Category 4 hurricanes [51]. This premium encompasses appropriate use of ballast and mechanical attachments, sufficient structural connection strength, structural calculations on record, vibration-resistant module connections, and similar concepts that must be taken into account to withstand winds of 175 mi/h (the strongest winds measured in hurricane Maria). For this study, this 5% premium is already included within the assumed cost of 2.00 USD/W.

4.3.3.3 Cost of solar O&M

The cost of operating and maintaining a PV system is based on NREL's U.S. Solar Photovoltaic System Cost Benchmark: Q1 2018 [52], without taking into account inverter replacement, and is assumed to be 0.012 USD/W/year for all cases.

4.3.3.4 Replacement cost of PCU

This study assumes a lifetime of 15 years for the power conversion unit (inverter and charge controller), consistent with industry standards reported on [53]. The replacement cost is based on [52] and is assumed to be 0.14 USD/W_{AC} (i.e., 0.14 USD for every watt of nameplate capacity on the inverter, not on the nameplate capacity of the PV system itself).

4.3.3.5 Cost of storage

The cost of a battery energy storage system is assumed to be 600 USD/kWh, the average cost of a standalone, behind-the-meter BESS on the basis of nameplate energy capacity, as reported by Lazard's levelized cost of storage analysis [54]. However, the federal investment tax credit also applies to battery storage systems, as long as they are paired with solar and are configured so that they cannot be charged by the utility grid. Considering the current ITC is 26%, the cost of storage is reduced to **445 USD/kWh, the final cost of initial capital investment for a BESS considered in this study**.

It is assumed, however, that the BESS has a battery life of 10 years, and because of this, replacements at year 10 and year 20 need to be made. Costs for this replacements are based on NREL's mid-cost projection for battery storage [55], and are assumed to be 525 USD/kWh in year 10, and 460 USD/kWh in year 20. However, since HOMER only allows for one single cost of storage replacement, and the system's projected lifetime of 30 years would require the BESS to be replaced in year 10 and year 20, **the model assumes a single replacement cost of 505 USD/kWh**. This replacement cost was chosen because the NPV of a 505 USD payment in year 10 and another 505 USD payment in year 20 is the same as the NPV of a 525 USD payment in year 10 and a 460 USD payment in year 20. The ITC does not apply for the battery's replacement cost, since it is expected to expire by 2022 [56].

4.3.3.6 Cost of generator and diesel

The cost per kW of a diesel generator is assumed to be 1,205 USD/kW, taken from [57]. The cost of diesel is usually 0.50 USD/liter, according to [58]. However, since the diesel generator is only considered in the resilient scenario, which assumes a severe weather taking place, a scarcity price of 1.50 USD/liter is assumed, consistent with observations of scarcity prices prior to several high-profile hurricanes [59] [60]. The generator's performance and efficiency calculations are not considered within this study, but can be found in [41].

4.3.3.7 Utility tariffs

The residential and commercial tariffs are assumed to be equal to the monthly average cost of electricity of 2019 for residential & commercial users, respectively, reported by the U.S. Energy Information Agency (EIA) [61]:

Table 7. Residential & commercial utility rates [61].

Month	Residential utility rate [USD/kWh]	Commercial utility rate [USD/kWh]
January	0.1907	0.2338
February	0.2185	0.2235
March	0.2184	0.2403
April	0.2289	0.2594
May	0.2471	0.2019
June	0.2037	0.2261
July	0.1972	0.2039
August	0.2222	0.2421
September	0.1936	0.2102
October	0.2150	0.2280
November	0.2115	0.2274
December	0.2313	0.2519
Average	**0.2148**	**0.2290**

While the utility rates shown above are the ones studied in this work, Puerto Rico is known for having historically volatile electricity prices, as shown Figure 24 [62]:

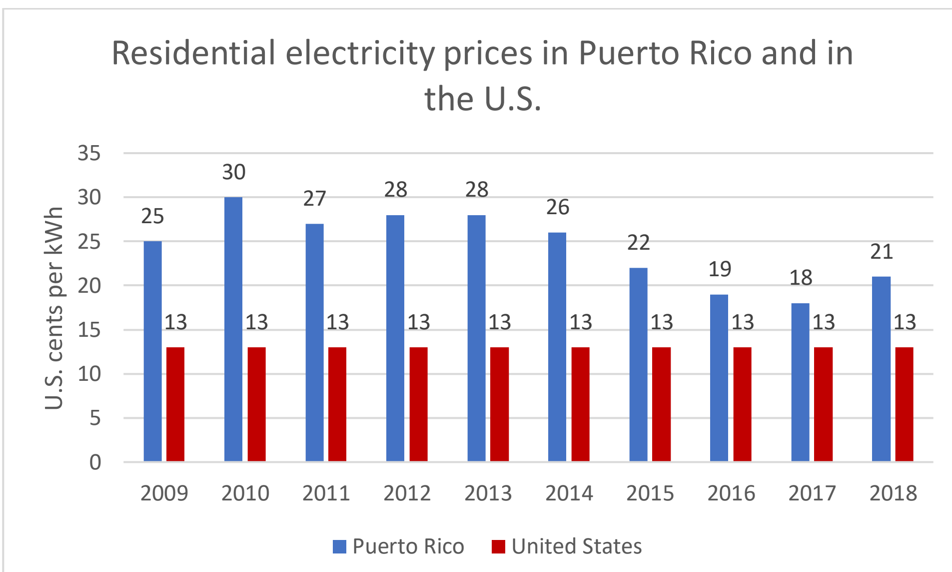


Figure 23. Comparison between residential electricity prices in Puerto Rico and in the U.S. [62].

4.3.3.8 Net metering

Finally, all of the utility tariffs assumed in this study consider net metering. Net metering applies to residential systems with a generating capacity of up to 25 kilowatts (kW) and non-residential systems up to one megawatt (MW) in capacity. Customer net excess generation (NEG) is carried over as a kilowatt-hour (kWh) credit to the following month, but NEG credit is limited to a "daily maximum" of 300 kWh for residential customers and 10 megawatt-hours (MWh) for commercial customers. Customers with excess credits remaining at the end of a 12-month period (ending in June) will be compensated as follows: 75% of the excess credits will be purchased by PREPA at a rate of $0.10 per kWh, while the other 25% excess credits will be "donated" to PREPA by the user [63]. To adjust for this accounting scheme, the model assumes all energy exported by the microgrid to the grid is bought at 0.075 USD/kWh.

4.3.4 Summary of economic assumptions

Table 8. Summary of economic assumptions.

Item	Value
Cost of PV (after ITC)	2.00 USD/W
Cost of PV O&M	0.012 USD/W/year
Cost of BESS	600 USD/kWh (445 USD/kWh after ITC) 1 USD/kW (for REopt)
BESS replacement cost	505 USD/kWh (for both year 10 and 20)
Cost of generator	1,205 USD/kW
Cost of diesel	1.50 USD/liter
Nominal discount rate	10%
Inflation rate	2%
Electricity tariff escalation rate	0%
Utility rates - residential	Average rate of 0.2148 USD/kWh
Utility rate - commercial	Average rate of 0.2290 USD/kWh
Net metering	Excess energy at the end of a 12-month period is bought by the utility at 0.075 USD/kWh

4.3.5 Summary of technical assumptions

Table 9. Summary of technical assumptions.

Item	Assumption
Annual PV degradation	0.5%
Battery roundtrip efficiency	90%
Battery throughput	3000 kWh/year
Inverter efficiency	95%
Rectifier efficiency	95%
Minimum state of charge	10%
Initial state of charge	100%
Resolution of proposed PV size	REopt • 0.1 kW HOMER • 0.5 kW for residential case • 5 kW for commercial case
Resolution of proposed BESS size	REopt • 0.1 kWh HOMER • 1 kWh for residential case • 5 kWh for commercial case

4.3.6 Data

4.3.6.1 Solar resource data

For Puerto Rico, solar resource data comes from NREL's National Solar Radiation Database (NSRDB) [64].

4.3.6.2 Temperature data

Temperature data is obtained from NASA's *Air temperature, monthly averaged values over 22-year period (July 1983 – June 2005)* database.

4.3.6.3 Load data

This report studies different load profiles for residential and commercial user segments in Puerto Rico, with data from the Puerto Rico IRP [15]. Load profiles are assumed to be the same every day for residential and commercial loads, and are shown below:

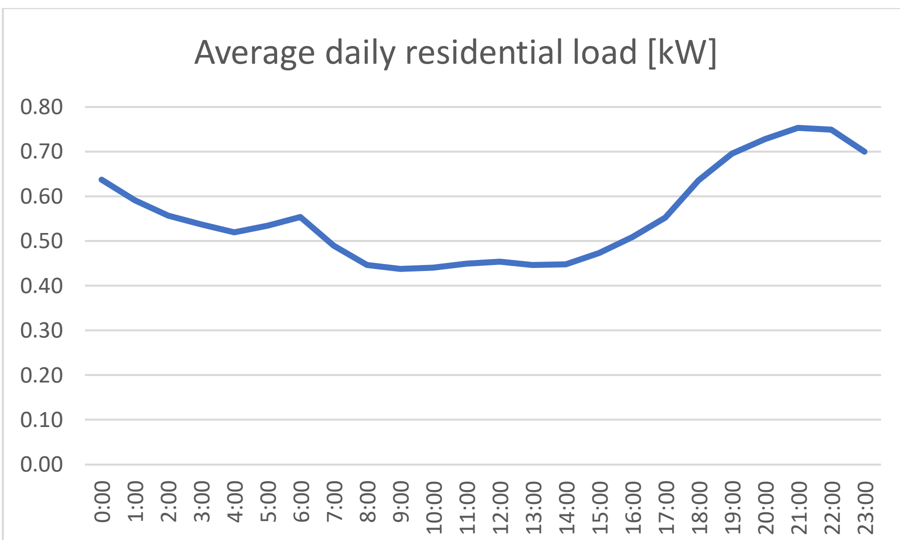


Figure 24. Average daily residential load.

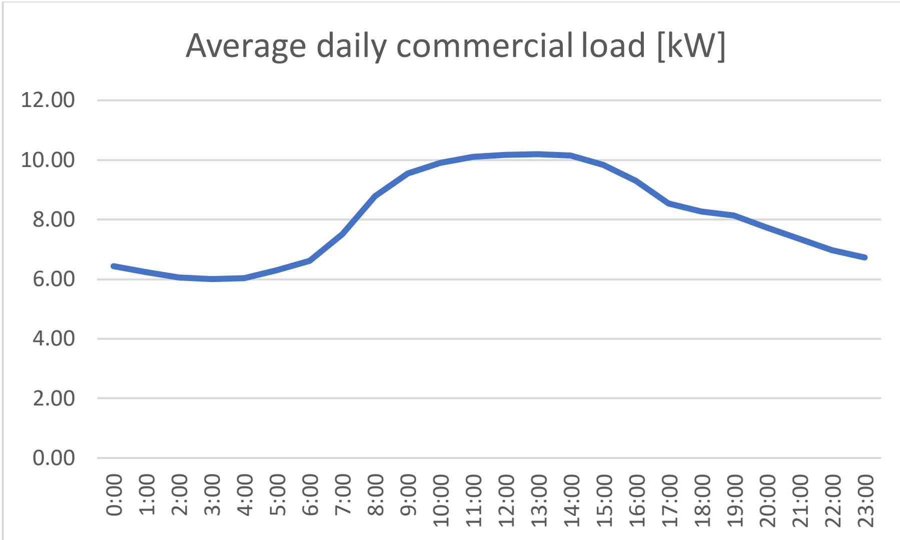


Figure 25. Average daily commercial load.

4.3.6.4 Critical load

The model defines a given user's critical load as a fraction of their normal (i.e., grid -connected) load, which must be energized even if the grid is not able to, and is assumed to be 50% for both residential and commercial users. In REopt, the critical load is simply stated as a fraction of the total load, while HOMER models the total load as into two separate loads, split into critical and non-critical, where the non-critical load automatically turns off when the grid is out.

4.3.7 Summary of load cases

The three different user segments are summarized in the following table:

Table 10. Summary of load cases.

User segment	Consumption [MWh/year]	Average Load [kW]	Peak Load [kW]	Critical Load [%]	Outage Cost [USD/kWh]
Residential	4.87	0.56	0.76	50%	2.63
Commercial	70.43	8.04	10.22	50%	78.21

4.4 Differences in modeling of storage systems

REopt models battery systems based on cost per kWh and cost per kW. In this sense, at a cost of 500 USD/kWh and 300 USD/kW, a 15kWh/5kW battery would cost 7,500 + 1,500 USD for a total of 9,000 USD.

HOMER, on the other hand, models them based solely on cost per kWh, and assumes a corresponding power rating based on the battery's energy capacity; i.e., HOMER allocates the entirety of the battery's cost on its capacity. In the previous example, HOMER would express the same battery's cost as simply 600 USD/kWh (9,000 USD divided by 15 kWh).

This discrepancy in modeling methods can result in much different microgrid configurations and costs; e.g., REopt could suggest a battery size of 10 kWh and 10 kW if not much power is required, while HOMER might automatically assume that a 10 kWh with a capacity of 30 kW. As a compromise between these two modeling approaches, battery costs inputs in REopt are expressed as they would be in HOMER, based solely on cost per kWh. In that sense, both modeling tools interpret a given battery as costing 600 USD per kWh, regardless of its power rating. Lastly, a symbolic cost of 1 USD/kW is assumed in REopt, to prevent the model from proposing batteries with unlimited power rating (e.g., if the cost per power rating were zero, REopt might suggest a battery with 10 kWh/1,000,000 kW), and simply suggest the actual power capacity required.

Chapter 5: Results

This chapter enlists the results obtained by running each scenario, for all load profiles considered, on HOMER. It details all of the results for a particular load profile, before moving on to the next. The results are catalogued by NPC and ROI, microgrid architecture, and energy balance. Additionally, the commercial load case expands the energy balance to showcase the way in which microgrid components behave throughout the year, particularly when an outage occurs.

5.1 Residential case

5.1.1 Base scenario

The base scenario is perhaps the simplest to model since neither DERs nor outage costs are considered; the LCC consists simply of cumulative electricity charges paid to the utility over the planning horizon, and discounted accordingly. Both REopt and HOMER calculate a yearly business-as-usual cost of 1,046 USD for electricity charges that, nominally, would account for 31,380 USD over a 30-year planning horizon, but after applying a 10% nominal discount rate and a 2% inflation rate, amount for a LCC of roughly 12,000 USD. This is visually represented on Figure 29:

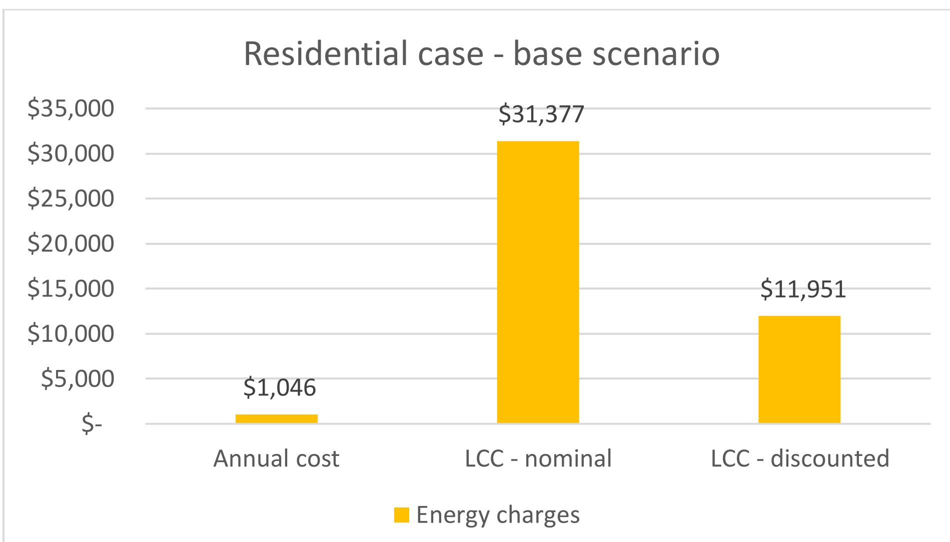


Figure 26. Annual, nominal life cycle, and discounted life cycle costs for the base scenario of the residential case.

5.1.2 Least-cost scenario

To minimize life cycle costs, REopt suggests deploying a PV system of 3.3 kW without any kind of storage. HOMER, on the other hand, suggests one with 3.5 kW of capacity, again without added storage. In other words, HOMER suggests a PV system size that is 6% larger than the one suggested by REopt, in part because of the reduced resolution of HOMER's search algorithm (limited by choice to intervals of 0.5 kW). In terms of life cycle costs, REopt estimates a LCC of

7,050 USD while HOMER calculates a LCC of roughly 7,500 USD, also a difference of 6% (see Figure 30 below):

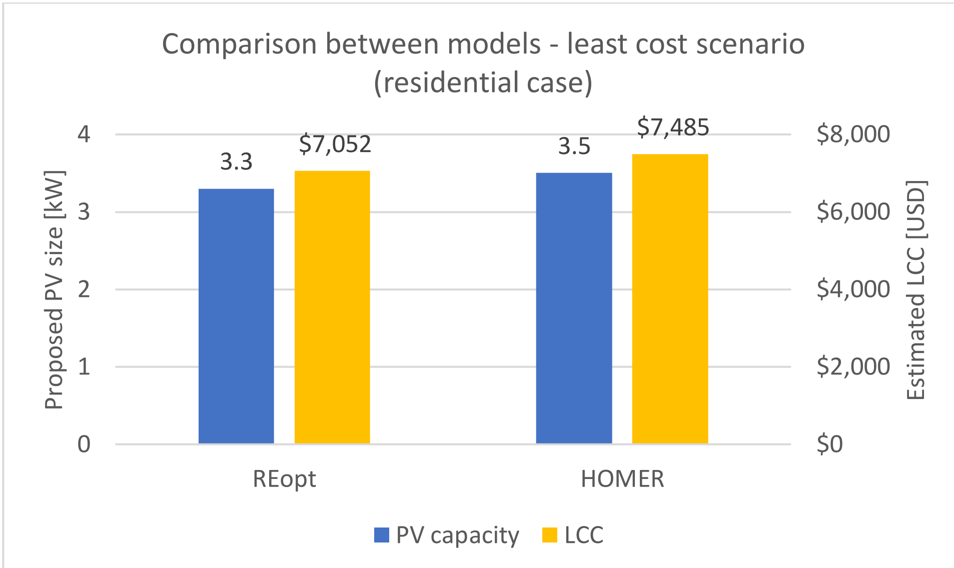
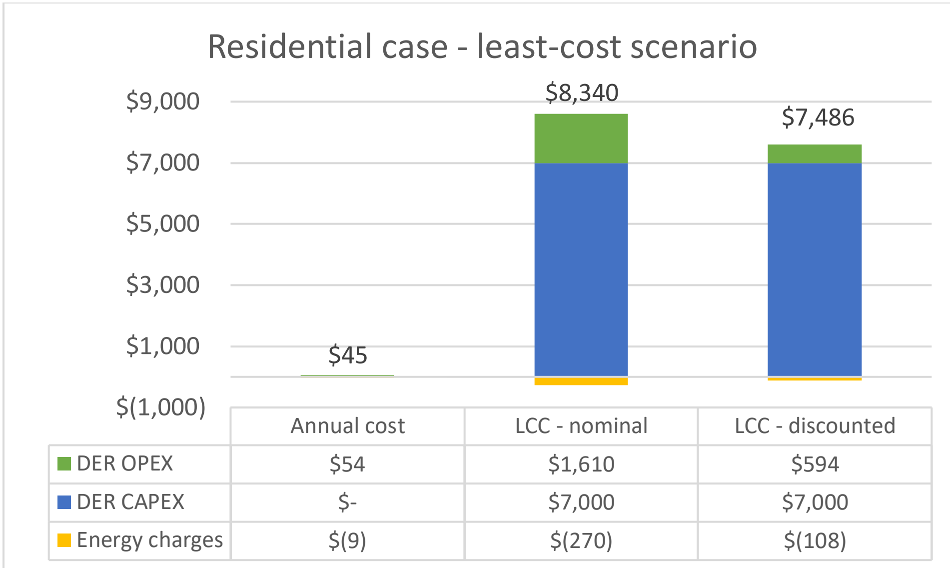


Figure 27. Comparison between PV capacity proposed, and life cycle costs calculated by REopt and HOMER for the least-cost scenario.

This can be explained by mainly two reasons: first, REopt assumes that any surplus energy exported to the grid at the end of a year, after offsetting energy imported from the grid, is not paid to the user and is simply unaccounted for in the cash flow. HOMER, on the other hand, considers that any surplus electricity is paid to the user at a rate of 0.075 USD/kWh, as explained in the economic assumptions described in the previous chapter. The second reason the LCCs differ is that each modeling tool has different ways of calculating electricity generation and consumption for every time step (also described in the previous chapter and in the Appendix), and there is reason to believe that the models are using dissimilar solar resource data (see Appendix 2).

Regardless of the slight variations in calculated LCCs, the least-cost scenario is noticeably cheaper than the base scenario, in terms of both nominal LCC and discounted LCC, as shown on Figure 31:



	Annual cost	LCC - nominal	LCC - discounted
DER OPEX	$54	$1,610	$594
DER CAPEX	$-	$7,000	$7,000
Energy charges	$(9)	$(270)	$(108)

Figure 28. Annual, nominal life cycle, and discounted life cycle costs for the least-cost scenario of the residential case.

By procuring the suggested 3.5 kW PV system proposed by HOMER, annual costs would drop from 1,046 USD in the base scenario, to 45 USD in the least-cost scenario. Nominal LCC would decrease from 31,400 USD to 8,300 USD, while the discounted LCC would decrease less drastically from 12,000 USD to 7,500 USD. As their name implies, the nominal LCC savings are much more significant than the discounted LCC savings because they still haven't been discounted according to their respective value in time. This, however, does not apply to the capital expenditures of the PV system, since CAPEX are assumed to take place in year 0, before any discount rate applies. This is why the CAPEX value is the same in the nominal LCC and discounted LCC, and why it is not considered in the annual cost of the scenario.

5.1.3 Resilient scenario

The resilient scenario is the one that differs the most between modeling tools; in particular because:

- As mentioned before, the models may be using different solar resource data and they make different assumptions when it comes to net metering.
- Both REopt and HOMER employ dissimilar battery storage models (the former calculates kWh capacity and kW rating separately, while the latter only focuses on kWh capacity and assumes an accompanying kW rating).
- Most importantly, REopt explicitly opts for the lowest-cost configuration that can sustain critical loads under an outage. HOMER, on the other hand, searches for the lowest-cost configuration while assigning a cost penalty to any unmet loads. In other words, even though HOMER accounts for the value of lost load, it may consider more economical to incur in a small capacity shortage penalty if the size of the microgrid necessary to meet the critical loads at all times results overly costly (more on this on the sensitivity analysis in Chapter 6)

The difference in sizes and LCCs obtained through both modeling tolls are shown in the next figure:

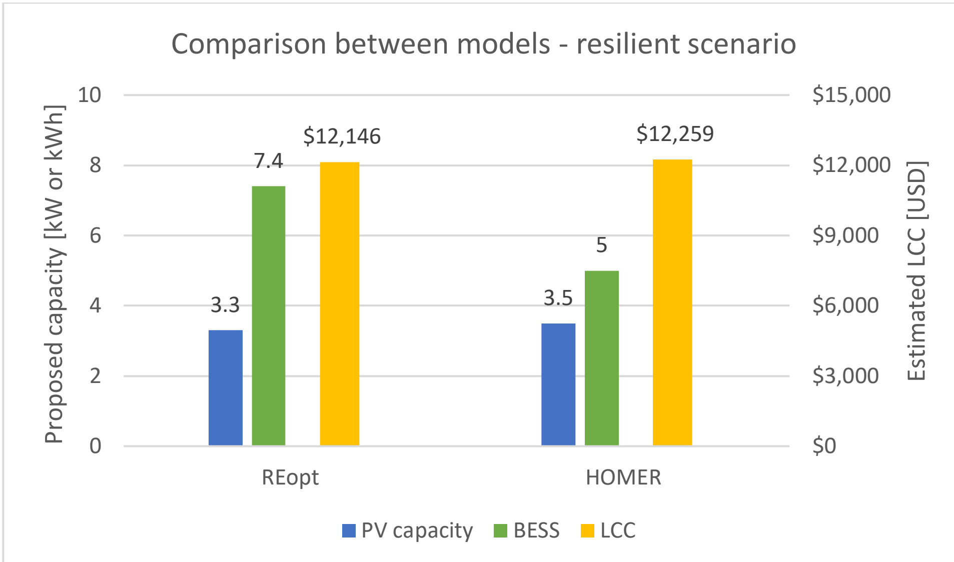
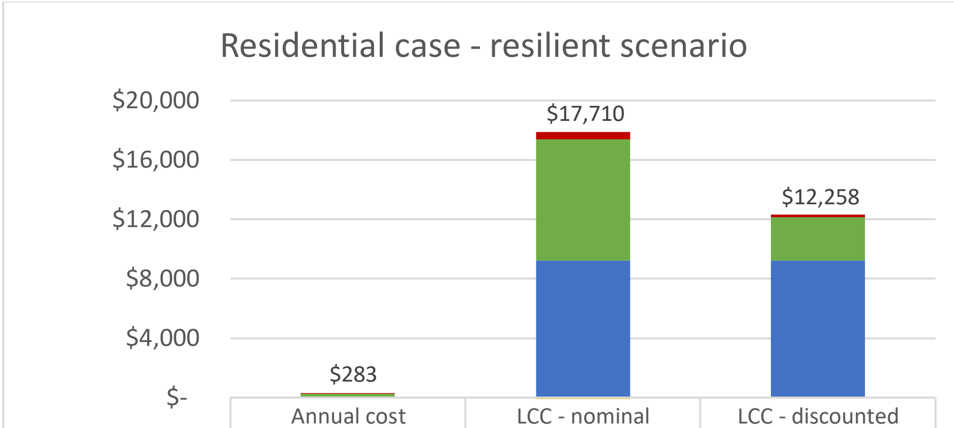


Figure 29. Comparison between PV capacity proposed, and life cycle costs calculated by REopt and HOMER for the resilient scenario.

Looking at the figure above, it is surprising that both models calculate LCCs within 1% of one another even though they proposed different sizes of BESS to achieve this. REopt calculates that its 3.3 kW PV / 7.4 kWh BESS microgrid is sufficient to power critical loads for the duration of the 2,000+ hour outage described in Chapters 3 & 4. HOMER, on the other hand, does not aim to explicitly power the critical loads during that outage, but it still powers them indirectly for most of the outage duration, given that a capacity shortage penalty equal to the VoLL is part of its objective function.

The annual, nominal life cycle, and discounted life cycle costs for the resilient scenario modelled in HOMER can be seen in the following figure:



	Annual cost	LCC - nominal	LCC - discounted
Outage costs	$17	$505	$192
DER OPEX	$272	$8,160	$2,909
DER CAPEX		$9,225	$9,225
Energy charges	$(6)	$(180)	$(68)

Figure 30. Annual, nominal life cycle, and discounted life cycle costs for the resilient scenario of the residential case.

By now, a recurring pattern is starting to show up; annual costs are again lower than the base scenario's, and the discounted LCC is again lower than the nominal LCC. This scenario, however, results more expensive than the least-cost scenario. This increase in costs comes mostly from an additional 5 kWh BESS system that was not included in the least-cost scenario. The BESS replacements in year 10 and 20 increase, along with additional O&M, increase DER OPEX substantially compared against the least-cost scenario. Furthermore, this scenario considers an additional cost component in the form of outage costs. While small in comparison to the cost of deploying and operating the microgrid, they are not zero, which means that this particular microgrid cannot be expected to entirely supply the critical loads in for 87 continuous days.

5.1.3.1 Unmet load in resilient scenario

The HOMER model estimates that, in the event of a 2,089-hour outage, the optimal microgrid will be unable to serve 30.9 kWh because of insufficient generation, equivalent to 0.72% of the total annual electrical load. This happens on particular instances when the grid is unavailable and solar availability is lacking, thus forcing the BESS to supply the critical loads for as long as it can before reaching its minimum SoC. This is represented by the two following graphs:

Figure 31. BESS SoC vs. total electrical load and unmet electrical load.

Figure 34 shows how the state of charge of the BESS almost never drops below its full capacity, until the simulated 2,000+ hour-outage starts on September 21. As soon as the prolonged outage starts, the noncritical loads are turned off, and only the critical loads remain powered by the PV + BESS system, whose SoC noticeably begins to fluctuate between its maximum of 100% and its minimum allowed SoC of 10%; Figure 35 shows how PV power output and SoC are closely correlated:

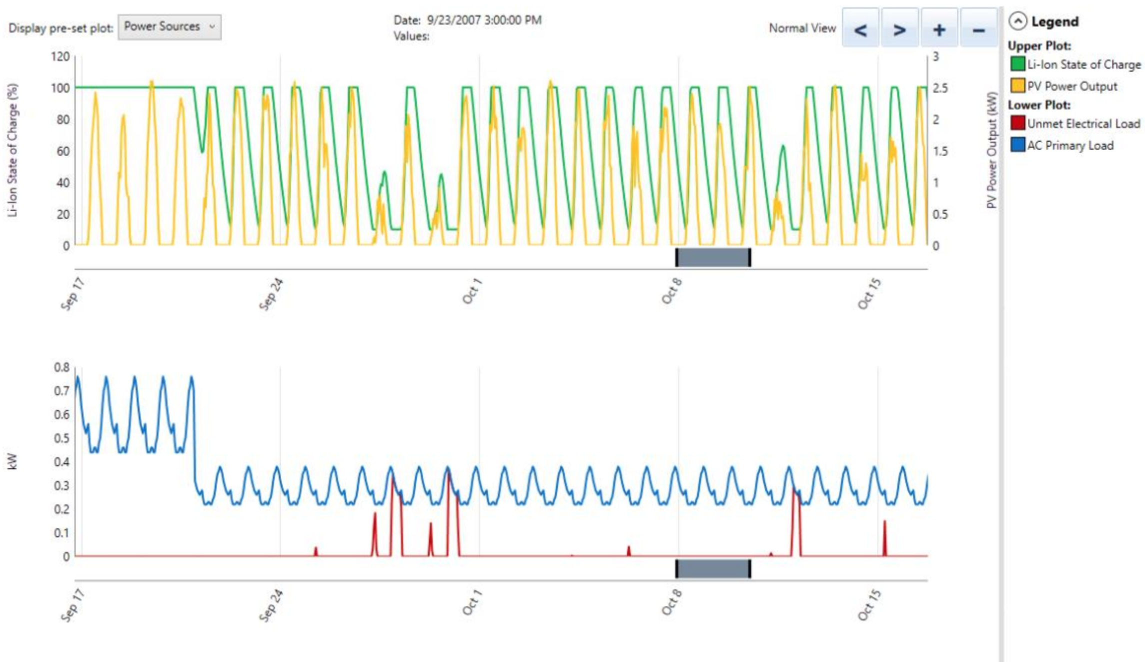


Figure 32. Zoomed-in version of the previous graph, with the addition of the PV power output in the upper graph.

However, the microgrid is not enough to supply power for the entirety of the 87-day outage. Instead, it is forced to disconnect the BESS whenever its SoC reaches 10%, thus forcing the critical load to remain unmet for certain time steps throughout the 87-day outage. Regardless of this, HOMER estimates that the proposed 3.5 kW PV / 5 kWh BESS microgrid is able to meet the critical load more than 99% of the year, and roughly 95% of the duration of the outage.

5.1.4 Expected outage costs in base scenario

Lastly, it's important to again point out that **a key assumption of this study is that an outage of this magnitude occurs once every 8.2 years**, as explained in Chapter 3. However, when accounting for the VoLL, the expected cost of enduring an 87-day blackout is large enough to intentionally oversize a microgrid even if that kind of outage is not expected every year, as shown Figure 36:

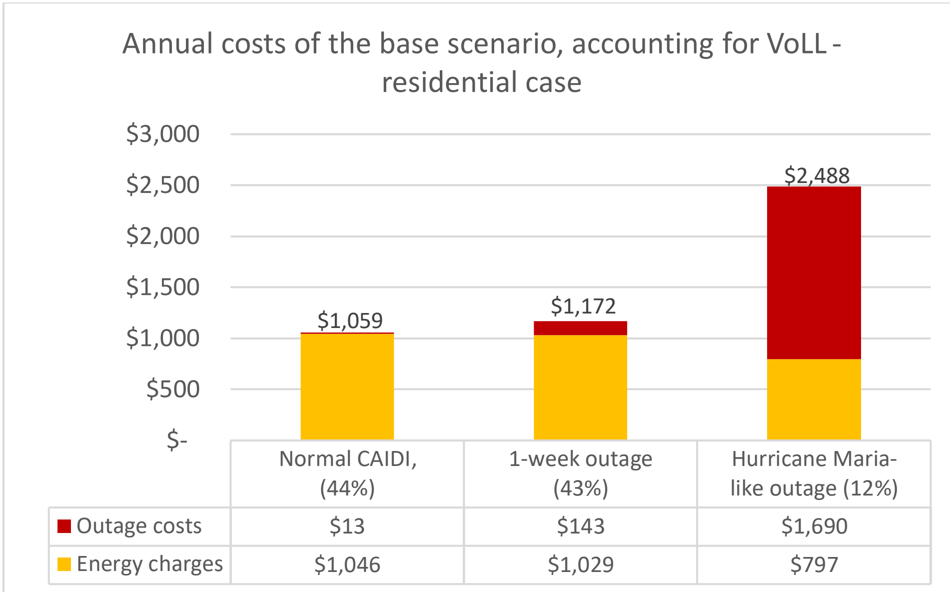


Figure 33. Annual costs of the base scenario of the residential case, accounting for the value of lost load. The outage costs are either based on the typical CAIDI for Puerto Rico, a one-week outage or an 87-day outage, which are in turn assumed to be the result of no hurricane, a low-category hurricane, or a high-category hurricane, respectively. The probability of each hurricane (or lack thereof) occurring on a given year is shown in parenthesis.

The first column, representing a year in which no weather-related takes place, is nearly identical to the annual cost of the base scenario shown in Figure 29 (1,046 USD), with the slight addition of a 13 USD annual outage cost related to the average CAIDI and SAIDI values in Puerto Rico [15], with their accompanying outage costs represented in HOMER as a capacity shortage penalty. If a one-week outage were modeled in HOMER, energy charges would decrease to 1,029 USD since the user would not be charged one week's worth of electricity, but their outage costs would in turn increase to 143 USD, this making that scenario costlier, as shown in the second column. Similarly, if the outage modeled lasted for 87-days instead, energy charges logically drop even further, to ~800 USD per year, but the total outage costs for that 87-day outage would be worth ~1,700 USD.

Since each of the three outage scenarios outlined above are assumed to have a specified probability of occurring on a given year, the weighted average of the three is obtained and a 30-year cash flow with this weighted average LCC is then compared to the LCCs of the other scenarios.

5.1.5 Comparison of all scenarios

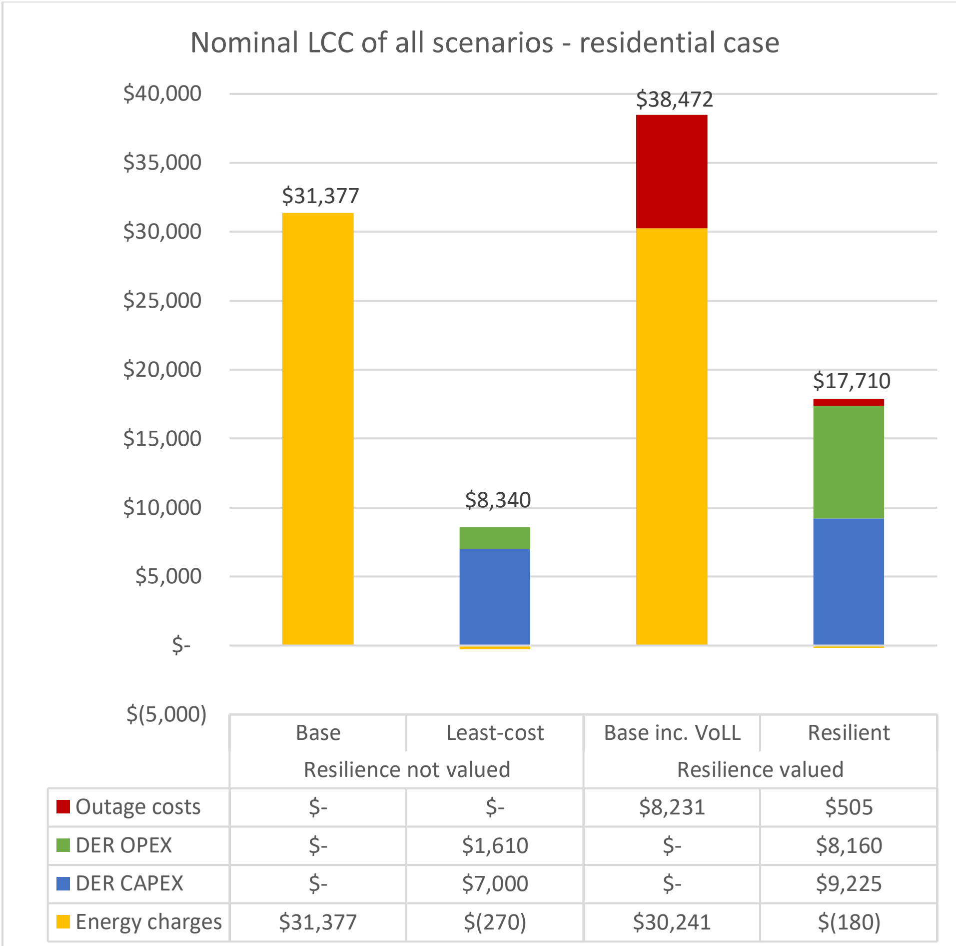


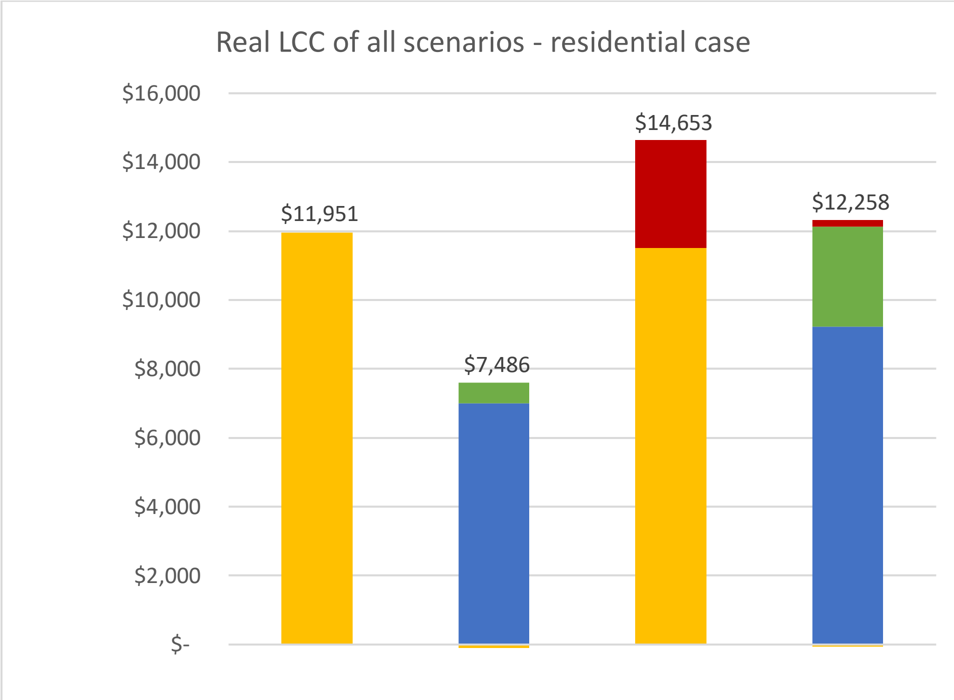
Figure 34. Nominal life cycle cost of all scenarios of the residential case.

Figure 37 shows the nominal LCC for all scenarios (including the base scenario with and without accounting for weather events and their accompanying outage costs). The first comparison to be made is between *the two scenarios that do not value resilience: the base scenario and the least-cost scenario*. As it would be expected, costs drop drastically from one to the other, as does their distribution: the LCC in the base scenario consists entirely of energy charges, while the LCC of the least-cost scenario mostly comes from the 7,000 USD of capital expenditures of procuring a PV system, with a smaller proportion of nominal operating expenditures, ~1,600 USD, distributed over the 30-year planning horizon. Even more so, the least-cost scenario expects net negative energy charges, implying the electric utility will reimburse the user for the surplus energy its PV system exports to the grid.

On the other hand, the *scenarios that do value resilience are the base scenario that accounts for the VoLL, and the resilient scenario*. Since the base scenario that accounts for the VoLL also considers recurring severe weather events over the planning horizon, its energy charges are slightly lower than the base scenario's. And, as its name implies, its LCC also accounts for roughly ~8,200 USD attributed to outage costs related to these weather events.

The alternative to an outage cost of that proportion is the resilient scenario, which considers the same amount of PV procured, but it adds to it a 5 kWh BESS, thus increasing its CAPEX to a small extent and its OPEX to a larger extent. That its OPEX increase much more than its CAPEX can be explained by the need to replace the battery twice throughout the 30-year planning horizon (which is considered OPEX since it's an expenditure that does not take place in year 0), plus the additional O&M costs of a BESS. And, as mentioned before, this resilient scenario considers a marginal outage costs of ~500 USD distributed throughout the 30-year planning horizon (roughly 17 USD per year). While it's not zero, it is two full orders of magnitude lower than the cost of the most severe outage modeled of ~1,700 USD, expected when a Hurricane Maria-scale event impacts Puerto Rico (see Figure 36).

However, after applying discount and inflation rates, the comparison between LCCs changes noticeably, as shown in Figure 38:



	Base	Least-cost	Base inc. VoLL	Resilient
	Resilience not valued		Resilience valued	
Outage costs	$-	$-	$3,135	$192
DER OPEX	$-	$594	$-	$2,909
DER CAPEX	$-	$7,000	$-	$9,225
Energy charges	$11,951	$(108)	$11,518	$(68)

Figure 35. Real (discounted) life cycle costs of all scenarios of the residential case.

By definition, what the discount and inflation rates do is distort all of the yearly costs incurred during the planning horizon except for the ones that occur in year 0, which is why some look dramatically lower (for instance, like energy charges dropping from a nominal ~30,000 USD to a discounted ~12,000 in the base scenario). This is why the only cost factor that remains unchanged from the nominal to the real estimate are capital expenditures, since no discount or inflation rate apply when they take place. This also explains why the least-cost scenarios is the one that is distorted the least by the time value of money, since nearly all of its LCC can be attributed to CAPEX. In contrast, the base scenarios consist entirely of annual costs, as does half of the resilient scenario in the form of OPEX.

It's interesting to point out that the LCC of the resilient scenario is just 2.5% higher than the LCC of the base scenario *without valuing resilience*. In other words, hedging against outage costs over a 30-year planning horizon raises total electricity costs by approximately 2.5%. On the other hand, the total microgrid costs of the resilient scenario are 61% higher than the PV system procured in the least-cost scenario. This 61% increase in costs can be described as a premium that would need to be paid to upgrade a savings-oriented PV system to a resilience-providing microgrid. However, if outage costs were also considered in the least-cost scenario, the premium would be reduced to 14%; not because the resilient scenario would decrease its LCC, but because the least-cost scenario would see its own raised by ~3,100 USD.

5.1.5.1 Net present value

As mentioned in Chapter 3, the net present value (NPV) of any other scenario is the difference between its real LCC and the real LCC of the base case, which may be positive, negative, or zero depending on the objective. Accordingly, two distinct NPVs are drawn; one for the least-cost scenario and another one for the resilient scenario (while account for the VoLL in the latter). The NPV of the least-cost scenario compared against the base scenario is 4,465 USD, while the NPV of the resilient scenario compared against the base scenario that includes VoLL is 2,395 USD, as shown on Figure 39:

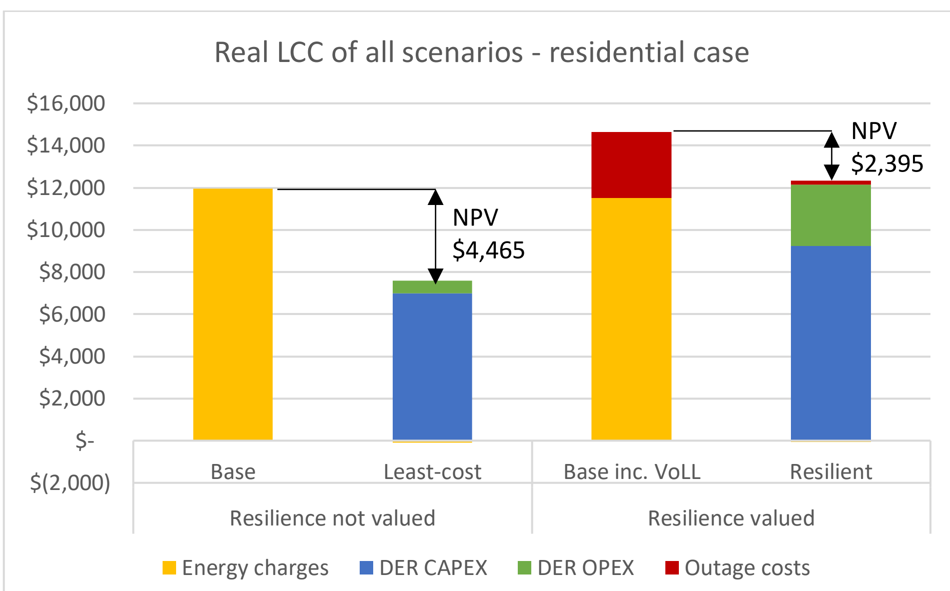


Figure 36. Net present values of the residential case.

5.1.5.2 Return on investment

As described in Chapter 3, the return on investment is defined as the average yearly difference in nominal cash flows over the project lifetime, divided by the difference in capital cost. For the least-cost scenario, this difference in cash flows represents a ROI of 11%, while the one for the resilient scenario results in a ROI of 7.5% (the cash flows are available on Appendix 3).

5..1.5.3 Value of resilience

Finally, resilience can be assigned a value by remembering Equation 9, which states that it is equal to the value of lost load times the difference in unmet load of the scenarios being compared:

$$VoR = VoLL \times \left(Load_{Unmet,base} - Load_{Unmet,resilient}\right)$$

Since the value of resilience is indexed to the load that would not be met in the base scenario, and since the base scenario assumes years under weather events of different magnitude), the resilience that a microgrid provides thus differs from one year to the other, as shown in the following table:

Table 11. Value of resilience for different outage durations, residential case.

Type of year	Probability [%]	Unmet load [kWh/year]			VoLL [USD/kWh]	**Value of resilience**
		Base	Resilient	Difference		
Normal CAIDI	44%	5	0	5	$2.63	**$13**
1-week blackout	43%	55	0	55		**$143**
87-day blackout	12%	643	53	590		**$1,552**

By applying each type of year's weight to its respective expected value of resilience, an average value of resilience can be obtained, equal to 257 USD per year.

Spread throughout the 30-year planning horizon, this represents **a total nominal value of resilience of 7,720 USD, or a real (discounted) value of resilience of 2,940 USD** for the average residential user.

These values are also visually represented in Figures 38 and 39 as the differences in outage costs between the third and fourth scenarios.

5.2 Commercial case

5.2.1 Base scenario

Like in the residential case, the simplest scenario to model is the base one, since the same energy expenses are made on a yearly basis, with no other costs to consider. The annual, nominal life cycle and discounted life cycle costs can be seen in Figure 40:

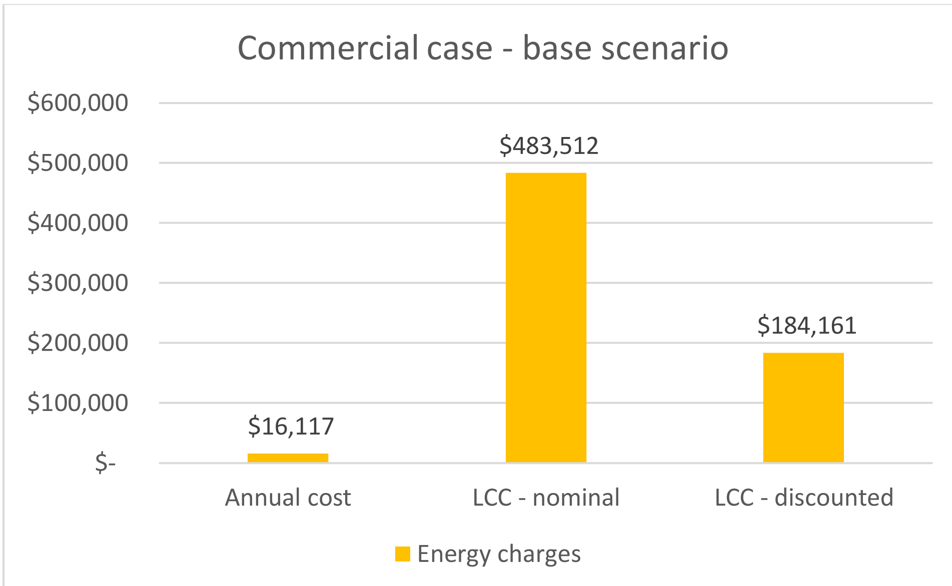


Figure 37. Annual, nominal life cycle, and discounted life cycle costs for the base scenario of the commercial case.

5.2.2 Discrepancies between models in REopt and HOMER

As mentioned before, both REopt and HOMER have different methods of modeling microgrids and calculating their costs and benefits. When it comes to optimizing financial savings, however, they both provide similar results:

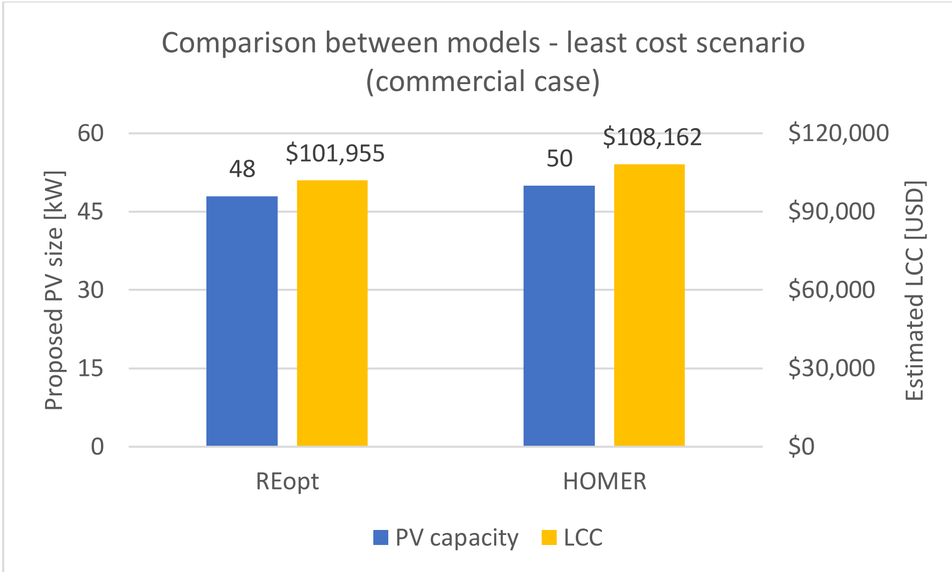


Figure 38. Comparison between PV capacity proposed, and life cycle costs calculated by REopt and HOMER for the least-cost scenario of the commercial case.

REopt suggests a 48 kW PV system will minimize net present cost, and will have a life cycle cost of ~102,000 USD. Alternately, HOMER proposes a 50 kW PV system, with an accompanying LCC of ~108,000 USD. The increase from 48 kW to 50 kW from one model to the other can be explained because of the 5 kW-intervals that HOMER is able to choose from. The difference in LCCs, on the other hand, can be attributed to the solar resource data used in each model, which in turn impact energy imported from and exported to the grid. All further comparisons in this study are done using the HOMER model.

5.2.3 Expected outage costs in base scenario

The second case analyzed in this study is the average Puerto Rican commercial load. This differs from the residential load not only in its shape (Figure 25) but most importantly in the value of 78.21 USD/kWh it assigns to its lost load (Figure 15).

By modeling the same outages with varying durations modeled for the residential case, the annual cost for each particular type of year for the commercial load can be calculated, shown here in Figure 42:

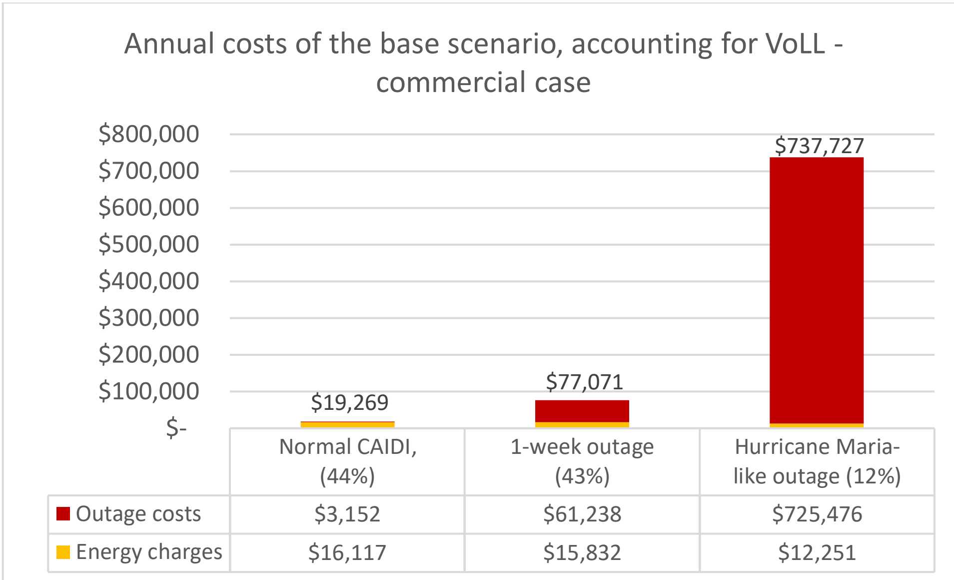


Figure 39. Annual costs of the base scenario of the commercial case, accounting for the value of lost load. The outage costs are either based on the typical CAIDI for Puerto Rico, a one-week outage or an 87-day outage, which are in turn assumed to be the result of no hurricane, a low-category hurricane, or a high-category hurricane, respectively. The probability of each hurricane (or lack thereof) occurring on a given year is shown in parenthesis.

Firstly, it's noteworthy how outage costs take the lion's share of the costs whenever an outage lasts one week or longer, but it's also surprising that, on a year where no hurricane hits, outage costs still make up 16% of total energy expenses, compared to 1% for the residential case with an equivalent CAIDI (Figure 36). Of course, this expense of ~3,200 USD in outage costs is not a specific payment that must be made because of an outage, but it's rather the embodied loss of economic activity that is unable to be performed because of an absence of electrical service. The fact that this number is drastically larger than in the residential case is explained by two simple reasons:

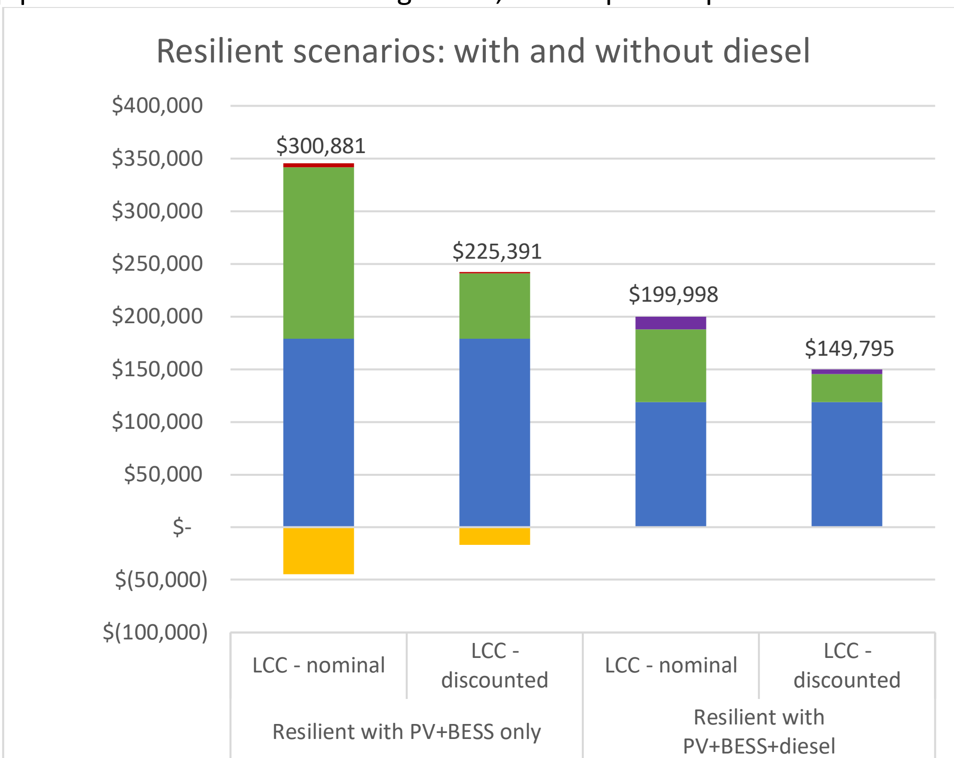
- The average commercial electricity user in Puerto Rico places a much higher value (78.21 USD/kWh) on their lost load than the average residential user (2.63 USD/kWh)
- At the same time, the average commercial electricity user consumes much more electricity than the average residential user

The combination of these two factors is why outage costs represent 16% of total energy expenses during a normal year (with an expected CAIDI of 2.5 hours/customer-year, and a SAIFI of 3.8 events/customer-year), 79% of total energy expenditures if the outage lasts one full week, and nearly the entirety (98%) of energy expenditures if the outage were to last 87 days. Inversely, the longer the outage duration, the less electricity that will be bought and paid to the utility, hence the decreasing energy charges as the outages increase in duration.

However, as mentioned before, these events do not have the same probability of occurring on a given year, which is why they're weighted and combined as a single scenario that is in turn compared to the other ones.

5.2.4 Two resilient scenarios

Two resilient scenarios were modeled for the commercial case; one that considers only solar and storage, and another that considers solar, storage, and a diesel generator. The reason for modeling two resilient scenarios is to better understand the impact of having a diesel generator as a backup power source. As shown in Figure 43, that impact is quite considerable:



	Resilient with PV+BESS only: LCC - nominal	Resilient with PV+BESS only: LCC - discounted	Resilient with PV+BESS+diesel: LCC - nominal	Resilient with PV+BESS+diesel: LCC - discounted
Fuel costs	$-	$-	$11,950	$4,551
Outage costs	$3,820	$1,455	$-	$-
DER OPEX	$162,487	$61,888	$69,163	$26,343
DER CAPEX	$178,950	$178,950	$118,910	$118,910
Energy charges	$(44,376)	$(16,902)	$(24)	$(9)

Figure 40. Nominal and discounted life cycle costs of resilient scenarios, with and without a diesel generator.

Without a diesel generator, the cost-optimal solution would be a 65 kW PV / 110 kWh BESS microgrid, with a price tag of ~180,000 USD in CAPEX. If diesel were to be considered, though, the cost-optimal solution would consist of a 50 kW PV / 10 kWh BESS / 12 kW generator, and the CAPEX would decrease one full third to ~120,000 USD. This drastic difference results from the need to oversize the BESS system until it's able to supply enough electricity under a blackout to minimize the value of lost. The required size of PV drops by 23%: from 65 kW to 50 kW. But what truly helps decreases costs is the decrease of 91% in required storage: from 110 kWh to just 10 kWh. To put this number into context, it's useful to remember that the average *daily* load is ~200 kWh/day, and the critical load is half of that, ~100 kWh/day. A large reason why this occurs is that by relying solely on solar and storage, the microgrid is forced to have enough solar to charge the BESS on a daily basis, and enough storage capacity to be able to provide power to the critical load (~100 kWh/day), again on a daily basis.

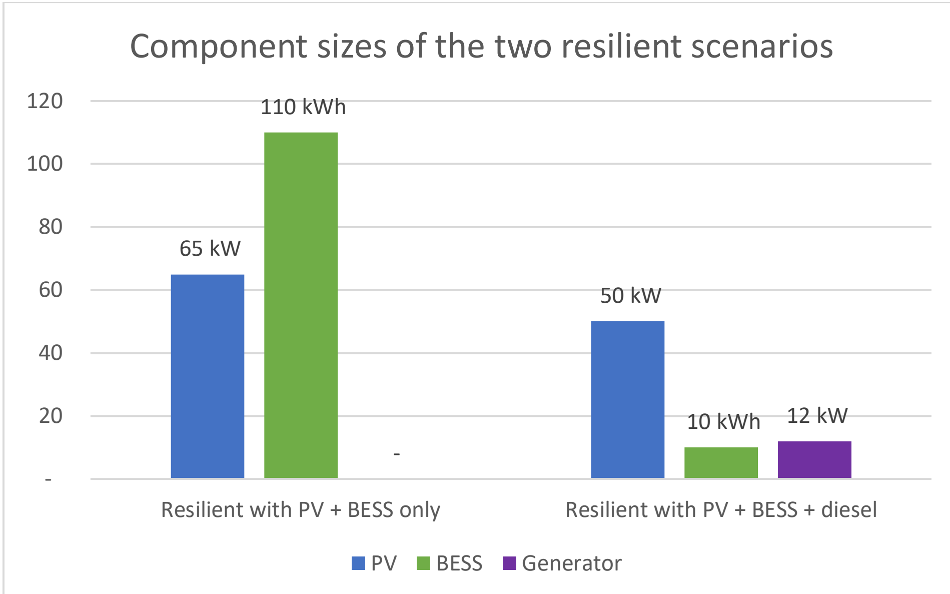


Figure 41. Component sizes of the two resilient scenarios of the commercial case.

The alternative to this is procuring a 12 kW diesel generator (Figure 44). Doing this provides the microgrid with a secondary backup source parallel to the PV + battery system, and allows them both to have a much less oversized capacity.

In other words, a 50 kW PV system paired with 10 kWh of storage and a 12 kW diesel generator is able to reliably supply 100 kWh of electricity per day, without the utility grid, for 87 continuous days *cheaper than* a 65 kW PV + 110 kWh battery system. This can be explained by looking at the load balance of both scenarios (with and without diesel), shown here in Figures 45, 46, 47 and 48.

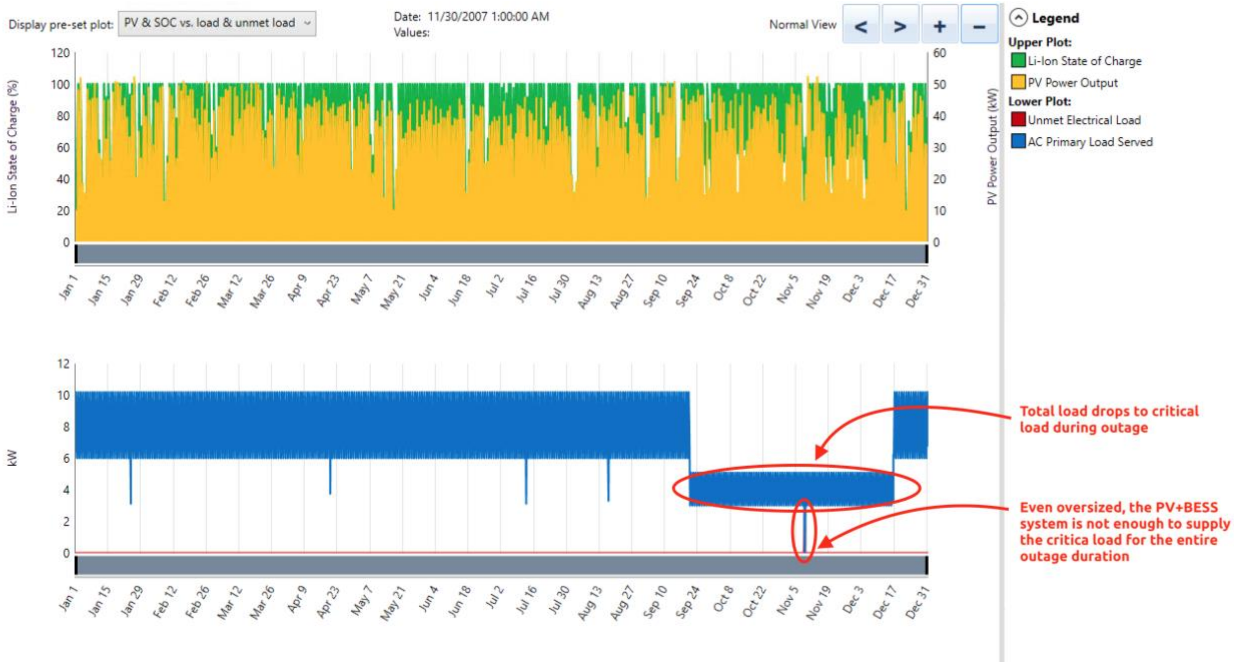


Figure 42. Time series plot of the resilient scenario without diesel backup.

Figure 45 shows a time series of solar output and the BESS' SoC in the upper plot, and the unmet electrical load on top of the total electrical load served in the lower plot. Even with an oversized PV system and battery backup, the microgrid is still unable to provide power to the critical loads for 87 continuous days. A closer look at the load balance shows how, without a backup generator, the BESS is the only source of power when the solar resource is unavailable:

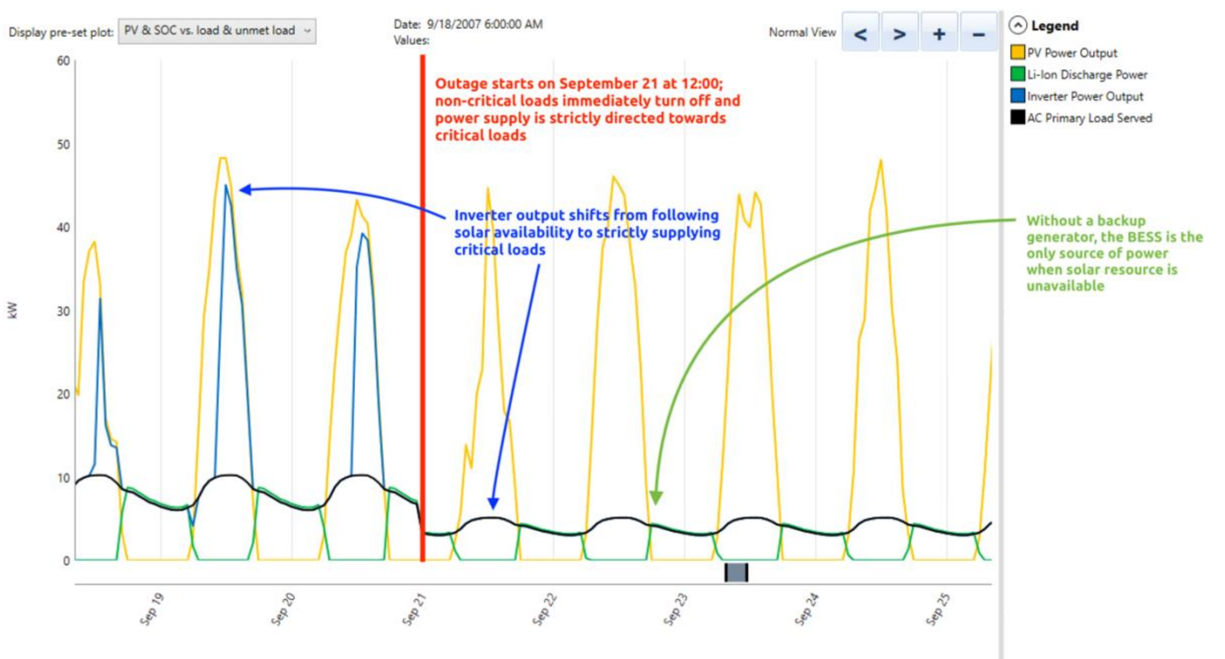


Figure 43. Load balance as soon as the 87-day outage starts. Without a backup generator, the BESS is the only source of power when the solar resource is unavailable.

In the scenario with a diesel generator, though, supplying power to the critical loads during an outage is much less constrained; the generator only turns on when the grid is unavailable, and its addition to the microgrid reduces any capacity shortages to zero (Figure 47):

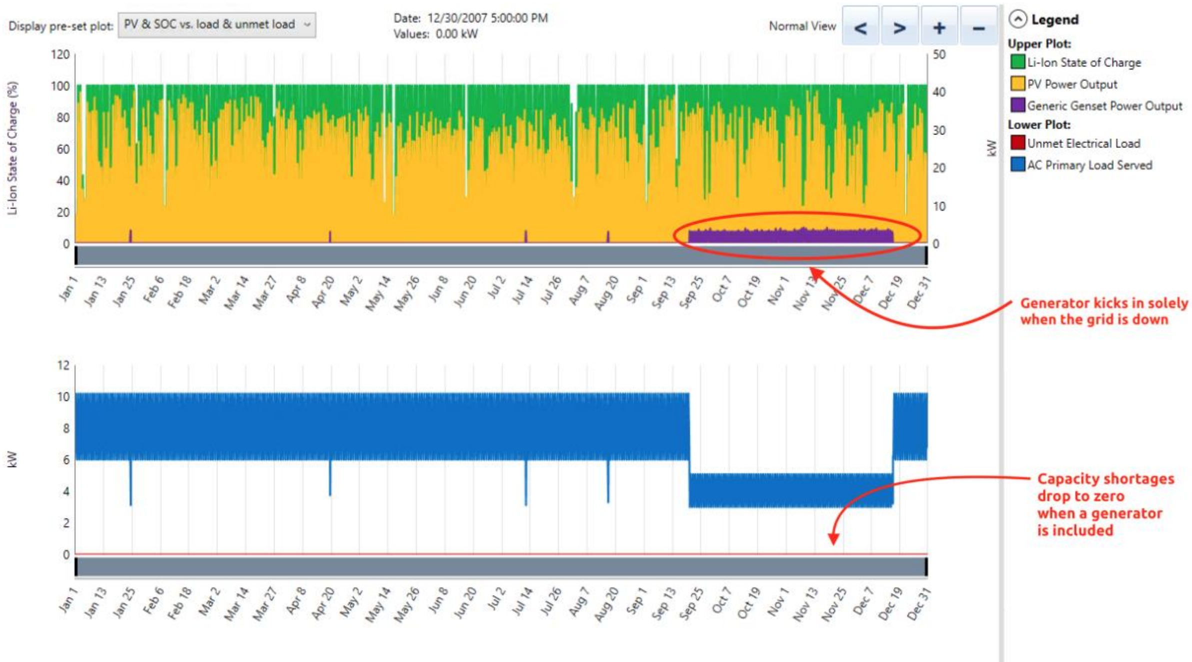


Figure 44. Time series plot of the resilient scenario with diesel backup.

The behavior of the microgrid at the moment the outage starts can be seen in Figure 48. Prior to the outage, the inverter makes as much use of the available solar generation to supply the full load, and exports any surplus generation to the grid. Then, the instant the grid goes down, the inverter "clips" solar production down until it's just enough to supply the critical loads and charge the BESS. When solar production is unavailable, the BESS and generator keep the critical loads fully met for the duration of the outage.

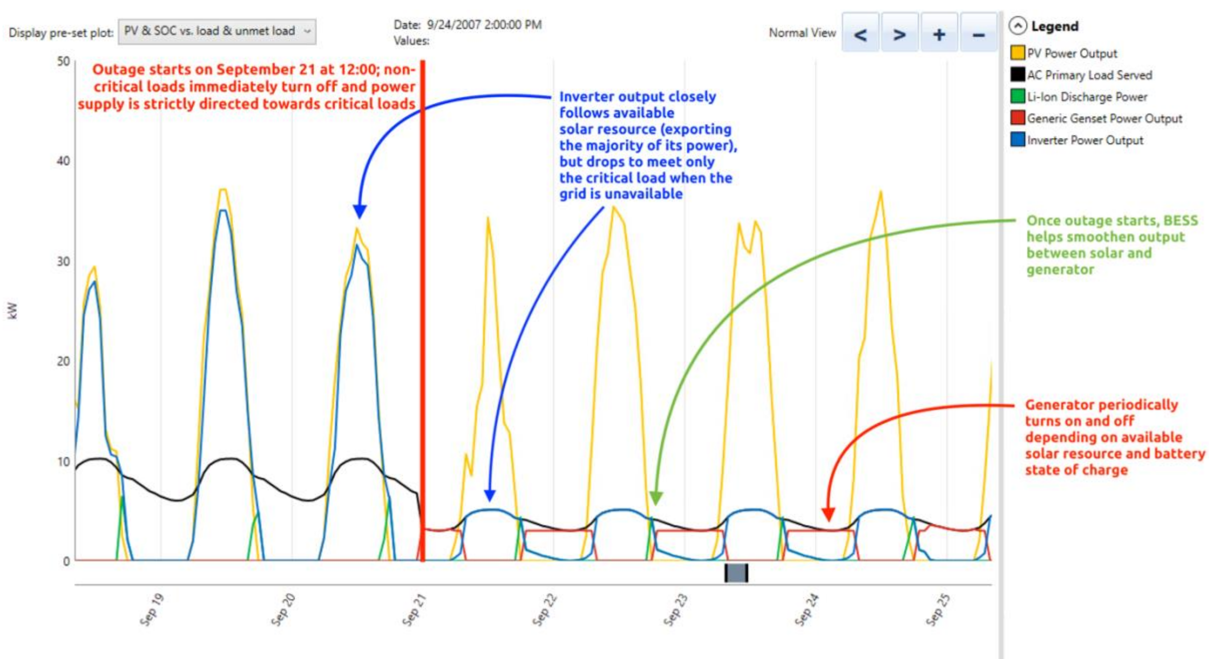
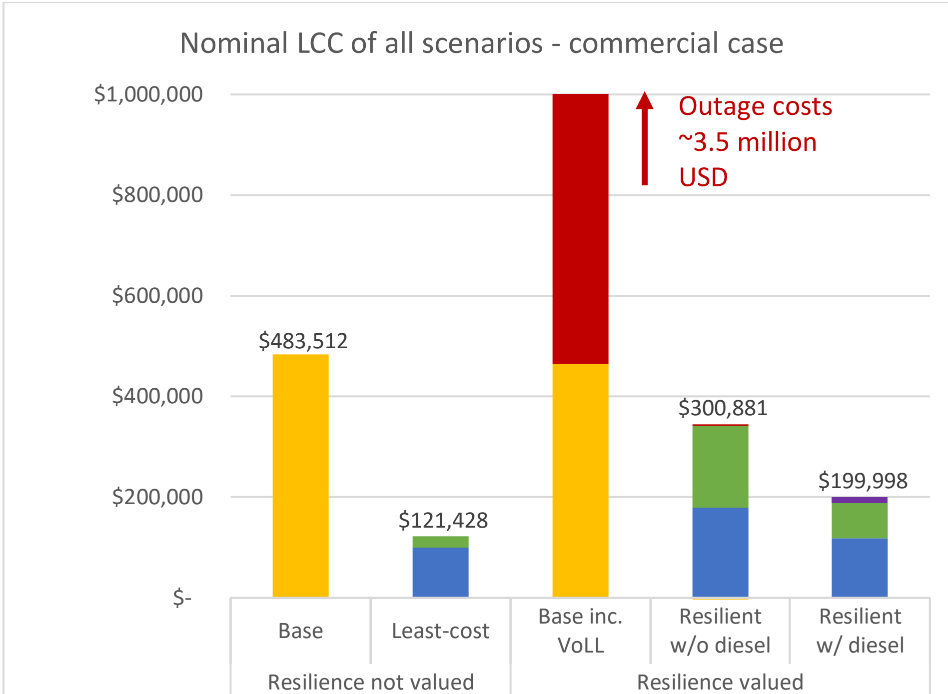


Figure 45. Load balance as soon as the 87-day outage starts. The backup generator and the battery system work in parallel to supply power to the critical loads.

A final consideration from this comparison between topologies with and without diesel is the amount of diesel required to make the generator run when its required. In the scenario of an 87-day outage, the necessary diesel is ~1,630 liters per year. Considering the entirety of that fuel is used only during the period the grid is unavailable (see the purple area in Figure 47), the daily fuel consumption can be reduced to approximately 20 liters per day. This value can be of use when estimating days of autonomy required, and any corresponding fuel storage infrastructure.

5.2.5 Comparison of all scenarios

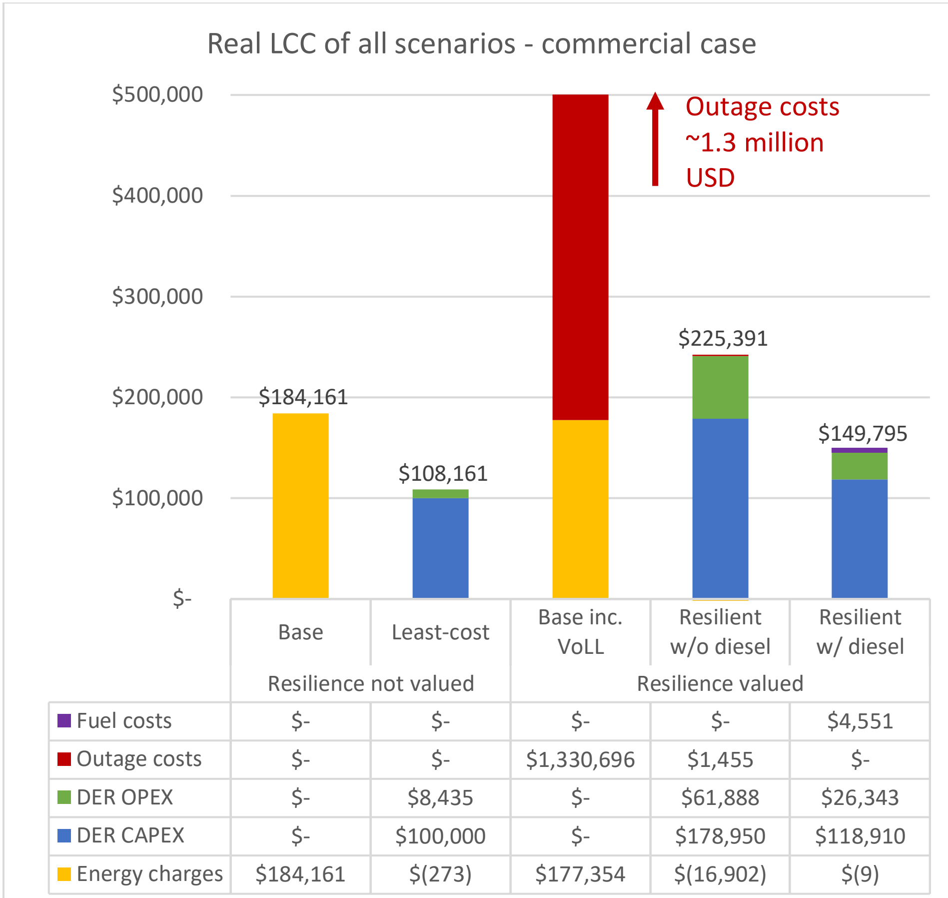


	Base	Least-cost	Base inc. VoLL	Resilient w/o diesel	Resilient w/ diesel
	Resilience not valued		Resilience valued		
Fuel costs	$-	$-	$-	$-	$11,950
Outage costs	$-	$-	$3,493,719	$3,820	$-
DER OPEX	$-	$22,145	$-	$162,487	$69,163
DER CAPEX	$-	$100,000	$-	$178,950	$118,910
Energy charges	$483,512	$(717)	$465,640	$(44,376)	$(24)

Figure 46. Nominal life cycle cost of all scenarios of the commercial case.

As previously mentioned, the ultimate goal of this study is to compare all of the aforementioned scenarios. This is facilitated by Figures 49 and 50. The former represents the nominal LCCs of all scenarios, while the latter represents their real (discounted) LCCs.

At first glance, the key takeaway from either graph is the disproportionate cost of outages expected in the base scenario that accounts for VoLL, even after weighting the likelihood of outages of different durations described before in Figure 42. These outage costs on their own (~3.5 million USD nominal, ~1.3 million USD discounted) outweigh the LCC of any other scenario, and are mainly the result of the probability of experiencing either seven-day or 87-day outages due to severe weather events.



	Base	Least-cost	Base inc. VoLL	Resilient w/o diesel	Resilient w/ diesel
Fuel costs	$-	$-	$-	$-	$4,551
Outage costs	$-	$-	$1,330,696	$1,455	$-
DER OPEX	$-	$8,435	$-	$61,888	$26,343
DER CAPEX	$-	$100,000	$-	$178,950	$118,910
Energy charges	$184,161	$(273)	$177,354	$(16,902)	$(9)

Figure 47. Real (discounted) life cycle costs of all scenarios of the commercial case.

The other comparisons to be made mainly come down to the decrease in LCC from the base to the least-cost scenario, when resilience is not valued. And when valuing resilience, either a microgrid with or without diesel represent a much less expensive scenario than the alternative of incurring in severe outage costs. That being said, the difference in LCC between a microgrid that relies solely on solar and storage and a microgrid that considers both plus diesel is still worth pointing out: adding a diesel genset to the mix reduces LCC by 30% both nominally and after applying discount rates.

5.2.5.1 Net present value

In terms of NPV, the least-cost scenario (a 50 kW PV system) represents a difference of 76,000 USD compared to the base scenario. By contrast, the NPV of the PV + BESS resilient scenario results in 1.28 million USD and the NPV of the PV + BESS + diesel resilient scenario is 1.36 million USD. If one last comparison could be made between the resilient scenarios, that would be the difference in LCC between both, resulting in an NPV of ~75,600 USD for the PV + BESS + diesel scenario over the PV + storage only scenario (Figure 51).

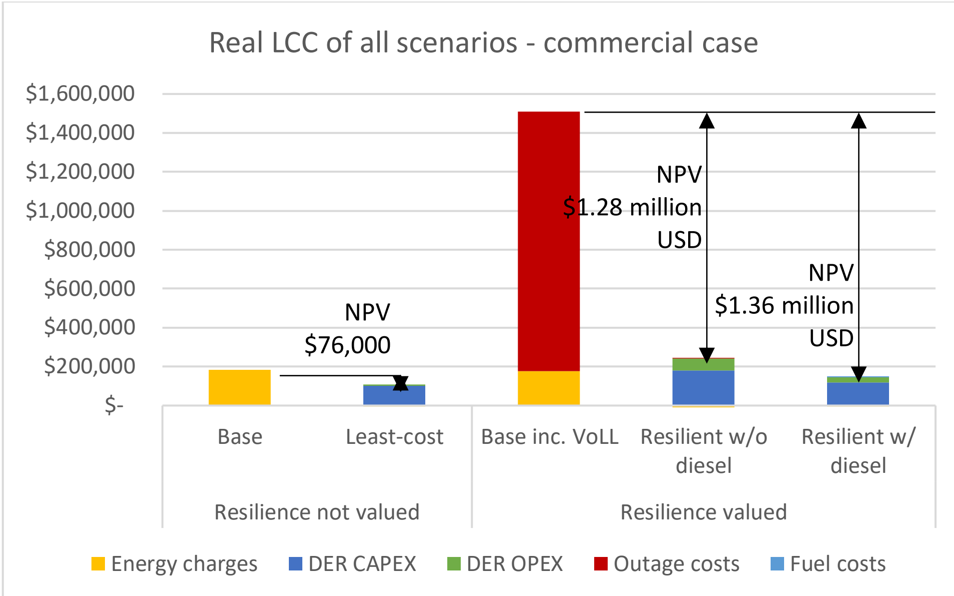


Figure 48. Net present values of the commercial case.

5.2.5.2 Return on investment

The return on investment of the least-cost scenario, as defined in Chapter 3, results in 12% when compared to the base scenario. In contrast, scenarios that value resilience see their return on investments skyrocket; a 68% ROI for the solar-and-storage-only scenario, and a whopping 105% ROI for the PV + storage + diesel backup scenario (the cash flows are available on Appendix 4). Again, t's important to point out that these values are not actual revenues that can be expected by deploying these solutions; the reason they're so high is because the alternative is much costlier.

5.2.5.3 Value of resilience

Equation 9 is summoned once more to assign a value to resilience. This time, the value depends on both the type of year modeled, and the resilient scenario in question, since the solar-and-storage-only scenario is not able to meet the critical load in its entirety when under an 87-day outage, while the solar+storage+diesel scenario is able to. In this way, the value of resilience is tabulated as follows:

Table 12. Value of resilience for different outage durations, commercial case.

Type of year	Probability [%]	Unmet load [kWh/year]			VoLL [USD/kWh]	**Value of resilience**
		Base	PV+BESS only	Difference		
Normal CAIDI	44%	40	0	40	$78.21	**$3,152**
1-week blackout	43%	783	0	783		**$61,238**

87-day blackout	12%	9,276	13	9,263		**$724,428**

Type of year	Probability [%]	Unmet load [kWh/year]			VoLL [USD/kWh]	**Value of resilience**
		Base	PV+BESS +diesel	Difference		
Normal CAIDI	44%	40	0	40	$78.21	**$3,152**
1-week blackout	43%	783	0	783		**$61,238**
87-day blackout	12%	9,276	0	9,276		**$725,476**

By applying each type of year's weight to its respective expected value of resilience, an average value of resilience can be obtained, equal to 116,367 USD per year for the solar-and-storage-only scenario, and 116,495 USD per year for the scenario that includes solar, storage, and diesel backup.

Spread throughout the 30-year planning horizon, this represents **a total nominal value of resilience of 3.5 million USD, or a real (discounted) value of resilience of 1.3 million USD** for the average commercial user.

Chapter 6: Sensitivity analysis

This chapter explores the impact of modifying several of the scenarios' inputs on their outputs. There are several reasons why sensitivity analyses are valuable to an energy resilience study. Firstly, the exact value of assumed variables (e.g., cost of solar, utility rates, outage length) might be one within a spectrum of values, or it might change over time (particularly for the cost of PV and BESS). A sensitivity analysis helps make sense of the different outcomes that can result out of a particular combination of variables.

Secondly, by specifying a range of values for a variable (e.g., a cost per watt of solar that ranges from 1 to 3 USD/W), a sensitivity study can help determine how important that specific variable is, and how the solution fluctuates depending on its value. In other words, it helps determine how "sensitive" the outputs are to a given input.

Thirdly, a sensitivity analysis helps make one study replicable to more than one particular case. E.g., if two office buildings have a similar load curve and the same utility rate, but one has twice as many occupants as the other, it might be useful to model one single study where the sensitivity variable is the annual energy consumption multiplied by factor of one for the smaller building and by a factor of two for the larger building, then a single analysis is sufficient to design both microgrid systems. The result is two separate studies within a single analysis.

The sensitivity variables chosen for this study are shown in the table below. The proposed variables are each multiplied by factors ranging from 0.50 to 1.50, at intervals of 0.10. Sensitivity analyses were performed for the resilient residential case, and the resilient commercial case with solar, storage, and diesel backup.

Table 13. Sensitivity variables for the resilient residential case. Values in blue are the ones described in Chapter 4 and used to calculate the results in Chapter 5.

Multiplier	Cost of PV [USD/W]	Cost of BESS [USD/kWh]	VoLL [USD/kWh]	Average load [kWh/day]	Discount rate [%]
0.5	1.00	223	1.32	6.68	5%
0.6	1.20	267	1.58	8.02	6%
0.7	1.40	312	1.84	9.35	7%
0.8	1.60	356	2.10	10.69	8%
0.9	1.80	401	2.37	12.02	9%
1	**2.00**	**445**	**2.63**	**13.36**	**10%**
1.1	2.20	490	2.89	14.70	11%
1.2	2.40	534	3.16	16.03	12%
1.3	2.60	579	3.42	17.37	13%
1.4	2.80	623	3.68	18.70	14%
1.5	3.00	668	3.95	20.04	15%

Table 14. Sensitivity variables for the resilient commercial case. Values in blue are the ones described in Chapter 4 and used to calculate the results in Chapter 5.

Multiplier	Cost of PV [USD/W]	Cost of BESS [USD/kWh]	VoLL [USD/kWh]	Average load [kWh/day]	Discount rate [%]
0.5	1.00	223	39.11	96	5%
0.6	1.20	267	46.93	116	6%
0.7	1.40	312	54.75	135	7%
0.8	1.60	356	62.57	154	8%
0.9	1.80	401	70.39	174	9%
1	**2.00**	**445**	**78.21**	**193**	**10%**
1.1	2.20	490	86.03	212	11%
1.2	2.40	534	93.85	232	12%
1.3	2.60	579	101.67	251	13%
1.4	2.80	623	109.49	270	14%
1.5	3.00	668	117.32	289	15%

The outputs considered in the sensitivity analyses are:

- Net present cost[3]
- Optimal size of PV
- Optimal size of storage
- Optimal unmet load
- Optimal outage cost
- Optimal fuel cost (for the commercial case)

6.1 Sensitivity analyses of the residential case

This section contains a scatter graph for each output analyzed. Tables for each sensitivity analysis can be found on Appendix 5.

[3] One small caveat of the sensitivity analysis is that it assumes the NPCs of the resilient scenarios as if they experienced the longest-expected outage of 87-days on a yearly basis. I.e., these NPCs are not adjusted for the probability of hurricanes of different magnitudes. For the residential case, this means an NPC of 13,600 USD instead of ~12,300 USD due to slightly greater outage costs. For the commercial case, an NPC of ~171,000 USD instead of ~150,000 USD due to slightly greater fuel costs.

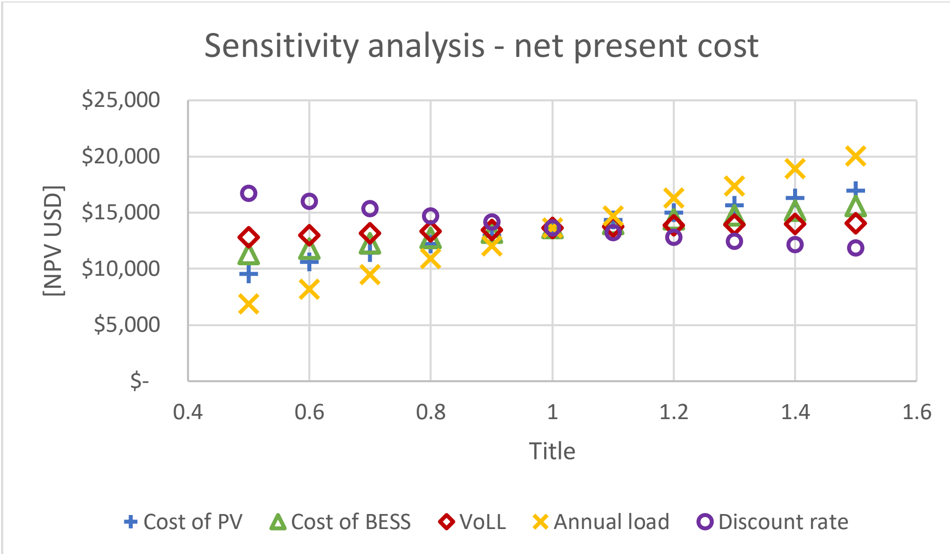


Figure 49. Residential sensitivity analysis - net present cost.

Net present cost appears to have a near-linear correlation with average annual load. This makes sense, considering a lower load requires less investment and less operating expenses, while a higher load will require more of both. An opposite correlation can be found in the discount rate; the lower it is, the higher value will be placed on future expenditures, which will in turn increase NPC. On the other hand, increasing the discount rate allocates less value to future cash flows, thus decreasing NPC. Lastly, changes in VoLL, cost of PV and cost of BESS have lower, but still lightly noticeable impacts on total net present cost.

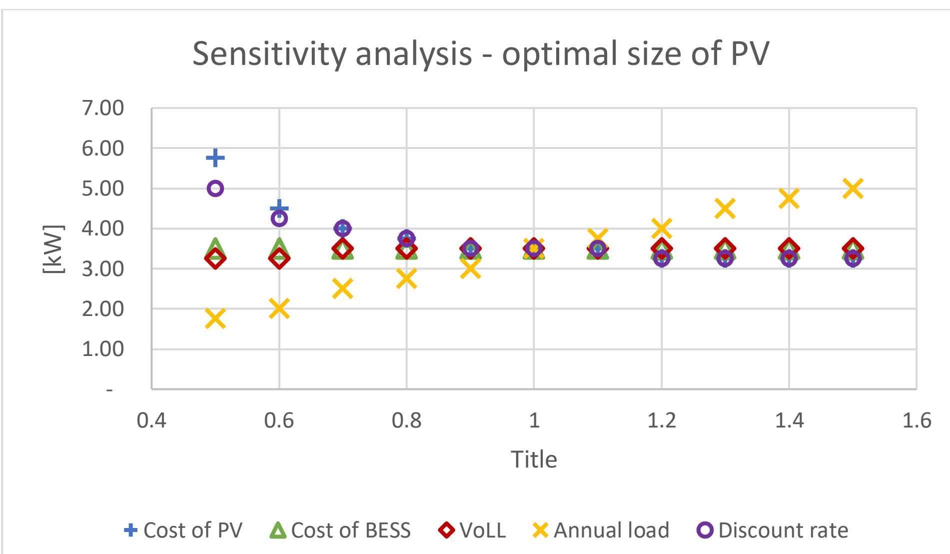


Figure 50. Residential sensitivity analysis - optimal size of PV.

The influence the cost per watt of solar on the optimal size to be installed is more notorious on the lower range; the cheaper solar gets, the more sense it makes to install more of it. However, when the cost per watt starts to increase beyond its original value of 2.00 USD/W, it stays fixed within the 3.50 to 3.25 kW range. The discount rate has nearly the same influence. The annual load, conversely, has a direct positive correlation on the optimal size of solar; the lower the load, the less solar required. The higher the load, the more solar will be needed to supply it.

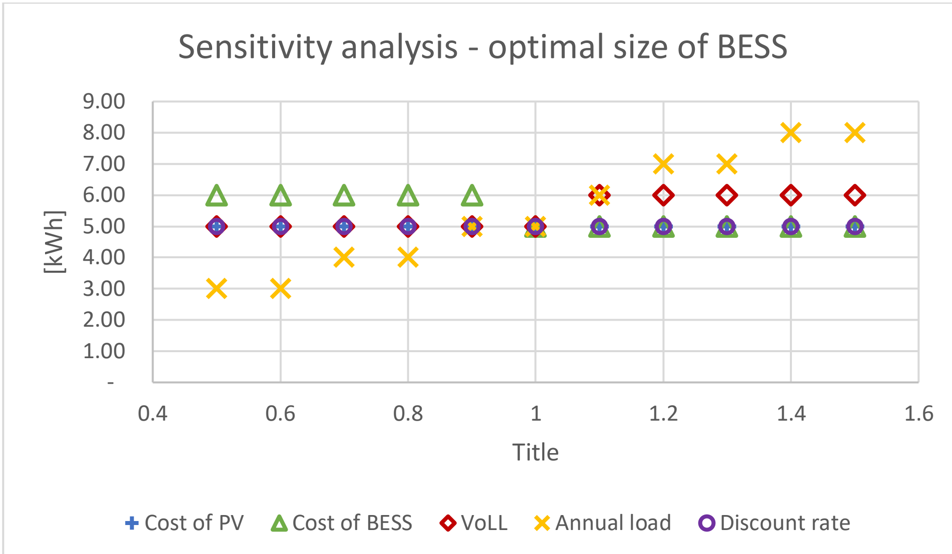


Figure 51. Residential sensitivity analysis - optimal size of BESS.

Variables having no influence on the optimal size of the BESS are the cost of solar and the discount rate. The cost of the BESS itself has a slight influence that increases the case of installing one extra kWh of storage if the cost is below its original value, and the VoLL has the opposite effect: if it increases just above its original value, the optimal size of storage increases by one extra kWh. Ultimately, the variable that has the largest influence over the optimal size of storage is the total annual load.

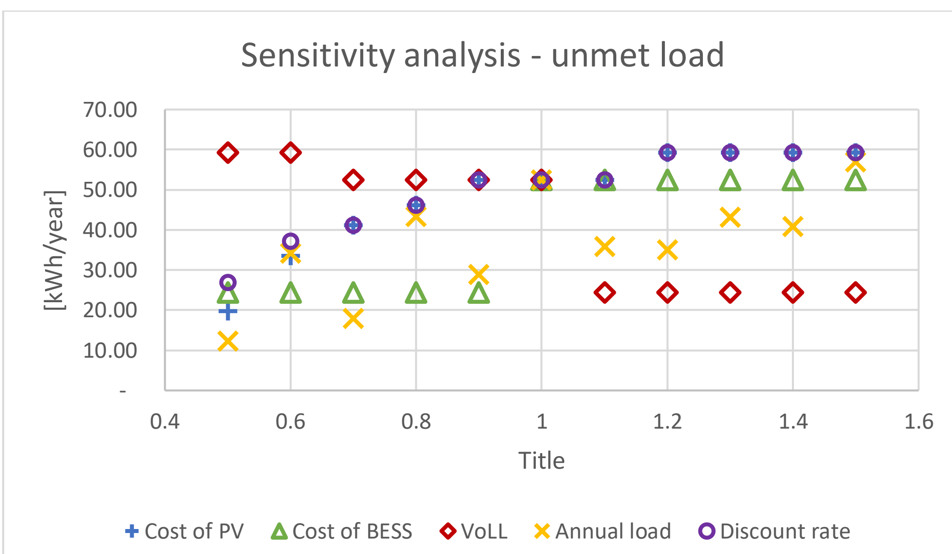


Figure 52. Residential sensitivity analysis - unmet load.

The yearly unmet load appears to be sensitive to all variables, but only after the cross their original threshold. When the cost of solar is below its original value, the unmet load tends to decrease along with it, but after the cost of solar passes its original value and starts to increase, the unmet load remains unchanged. The discount rate appears to have a similar effect, as does the cost of storage, although the latter's correlation appears to take the form of a step function rather than a linear trend. The same occurs with the VoLL, but in the opposite direction.

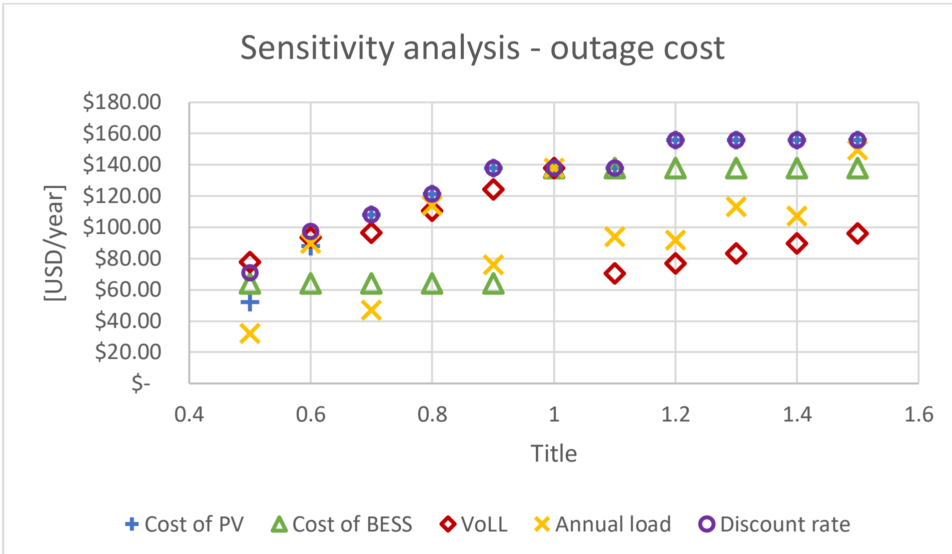


Figure 53. Residential sensitivity analysis - outage cost.

Lastly, the outage cost goes hand in hand with the unmet load. The influence of the cost of storage over the outage cost takes the form of a step function, crossing at the original value of 445 USD/kWh. The VoLL also has a step function-like influence, but with an upward slope; this is because the outage cost is directly proportional to the VoLL.

6.2 Sensitivity analyses of the commercial case

This section contains a scatter graph for each output analyzed. Tables for each sensitivity analysis can be found on Appendix 6.

All sensitivity analyses done on the commercial case have one thing in common: all outputs are impervious to changes in the value of lost load, because no scenario considers a single lost kWh of load. The cost associated with not meeting the load is onerously high on the objective function, resulting in all scenarios meeting the load at all times, without exception.

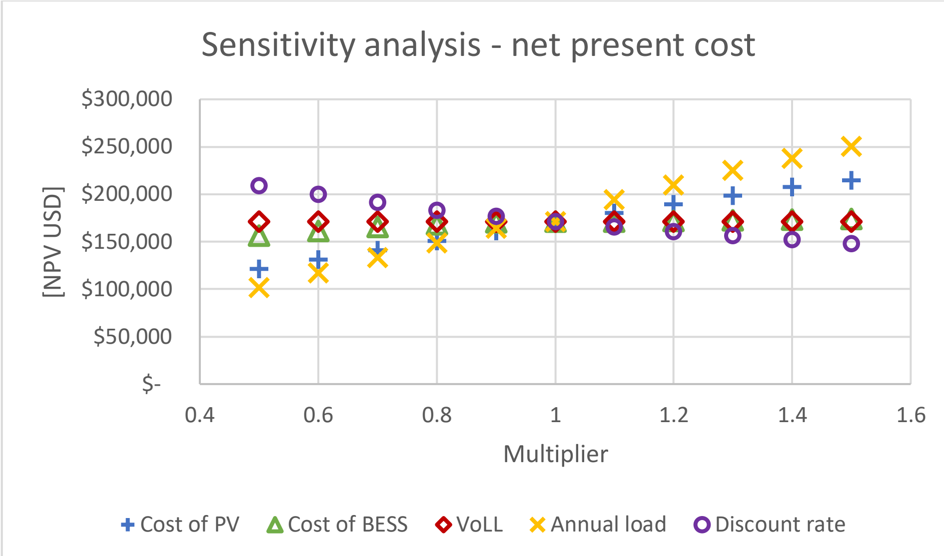


Figure 54. Commercial sensitivity analysis - net present cost.

Four sensitivity variables have linear, direct influences over the net present cost, but with different slopes: the NPC is positively correlated to the cost of PV, cost of BESS and average annual load. Conversely, its negatively correlated to the discount rate.

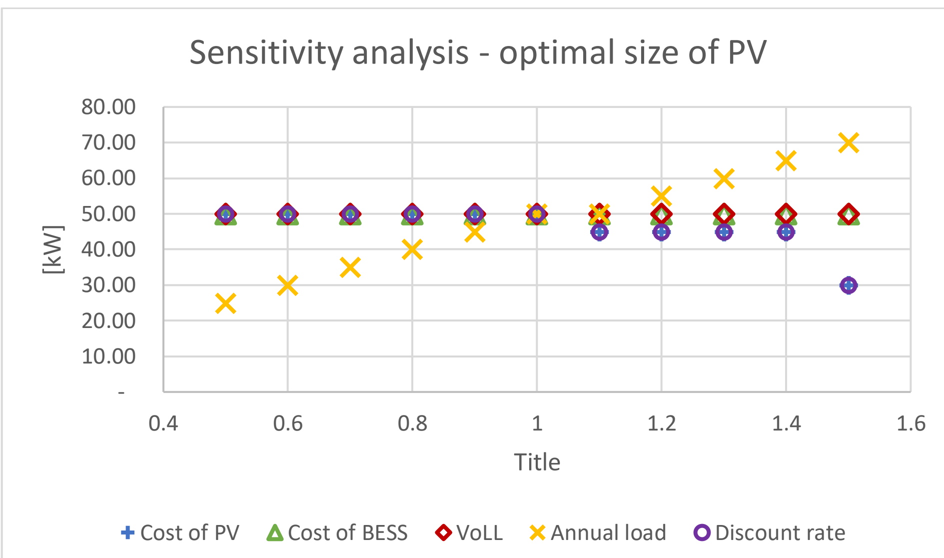


Figure 55. Commercial sensitivity analysis - optimal size of PV.

The optimal size of PV appears to be near impervious to its cost per watt, decreasing just slightly after it cost increases past its original value. Then, at the higher end of 3 USD/W, it significantly drops to an optimal value of 30 kW of PV. The discount rate has the exact same effect, while the average annual load shows a positive correlation.

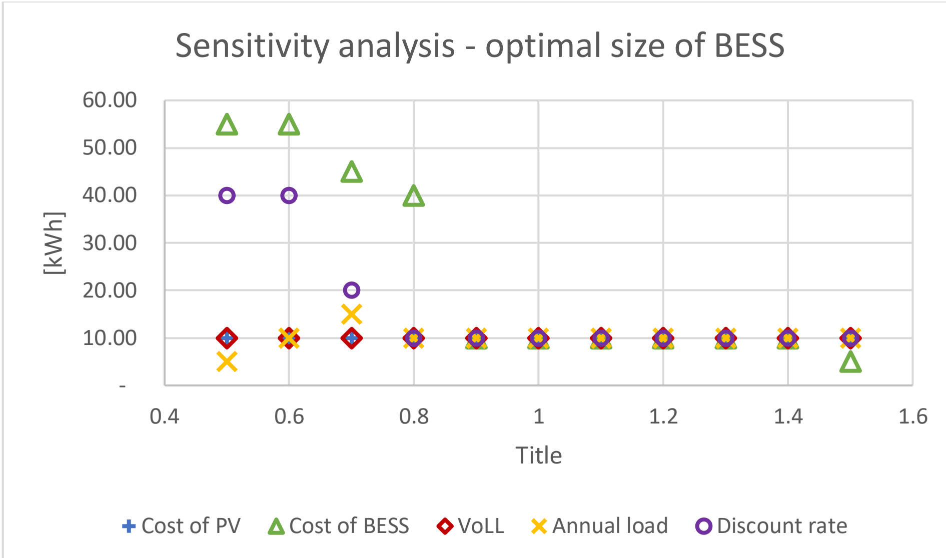


Figure 56. Commercial sensitivity analysis - optimal size of BESS.

The variable that has the largest influence over the optimal size of storage is its own cost; if its cost per kWh drops below 90% of its original value, the optimal size of storage increases to 40 kWh, or 45 if its 70% of its original value. If, however, the cost drops below 70%, the optimal storage size rises to 55 kWh. A similar, but less significant correlation is found with the discount rate. Lastly, the other sensitivity variables have nearly zero influence over this output.

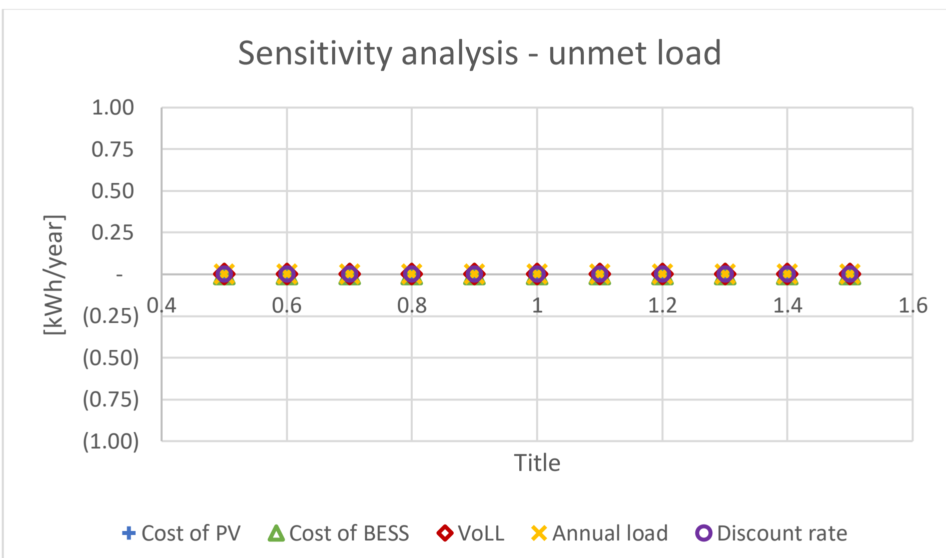


Figure 57. Commercial sensitivity analysis - unmet load.

As mentioned before, no scenario considers any unmet load, which is why no sensitivity variable has any influence over it.

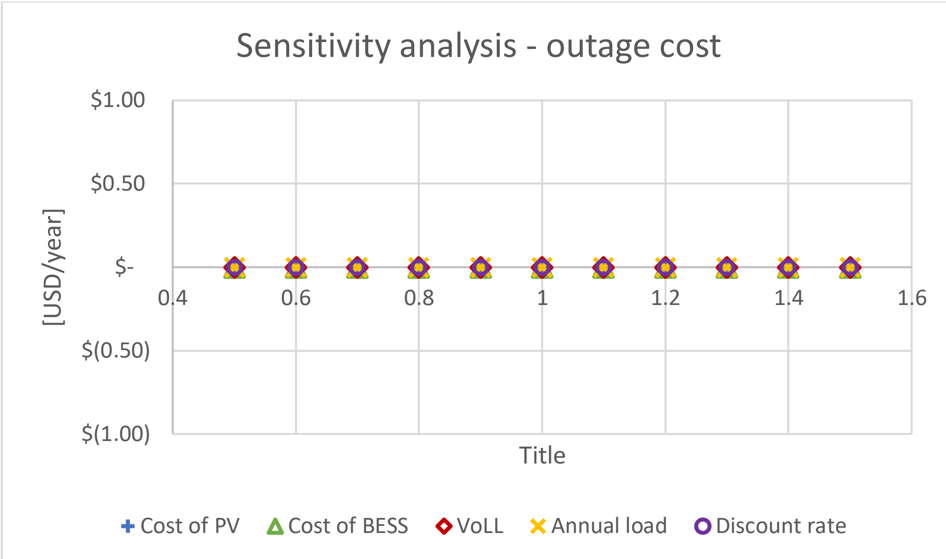


Figure 58. Commercial sensitivity analysis - outage cost.

This also applies to the outage cost: there are no outage costs considered, since adding the VoLL to the objective function results in all scenarios meeting the load at all times.

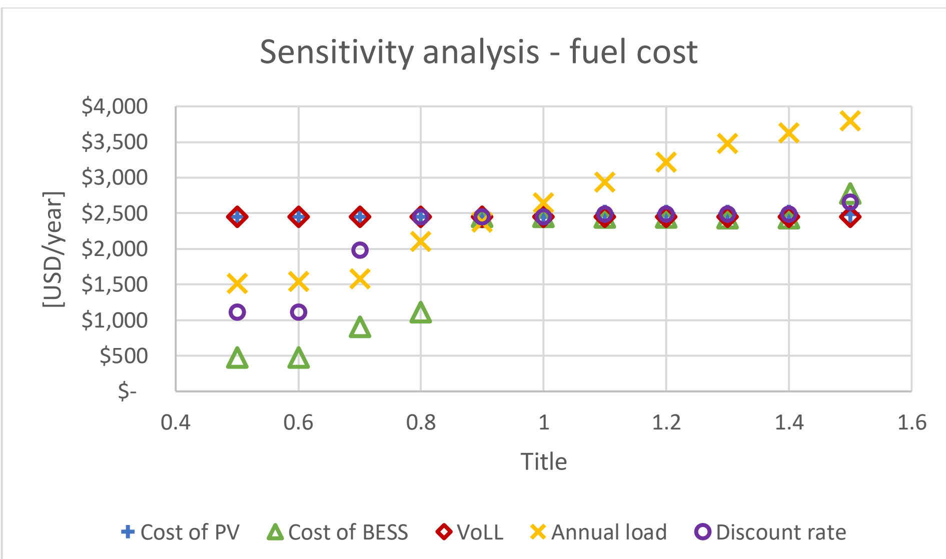


Figure 59. Commercial sensitivity analysis - fuel cost.

One key variable that shows influence on the fuel cost is the cost of storage. In the lower range, its more economical to procure more battery storage than to rely on diesel fuel (although the reliance on diesel never entirely disappears). The discount rate also shows a similar influence. After all of these increase past their original value, however, the cost of fuel remains fairly constant. The sole exception to this is the average annual load.

6.3 Conclusions on sensitivity analyses

It's interesting how some sensitivity variables hold an influence over some outputs, but not over others. The average annual load is perhaps the most consistent of all: nearly all outputs are aligned with its decrease or increase. The cost of solar, on the other hand, has a strong influence over its own optimal size in the residential case as long as its lower than its original value. The cost of storage has less of an influence on its own optimal size, while outage costs naturally increase if the VoLL does.

On the commercial case, however, the VoLL stands out by having absolutely no influence over any output variable. This implies that the VoLL is already high enough as it is, which raises an interesting question: how low does the VoLL have to be in order to change the life cycle cost of the resilient scenario? In other words,

> How low does the VoLL have to be so that it makes more economic sense to suffer an outage than to invest in preventing one?

While beyond the scope of this study, it's an interesting question that should be addressed in future research.

Chapter 7: Discussion

Chapter 2 offered a literature review on energy resilience, islands, estimation of outage costs, and Puerto Rico's experience under Hurricane Maria. Chapter 3 then merged a reframed a methodology first used by [12] with the Resiliency Analysis Process of [28] to compare different scenarios of DER deployment & severe weather events, as well as its accompanying costs. Chapter 4 described the model used to compare those scenarios, and Chapter 5 & 6 discussed the results and how they change if the inputs do.

Now that the results and sensitivity analysis have been shown, a short discussion to frame them into context is in order.

7.1 Model limitations

It is important to first mention the model's shortcomings. It assumes that energy demand for each load profile remains constant over the 30-year planning horizon, which Puerto Rico's Integrated Resource Planning expects will not be the case. In fact, it expects energy demand will decrease by 35% within the next 20 years solely because of energy efficiency measures taken by homeowners and businesses [15]. This measures can be expected to have contrasting effects on the sizing of a resilient microgrid:

- Consuming less energy typically leads to requiring a smaller PV (and BESS) system, which would in turn reduce microgrid sizes and costs
- On the other hand, it can be argued that requiring less energy to perform the same tasks places a greater value on each kWh of unmet load, i.e., with greater efficiency the VOLL might increase, leading to a greater incentive to procure a resilience-oriented microgrid

Furthermore, while the PV systems considered in the model do account for the 5% cost premium that Rocky Mountain Institute reports to be needed to make them robust enough to endure winds of up to 175 mph [51], **this study does not model the cost impacts of having to replace PV systems due to hurricane damage**, not to mention damages to building infrastructure because of flooding, debris, or other natural disasters like hurricanes or droughts.

Lastly, noticeable modeling differences were found between REopt and HOMER. On the one hand, REopt provides modeling transparency by making public all of its parameters, variables and equations, but its online version used in this study is not able to estimate outage costs and perform sensitivity analysis, which is why HOMER is ultimately prioritized. Both optimization tools differ particularly when it comes to modeling battery systems; REopt calculates a battery's capacity and power rating separately, while HOMER focuses solely on the battery's capacity and assumes an accompanying power rating. This heavily influences the results suggested by each platform.

7.2 Validating the value of lost load

Puerto Rico's Integrated Resource Planning (IRP) provides its own VoLL for its different user segments, using two different approaches [15]. Its first approach is based on comparing Puerto Rico's electricity market against several electricity markets from different countries (e.g., the U.S. Southwest and MISO markets, as well as Austria, New Zealand, Victoria, Australia, and the Republic of Ireland) whose VoLL's are already known. From this, they correlate Puerto Rico's economic, demographic, and electricity metrics with the metrics from the aforementioned markets to estimate Puerto Rico's VoLL.

Their second approach is the same one used in this study: LBNL's Interruption Cost Estimate database. One key disparity from this study, however, is that the IRP uses different parameters than the ones assumed in this report, thus resulting in different VoLL, shown below:

Table 15. Differences in value of lost load estimated in this study and in Puerto Rico's IRP.

	Estimated VoLL [USD/kWh]		
	This study	IRP's first approach	IRP's second approach
Residential	**2.63**	12.27	4.04
Commercial	**78.21**	84.05	219.24
Industrial	**95.94**	33.40	57.49

While there is no way to accurately compare this study's VoLL's with the IRP's VoLL's from their first approach, they can be compared with their second approach. One key difference is the assumed CAIDI value: 178 minutes/event-customer according to the IRP, but 960 minutes/event-customer in this study (see Table 3 in Chapter 3). Additionally, the IRP assumes an average household income of 27,000 USD, while this study relies on the 20,166 USD income reported by the U.S. Census Bureau [39].

Regardless of whether the IRP's values or the ones used in this study are the right ones, the value of resilience could simply be recalculated with updated VoLL's. **Assuming the same microgrids proposed in Chapter 5 and everything else being equal, if resilience where to be assigned a value based on the VoLL's proposed by Puerto Rico's IRP, the value of resilience for residential users would increase by 54%, and by 180% for commercial users**.

7.3 The benefits of including diesel generators in a microgrid

Advocates of 100% renewable generation are quick to disregard diesel generators as "unnecessary relics" of a bygone era. On the other hand, people unfamiliar with modern DERs like PV and battery storage think of generators as the only alternative when the grid is unavailable. This study takes a pragmatic approach to diesel generators, and recognizes them as valuable components of a resilient microgrid. While expensive in terms of LCOE (the marginal generation cost of a diesel genset is 0.35 USD/kWh, in the single scenario that considers one), the price of accounting for this extra energy source (roughly 14,500 USD) is much less than the cost of oversizing PV+BESS microgrid to the point where it can singlehandedly supply power at all times the grid is expected to be unavailable (roughly 60,000 USD).

7.4 Considerations for stakeholders and decision makers involved in Puerto Rico's energy infrastructure

What if every residential and commercial user in Puerto Rico[4] decided to install microgrids like the ones described in the resilient scenarios? Ignoring the fact that there would be a crippling abundance of PV generation during the day and its accompanying curtailment (like California is already being forced to regularly manage [65] [66]), and one critical fact that allows these microgrids to be so economical is the existence of net metering (which, if allowed to expand rampantly, can lead into the infamous utility death spiral [67]), an interesting thought experiment would be to compare the necessary investment and tentative savings of converting all of Puerto Rico's users to resilient microgrids en masse.

Table 16. Theoretical extrapolation of research findings to every residential and commercial user in Puerto Rico.

Without resilience valued					
User segment	Number of users	CAPEX [USD/user]	Total CAPEX [USD/user segment]	Savings relative to base scenario [USD/user]	Total savings [NPV USD/user segment]
Residential	1,335,643	$9,225	$12,321,306,675	($307)	($410,042,401)
Small C&I	116,094	$118,910	$13,804,737,540	$34,366	$3,989,686,404
Total investment needed			**$22,708,138,035**	**Total savings**	**$3,579,644,003**

With resilience valued					
User segment	Number of users	CAPEX [USD/user]	Total CAPEX [USD/user segment]	Savings relative to base scenario [USD/user]	Total savings [NPV USD/user segment]
Residential	1,335,643	$9,225	$12,321,306,675	$2,395	$3,198,864,985
Small C&I	116,094	$118,910	$13,804,737,540	$1,358,255	$157,685,255,970
Total investment needed			**$22,708,138,035**	**Total savings**	**$160,884,120,955**

The theoretical total investment (without considering curtailment, grid modifications, and the eroding effects of everyone relying on net metering) is in the order of 22.7 billion USD, and would result in a net cost of 19.1 billion USD before valuing resilience. When valuing resilience, however, this results in net savings of 138 billion USD (for comparison, this is 38% higher than Puerto Rico's gross domestic product). While this number might seem exorbitant, it is not out of the realm of possibility; this theoretical investment is ~30% higher than the one suggested by the Puerto Rico Energy Resilience Working Group in their 2017 report following hurricane Maria [10] (the Group estimated a total of 17.6 billion USD were needed to rebuild the grid to 21st century standards,

[4] Medium and large commercial and industrial were not considered within this calculation.

most of it going to T&D overhead lines), but, most importantly, it would result in theoretical savings in the order of ~130 billion USD.

7.5 Why not fortify the grid instead of investing in DERs?

Much has been discussed about whether fortifying the grid or prioritizing distributed resources better serves energy resilience. As explained in Chapter 2, hurricanes are the most disruptive threat power grids face, particularly in islands, and most particularly in Puerto Rico [6]. A recurring suggestion whenever a weather-related blackout occurs is to bury overhead power lines in the ground so they can be protected from strong wind and debris. While this is certainly possible in theory, it is overly laborious and prohibitively expensive, as the Edison Electric Institute showed in 2013 [68]:

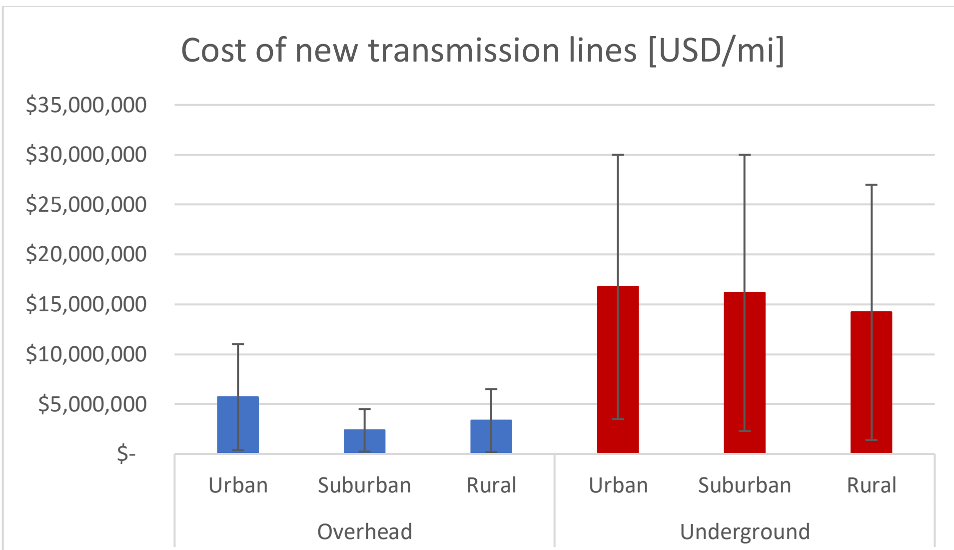


Figure 60. Cost of new overhead and underground transmission lines [68].

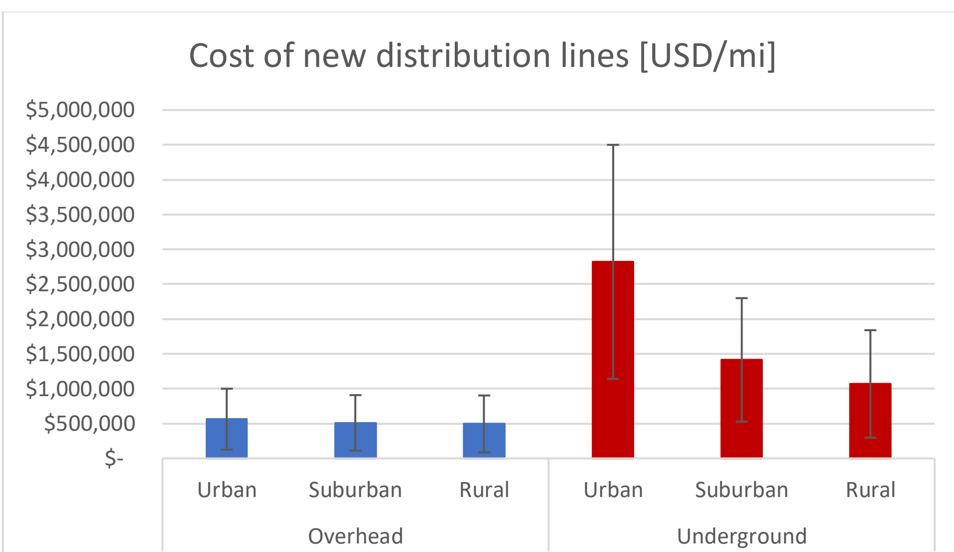


Figure 61. Cost of new overhead and underground distribution lines [56].

Given that Puerto Rico's transmission network consists of 2,478 miles of lines and its distribution network encompasses more than 30,000 miles of lines [10], converting the whole grid from an overhead topology to an underground one is likely one of the most expensive alternatives to provide energy resilience. Even assuming the lower-end costs of burying 10% of the Puerto Rican T&D lines shown in the previous two graphs would require an investment of well over 1.2 billion USD, a cost that would likely be passed on to ratepayers who already have to pay overly expensive rates. Furthermore, burying power lines does not protect them from flooding and storm surges, two other risks that Puerto Rico is already accustomed to, and has been found to disrupt underground power lines under hurricane exposure [69]. On the other hand, this does not take into account the increased cost in line maintenance, repairs, and higher probability of longer outages that accompany underground lines [70]. Finally, this alternative would not do much to reduce utility rates, which attribute its high costs to the bunker fuel PREPA mostly relies on to generate electricity [15].

7.6 Other approaches to energy resilience

A recurring fallacy around grid operators and decision makers is that securing the supply of fuel to power plants will ensure the grid's reliability. However, it has been shown that of all the major power disruptions in Puerto Rico and the U.S. as a whole since 2012, only 0.00007% of them were due to fuel supply issues. The vast majority were the result of severe weather events disrupting the T&D system, not the generation system itself [71]. Overall, securing fuel supplies for fossil generators can mitigate fuel supply chain risks, but does nothing to address the actual causes of power outages:

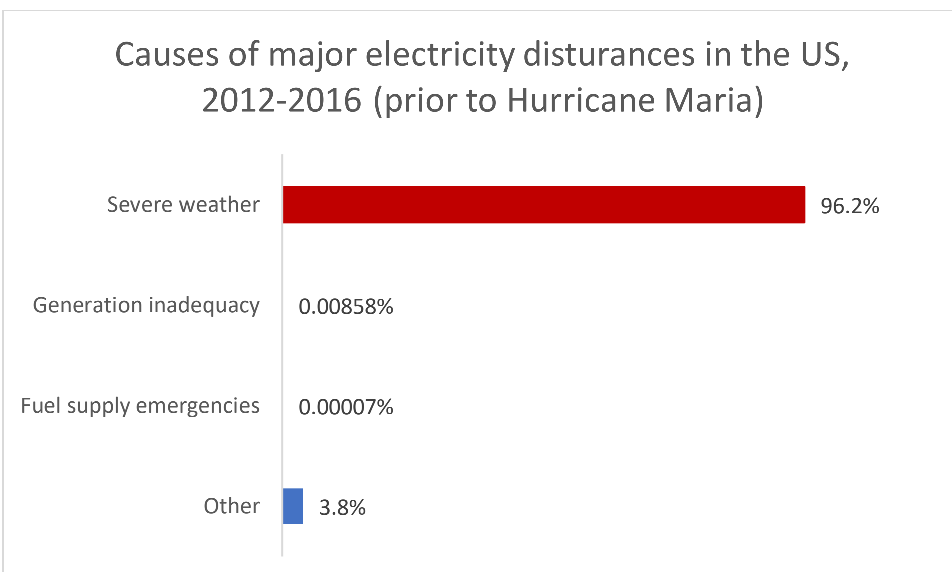


Figure 62. Causes of major electricity disturbances in the U.S., 2012-2016 [71].

Similarly, increasing generation reserve margins does not prevent against issues at the transmission or distribution level, where most disturbances tend to occur. Following the supply chain downstream, transmission and distribution system hardening is, then, an option but an overly expensive one, as explained in the previous section. This leaves distributed generation, particularly generation at or near the point of consumption, as the most effective solution to ensure energy resilience [1].

7.7 Comparison with grid restoration investments of 2017

As mentioned in Chapter 1, the total cost of Hurricane Maria was estimated to be $90 billion, according to NOAA [5]. Out of this total, Moody's Analytics estimates that as much as $25 billion can be attributed to economic output lost due to impassable roads and lost power [72]. The estimates of how much money the grid restoration process of 2017 and 2018 costed are nebulous, with PREPA claiming it was $2 billion, while the DOE has $3.2 billion written down on its books as expenses and disbursements going to FEMA (the Federal Emergency Management Agency) and the U.S. Army Corps of Engineers; both of whom were in charge of most of the restoration process. While these numbers are much lower than the total cost of the hurricane, it is clear much more investment is needed in order to properly fortify Puerto Rico's energy infrastructure to prevent further economic losses due to outages.

7.8 The long tail of power restoration

It's important to point out that the island's electrification rate **did not** reach 100% on day 196 after landfall (the date this report assumes the cases studied saw power restored). The government of Puerto Rico reported that it wasn't until day 328 that the last neighborhood saw power being restored [7]. However, the data from the Department of Energy stopped being recorded on day 196, when the electrification rate reached 96%. This implies that it took 132 days, a full 40% of the total outage duration, to restore power to the last 4% of the Puerto Rican users:

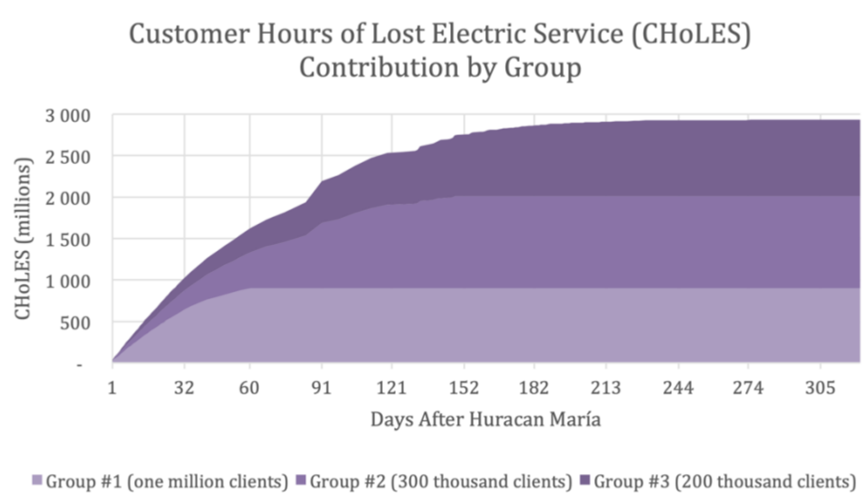


Figure 63. Customer-hours of lost electric service (CHoLES) contribution by group [9].

Ultimately, this "long tail" of users, those who had to wait the longest to see their lights back on after the hurricane, should be prioritized when planning microgrid deployments throughout

Puerto Rico. In 2008, a research group at the University of Puerto Rico Mayagüez estimated that installing PV on two thirds of all residential roofs on the island would be enough to meet the total daytime peak demand, about 3 GW, for the entire island [73]. As Castro-Sitiriche has proposed [74], the 200,000 households that were the last to be reconnected to the grid following Hurricane Maria are the ones to whom PV would be the most valuable.

7.9 Increasing magnitude and frequency of hurricanes

As mentioned in Chapter 3, archived data from NOAA shows that Puerto Rico is affected brushed or hit by a tropical storm or hurricane every 3.4 years, and is directly struck by one once ever 12.3 years [40]. This frequency is represented by the following figure, also by NOAA:

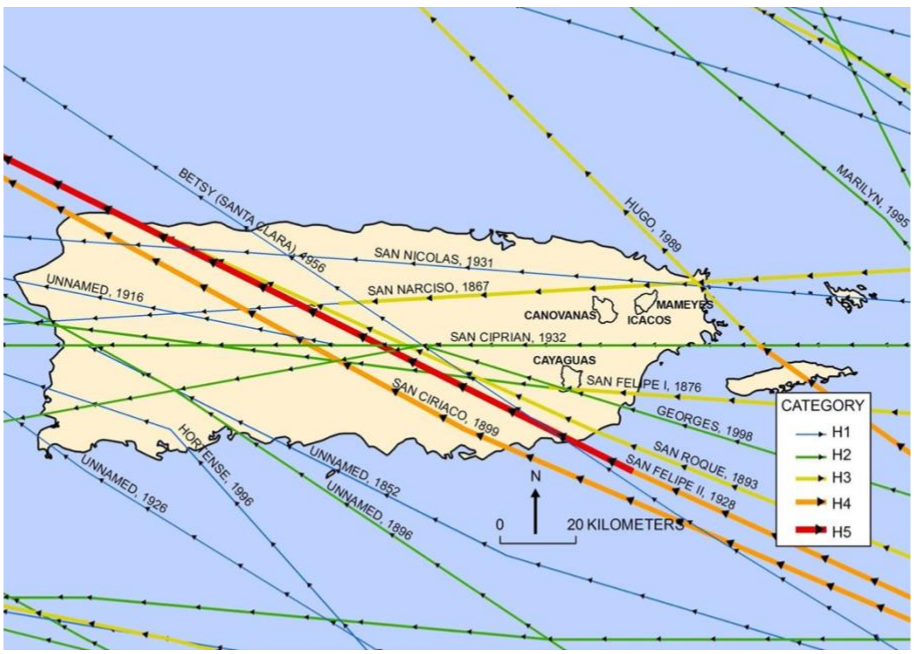


Figure 64. Path of hurricanes that struck Puerto Rico between 1850 and 2000 [75].

On the other hand, Kossin [3] recently estimated that the probability of a major hurricane forming in the North Atlantic (including the Caribbean) has increased at a rate of almost 50% per decade over the last four decades, compared to the global average increase of 8% per decade. Between 1979 and 1997, there were 777 tropical cyclones in the North Atlantic, 136 of which were categorized as major (Category 3 or greater). On the other hand, the period of 1998-2017 experienced 1,572 tropical cyclones, 529 of which were Cat 3 or greater [3].

Following this trend, Puerto Rico instead might expect to be affected by a hurricane every 2.3 years instead of every 4.6 years, and be directly struck by one once every 8.2 years instead of every 31.9. This increase in hurricane activity, both in frequency and magnitude, reinforce the necessity of energy resilience.

Chapter 8: Conclusion

This study started by stating its problem: the fragility of Puerto Rico's electricity system to natural disasters. It then proposed energy resilience as the solution to this problem, and then dedicated a chapter to review previous literature done on the topic, and subsequent chapters describing the methodology used to assign a value to energy resilience and the computational models used to run the scenarios necessary to answer the research questions. Next, the results from said models where presented, described, and compared to one another, followed by sensitivity analyses that aimed to answer "what-if?" scenarios, where input variables could have a range of different values to better understand their impact on the model outputs. After this, a brief discussion listed the limitations of the models used in this study, as well as the discrepancies between them. Also, an attempt to validate one key metric, the value of lost load, was done by comparing the one used in this study to the one mentioned in Puerto Rico's Integrated Resource Plan.

The rest of the discussion was related to the benefits of considering diesel generators when designing a microgrid; the theoretical investments required and potential savings that could result by deploying resilient microgrids, like the ones modeled in this study, to all users in Puerto Rico. These theoretical investments were then brought into context by comparing them to a budget aimed to increase resilience previously proposed by the Puerto Rico Energy Resilience Working Group, and also to the cost of hardening the transmission and distribution system instead of investing in non-wire solutions like distributed energy resources. Finally, two critical aspects of Puerto Rico's energy infrastructure were introduced: the inequality in energy access following hurricanes, and the observed increase in their frequency and magnitude.

The last pages of this study are intended to highlight key findings, concretely answer the research questions, and provide recommendations for further research in this field.

8.1 Key findings

8.1.1 Different user segments experience different outage costs

When accounting for the value of lost load, outage costs considerably increase residential energy expenditures, but outweigh commercial energy expenditures by nearly an order of magnitude. This is because:

- Residential users place a much smaller value of their lost load than do commercial users (Figure 15)
- Commercial users consume, on average, approximately 15 times more electricity than the average residential user (Figures 24 and 25)

8.1.2 When sizing a microgrid for resilience, diesel generators help decrease costs

This is because combining a PV + storage system with a diesel generator avoids the necessity of oversizing the storage system to account for several hours or days of autonomy. This way, the PV system can still supply the local load and export any surplus production to the grid. Whenever the grid is down, the BESS and the diesel generator work in tandem to power the critical loads when solar production is not enough (Figures 42-45).

8.1.3 The commercial VoLL is high enough that no cost-effective scenario considers incurring in outage costs

As mentioned in the sensitivity analysis of the commercial case, no value of lost load considered was low enough to merit experiencing an outage cost. This "break-even" VoLL could be the focus of further research.

8.1.4 Valuing resilience decreases the NPV of the residential case, but increases the NPV of the commercial case

In the residential case, the NPV of sizing a microgrid to maximize savings is ~4,500 USD. On the other hand, the NPV of sizing a microgrid to maximize resilience is ~2,400 USD. This is due to the way in which NPV is calculated, as the difference between life cycle costs of two scenarios. When valuing resilience, the difference between LCCs (of the base scenario and cost-optimal resilient scenario) turns out to be less than the difference between LCCs when not valuing resilience. In contrast, valuing resilience in the commercial scenario increases the NPV nearly 18-fold. The difference in LCCs before valuing resilience is ~76,000 USD. When valuing resilience, however, the difference in LCCs rises to ~1.36 million USD. As would be expected, this is because of the considerably larger VoLL and annual load of the commercial case.

8.1.5 Even outage costs during a year without weather events are considerable enough to consider avoiding them

The average commercial user can expect to incur in ~3,200 USD of outage costs per year solely because of the Puerto Rican grid's unreliability. This cost is already high enough to consider procuring distributed energy resources to avoid them.

8.2 Answers to research questions

To bring this study back full circle, each research question with its respective answer is listed as follows:

1. **How many hours of lost electrical service do Puerto Rico's users experience because of extreme weather events?**

On average, a Puerto Rican user can expect to experience an outage roughly three months (87 days) in duration, based on observations of the grid-restoration timeline following Hurricane Maria in 2017. This average duration, however, is not entirely representative of all electricity users, and is highly dependent on the type of damage done to the electricity infrastructure, and the geographical location and remoteness of the user. A long-tailed distribution was observed during the grid-restoration timeline after the 2017 hurricane season, and the last 4% of users to whom electricity was restored represent 40% of the total outage duration of ~3.4 billion CHoLES.

2. **What is the value of lost load for Puerto Rico's electricity user segments?**

The value of lost load for Puerto Rico's different user segments was calculated as 2.63 USD/kWh for residential users, 78.21 USD/kWh for commercial users, and 95.94 USD/kWh for industrial users, based on Lawrence Berkeley National Laboratory's Interruption Cost Estimator database and Puerto Rico's economic, demographic, and reliability indexes.

3. **What is the net present cost of a PV + storage system sized to optimize savings and how does it compare to the net present cost of not deploying one?**

For the average residential user, at a 10% nominal discount rate the net present cost of procuring a 3.5 kW PV system, without storage, is ~7,500 USD, compared to a net present cost of not deploying one of ~12,000 USD. This difference results in a net present value of ~4,500 USD of the cost-optimal PV system. For the average commercial user, at a 10% nominal discount rate the net present cost of procuring a 50 kW PV system, without storage, is ~108,000 USD, compared to a net present cost of not deploying one of ~184,000 USD. This difference results in a net present value ~76,000 USD of the cost-optimal PV system.

4. **How does valuing resilience when sizing a PV + storage system impacts its capacity, components and net present cost?**

For the average residential user, valuing resilience raises the net present cost of a business-as-usual scenario from ~12,000 USD to ~14,600. Because of this, the cost-optimal PV + storage system when valuing resilience is a 3.5 kW PV system paired with 5 kWh of battery storage. This raises net present cost from ~7,500 USD to ~12,200 USD. The difference between these two life cycle costs that value resilience is a net present value of ~2,400 USD for the resilience-optimal microgrid. For the average commercial user, however, valuing resilience raises the net present cost of a business-as-usual scenario from 108,000 USD to 1.5 million USD, mostly because of the high value associated to lost load. For this reason, the cost-optimal microgrid when valuing resilience is a 50 kW PV system paired with 10 kWh of battery storage and a 12 kW backup generator. This raises net present cost from ~108,000 USD when not valuing resilience to ~150,000 USD when valuing it. The difference between these two life cycle costs that value resilience is a net present value of ~1.36 million USD for the resilience-optimal microgrid.

As for the main research question:

What is the value of the energy resilience that solar microgrids can provide to users in Puerto Rico?

The value of the energy resilience that solar microgrids can provide to residential users in Puerto Rico is 13 USD on a year where no long-duration outage takes place, 140 USD if a one-week outage occurs, and 1,550 USD if a user can expect a nearly 3-month long outage.

For commercial users, the value of the energy resilience that solar microgrids can provide is 3,150 USD per year solely by preventing regular outages based on Puerto Rico's reliability indexes, 61,200 USD if the user expects a one-week outage, and 725,000 USD if the avoided outage lasts nearly 3 months.

Considering the increase in frequency and magnitude of severe weather events over the past decades, **the total nominal value of resilience for a residential user is 7,700 USD over a 30-year period, equal to a real (discounted) value of resilience of 2,900 USD**.

For commercial users, **the total nominal value of resilience is 3.5 million USD, equal to a real (discounted) value of resilience of 1.3 million USD**.

8.3 Recommendations for further research

This study mainly focused on the average residential and commercial electricity users in Puerto Rico. However, with more granular user and load data, it would be possible to extrapolate these findings to different case studies; a school, a hospital, an office building or an affordable housing complex. More diverse data would provide a better understanding of the value of resilience that can be provided by distributed energy resources.

In a similar sense, the values of lost load used in this study were calculated using a pre-existing database. A more accurate method, however, would be to estimate a more accurate VoLL based on Puerto Rico's circumstances and customer input; customer surveys would likely be necessary for this, but it would help improve the accuracy of these findings.

Additionally, it would be useful to consider project financing in a following study, and provide insight on the benefits of third-party financing like power-purchase agreements or lease arrangements.

A most important study, though, is perhaps the combination of these findings with an analysis of the geographical distribution of the Puerto Rican communities that had to wait the longest to see their lights back on. The outages modeled in this study were the ones that were observed around urban communities and densely-populated areas; one can only imagine the difference in the value of resilience that could be provided with DERs if the outages modeled had lasted six, nine, or almost twelve months.

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Appendix 1 – REopt model parameters, variables & equations

Indices and sets

- $s \in \mathcal{S}$: set of segments defining the capital costs
- $c \in \mathcal{C}$: set of technology classes (for this study, $c =$ PV)
- $t \in \mathcal{T}$: set of technologies
- $t \in \hat{\mathcal{T}}_c$: set of technologies that belong to technology class c
- $t \in \tilde{T}_d$: set of technologies that can satisfy demand type d
- $d \in \mathcal{D}$: set of demands (or loads) 1…6, where 1 is the electric load, 2 is natural gas, 3 is propane, and so on
- $d \in \mathcal{D}^E$: set of demands being served through electric generation
- $d \in \mathcal{D}^{E^{os}}$: set of demands being served through electric generation for use on-site (os)
- $d \in \mathcal{D}^{E^{sb}}$: set of demands being served through electric generation to be sold back (sb)
- $d \in \mathcal{D}^T$: set of demands being served through thermal generation*
- $h \in \mathcal{H}$: set of time steps
- $h \in \mathcal{H}_r$: set of time steps in ratchet r
- $h \in \mathcal{H}_m$: set of time steps in month m
- $l \in \mathcal{L}$: set of locations
- $l \in \mathcal{L}^z$: set of locations at which net-zero electricity is required
- $v \in \mathcal{V}$: set of net metering levels
- $v \in \hat{\mathcal{V}}_t$: set of net metering levels for technology t
- $u \in \mathcal{U}$: set of fuel bins
- $m \in \mathcal{M}$: set of months
- $m \in \mathcal{M}^{LB}$: set of look-back months
- $r \in \mathcal{R}$: set of ratchets

Parameters

Counting parameters

- $n^{\dot{p}}$: number of points defining capital costs (unitless)

Losses, factors, and ratios

- f^p_{dtlh}: hourly capacity factor for demand d for technology t at location l in time step h (unitless)
- f^{pl}_t: power loss factor for technology t (unitless)
- f^M_{ltdu}: variable fuel consumption per time step at location l for demand for fuel bin u

- f_{ltdu}^{B}: fixed fuel consumption per time step at location l for demand for fuel bin u
- f_l^{lb}: the look-back percent of demand for location l

Demand and supply parameters

- $\bar{\delta}_l$: annual electric load at location l [kWh]
- $\hat{\delta}_{dl}$: total fuel demand capacity for demand d at location l [kW]
- q_{ltu}^{U}: the amount of fuel available in location l for technology t for fuel bin u

Incentives

- $\bar{\iota}_{tl}$: maximum production incentive at location l for technology t [USD]
- i_{dtl}^{r}: production incentive rate for demand d at location l for technology t [USD/kWh]
- $\bar{\iota}_{tl}^{\sigma}$: maximum system size eligible for a production incentive at location l for technology t [kW]

Costs

- $c_{ltn^{\dot{p}}}^{K_x}$: x-value (i.e., system size) capital cost for technology t and point $n^{\dot{p}}$ [kW]
- $c_{ltn^{\dot{p}}}^{K_y}$: y-value (i.e., cost at a given system size) capital cost for technology t and point $n^{\dot{p}}$ [USD]
- c_{dtl}^{o}: operating cost for demand d of technology t at location l [USD/kWh]
- $c_l^f t$: fixed cost for technology t at location l [USD]
- c_{tl}^{om}: operating and maintenance cost per unit system size at location l for technology t [USD/kW]
- c_{dtlh}^{e}: sellback cost for demand d of technology t at location l in time step h [USD/kWh]
- c_{ts}^{KA}: capital cost coefficient A (slope) for technology t in segment s [USD/kWh]
- c_{ts}^{KB}: capital cost coefficient B (y-intercept) for technology t in segment s [USD]
- y_{ts}^{K}: y-intercept for capital cost calculations for technology t in segment s [USD]
- c_{ltuh}^{U}: the cost of fuel in location l for technology t for fuel bin u in time step h
- c_{lr}^{D}: the cost of demand at location l for ratchet r
- $c_{lm}^{D^m}$: the cost of demand at location l for month m
- $c_l^{b^{kW}}$: the capital cost of the battery per kW at location l [USD/kW]
- $c_l^{b^{kWh}}$: the capital cost of the battery per kWh at location l [USD/kWh]

System sizing and performance

- $b_{tl}^{\bar{\sigma}}$: bound on system size for technology t at location l [kW]
- $b_{t}^{\underline{\sigma}}$: minimum values for sub-technology t [kW]
- $b_{lt}^{\underline{\sigma}}$: minimum values for technology t at location l [kW]
- b_{dlh}^{p}: bound on production size for demand d at location l in time step h [kW]
- $b_{dlh}^{\bar{p}}$: bound on maximum production size for demand d at location l in time step h [kW]
- b_{lv}^{cnm}: capacity for net metering level v at location l [kW]
- $b_{lc}^{\bar{\bar{\sigma}}}$: bound on technology class, largest possible size for technology class c [kW]
- $\underline{m}_{t}$: minimum turndown for technology t (unitless)

Storage parameters

- $w_{l}^{\bar{b}}$: the maximum size of the battery [kWh]
- $w_{l}^{\underline{b}}$: the minimum size of the battery [kWh]
- $b_{l}^{\bar{b}}$: the maximum size of the battery [kW]
- f_{ltd}^{b}: roundtrip inverter efficiency
- $t_{l}^{\underline{b}}$: the minimum state of charge (SoC) of the battery at location l

Decision variables

Binary variables

- Z_{l}^{SHW}: 1 if the technology is SHW at location l, 0 otherwise
- Z_{l}^{SVP}: 1 if the technology is SVP at location l, 0 otherwise
- Z_{l}^{GSHP}: 1 if the technology is GSHP at location l, 0 otherwise
- Z_{tl}^{p}: 1 if technology t is built at location l, 0 otherwise
- Z_{t}^{σ}: 1 if technology t is of acceptable size, 0 otherwise
- $Z_{tl}^{\bar{\sigma}}$: 1 if technology t is above the size at which it obtains a production incentive at location l, 0 otherwise
- Z_{ltc}: 1 if at location l technology $t \in \mathcal{T}_c$ is selected from technology class c, 0 otherwise
- Y_{lv}: 1 if system is operating at net metering level v at location l, 0 otherwise
- Y_{tlh}^{o}: 1 if technology t is operational at location l in time step h, 0 otherwise
- $\hat{Y}_{lt}^{o}$: 1 if technology t is operational, 0 otherwise
- $\dot{Y}_{tls}$: 1 if technology t at location l operates in segment s of the cost curve, 0 otherwise
- Y_{lth}^{c}: 1 if technology t at location l in time step h is an operational CHP optional technology, 0 otherwise
- $Z_{lh}^{\hat{b}}$: 1 if in time step h the battery is being discharged, 0 otherwise
- $Z_{lh}^{\check{b}}$: 1 if in time step h the battery is being charged, 0 otherwise

Nonnegative variables

- $\hat{X}^{q}_{dtlhs}$: rated power supplied for demand d and technology t at location l in time step h in segment s [kW]
- X^{E}_{dtlhs}: extra electric power consumed by a technology with an electric penalty (SHW and SVP) for demand d and technology t at location l in time step h in segment s [kW]
- X^{σ}_{tls}: system size for technology t at location l operating in segment s [kW]
- X^{U}_{ltu}: amount of fuel used at location l for technology t for fuel bin u (fuel unit)
- $X^{U^c}_{ltu}$: total cost of fuel used at location l for technology t for fuel bin u [USD]
- I_{tl}: production incentive value for technology t at location l [USD]
- W^{D}_{lr}: the peak demand at location l in ratchet r [kW]
- $W^{D^l}_{l}$: the look-back peak demand at location l [kW]
- $W^{D^m}_{lm}$: the monthly peak demand at location l for month m [kW]
- $W^{b^{kW}}_{l}$: battery system size at location l [kW]
- $W^{b^{kWh}}_{l}$: battery system size at location l [kWh]
- $X^{\check{b}}_{lh}$: power supplied to the battery in time step h at location l [kW]
- $X^{\hat{b}}_{lh}$: power supplied from the battery in time step h at location l [kW]
- X^{b}_{lh}: the amount of energy stored in the battery in time step h at location l [kWh]

Auxiliary and fixed variables

- $c^{KA}_{ts} = \frac{c^{K_y}_{tn^p} - c^{K_y}_{tn^{p}-1}}{c^{K_x}_{tn^p} - c^{K_x}_{tn^{p}-1}}$ [USD/kWh]
- $c^{KB}_{ts} = c^{K_y}_{tn^{p}-1}$ [USD]
- $y^{K}_{ts} = c^{K_y}_{tn^p} - c^{KA}_{ts} \cdot c^{K_x}_{tn^p}$ [USD]

Objective function

$$\min \sum_{t\in\mathcal{T},l\in\mathcal{L},s\in\mathcal{S}} c_{ts}^{KA}\cdot X_{tls}^{\sigma} + y_{ts}^{K}\cdot \dot{Y}tls +$$
$$\sum_{t\in\mathcal{T},dl\in\mathcal{L},d\in\mathcal{D},h\in\mathcal{E},s\in\mathcal{S}} \cdot f_{dtlh}^{p}\cdot (d_{dtl}^{o} + c_{dlth}^{e})\cdot \hat{X}_{dtlhs}^{q} +$$
$$\sum_{l\in\mathcal{L},r\in\mathcal{R}} W_{lr}^{D}\cdot c_{lr}^{D} + \sum_{l\in\mathcal{L},m\in\mathcal{M}} W_{lm}^{D^m}\cdot c_{lm}^{D^m} +$$
$$\sum_{l\in\mathcal{L}} W_{l}^{b^{kWh}}\cdot c_{l}^{b^{kWh}} + \sum_{l\in\mathcal{L}} W_{l}^{b^{kW}}\cdot c_{l}^{b^{kW}} +$$
$$\sum_{t\in\mathcal{T},l\in\mathcal{L},d\in\mathcal{D}^{E^{os}},h\in\mathcal{H},s\in\mathcal{S}} c_{dtlh}^{e}\cdot X_{dtlhs}^{E} +$$
$$\sum_{t\in\mathcal{T},l\in\mathcal{L},s\in\mathcal{S}} c_{tl}^{om}\cdot X_{tls}^{\sigma} -$$
$$\sum_{t\in\mathcal{T},l\in\mathcal{L}} I_{tl} +$$
$$\sum_{t\in\mathcal{T},l\in\mathcal{L}} c_{l}^{f}\cdot Z_{tl}^{p} +$$
$$\sum_{ltu} X_{ltu}^{U^c}$$

Load constraints

A1.1 requires that across all technologies except SHW (not considered in this study), for every time step the amount of electricity offsetting on-site demand must be greater than or equal to the sum of the site load and the extra electricity associated with technologies that consume electricity in their operation.

$$\sum_{t\in\mathcal{T}\backslash\hat{\mathcal{T}}_{SHW},s\in\mathcal{S},u\in\mathcal{U}} f_{dtlh}^{p}\cdot \hat{X}_{dtlhsu}^{q} + X_{lh}^{\hat{b}} \geq b_{dlh}^{p} + \sum_{t\in\mathcal{T},s\in\mathcal{S}} X_{dtlhs}^{E}$$
$$- \sum_{t\in\mathcal{T}^{SHW},s\in\mathcal{S},u\in\mathcal{U}} f_{dtlh}^{p}\cdot \hat{X}_{dtlhsu}^{q} \quad \forall d\in\mathcal{D}^{E^{os}}, l\in\mathcal{L}, h\in\mathcal{H}$$

A1.2 requires that across all technologies except SHW and all fuels except electricity, for every time step the total energy supplied must be less than or equal to the site load for that fuel.

$$\sum_{t\in\hat{\mathcal{T}}_{d}\backslash\mathcal{T}^{SHW},s\in\mathcal{S},u\in\mathcal{U}} f_{dtlh}^{p}\cdot \hat{X}_{dtlhsu}^{q} \leq b_{dlh}^{p} \quad \forall d\in\mathcal{D}\backslash\mathcal{D}^{E^{os}}, l\in\mathcal{L}, h\in\mathcal{H}$$

A1.3 requires that for all fuels except electricity, the total energy supplied for each fuel (summed across all time steps) must be greater than or equal to the annual load for the fuel.

$$\sum_{t\in\mathcal{T},h\in\mathcal{H},s\in\mathcal{S},u\in\mathcal{U}} \hat{\delta}_{dl} \geq f^{p}_{dtlh} \cdot \hat{X}^{q}_{dtlhsu} \quad \forall d \in \mathcal{D}\backslash\mathcal{D}^{E}, l \in \mathcal{L}$$

A1.4 requires that across all technologies and all fuels, for every time step the amount of energy offsetting on-site demand must be less than or equal to the maximum load plus extra electricity associated with technologies that consume electricity in their operation for electric load.

$$\sum_{t\in\mathcal{T}_d,s\in\mathcal{S},u\in\mathcal{U}} f^{p}_{dtlh} \cdot \hat{X}^{q}_{dtlhsu} \leq b^{\bar{p}}_{dlh} + \sum_{t\in\mathcal{T},s\in\mathcal{S}} X^{E}_{dtlhs} \quad \forall d \in \mathcal{D}\backslash\mathcal{D}^{E}, l \in \mathcal{L}, h \in \mathcal{H}$$

A1.5 requires that the sum of all electricity offsetting on-site demand and exported under net metering be less than the annual electric load.

$$\sum_{t\in\mathcal{T}_d\backslash\mathcal{T}^{grid},d\in\mathcal{D}^{E^{os}}\cup\mathcal{D}^{E^{sb}},h\in\mathcal{H},s\in\mathcal{S},u\in\mathcal{U}} f^{p}_{dtlh} \cdot \hat{X}^{q}_{dtlhsu} \leq \bar{\delta}_{l} + \sum_{t\in\mathcal{T},d\in\mathcal{D}^{E^{os}},h\in\mathcal{H},s\in\mathcal{S}} X^{E}_{dtlhs} \forall l \in \mathcal{L}$$

System size constraints

A1.6 ensures that the system size for every technology cannot exceed the maximum size.

$$X^{\sigma}_{tls} \leq b^{\bar{\sigma}}_{tl} \quad \forall t \in \mathcal{T}, l \in \mathcal{L}, s \in \mathcal{S}$$

A1.7 ensures that only one technology from each technology class may be present in the model.

$$\sum_{s\in\mathcal{S}} X^{\sigma}_{tls} \leq b^{\bar{\sigma}}_{tl} \cdot Z_{ltc} \quad \forall c \in \mathcal{C}, t \in \hat{\mathcal{T}}_c, l \in \mathcal{L}$$

A1.8 constraints the binary from the previous constraint, ensuring that only one technology can exist in each technology class.

$$\sum_{t\in\mathcal{T}} Z_{ltc} \leq 1 \quad \forall l \in \mathcal{L}, c \in \mathcal{C}$$

A1.9 ensures that the system size for the technology in each class cannot exceed the maximum technology class size.

$$\sum_{s\in\mathcal{S},t\in\hat{\mathcal{T}}_c} X^{\sigma}_{tls} \leq b^{\bar{\bar{\sigma}}}_{lc} \quad \forall c \in \mathcal{C}, l \in \mathcal{L}$$

A1.10 ensures that the system size for the technology in each tech class is greater than the minimum technology class size.

$$\sum_{t\in\mathcal{T},s\in\mathcal{S}} b_{lc}^{\overline{\overline{\sigma}}} \leq X_{tls}^{\sigma} \quad \forall l \in \mathcal{L}, c \in \mathcal{C}$$

A1.11 ensures that the system size for every technology is greater than the minimum technology size.

$$\sum_{s\in\mathcal{S}} b_{lt}^{\underline{\sigma}} \leq X_{tls}^{\sigma} \forall l \in \mathcal{L}, t \in \mathcal{T}$$

A1.12 defines the binary associated with ensuring the minimum subtechnology size.

$$\sum_{s\in\mathcal{S}} X_{tls}^{\sigma} \leq b^{\overline{\sigma}} \cdot Z_t^{\sigma} \quad \forall t \in \mathcal{T}, l \in \mathcal{L}$$

A1.13 ensures that if the technology is selected by the model, it must be larger than the subtechnology minimum size.

$$b_t^{\underline{\sigma}} - \sum_{s\in\mathcal{S}} X_{tls}^{\sigma} \leq b^{\overline{\sigma}} \cdot (1 - Z_t^{\sigma}) \quad \forall t \in \mathcal{T}, l \in \mathcal{L}$$

A1.14 states that the energy capacity of the battery (in kWh) cannot be larger than the maximum allowable capacity.

$$W_l^{b^{kWh}} \leq w_l^{\bar{b}} \quad \forall l \in \mathcal{L}$$

A1.15 states that the energy capacity of the battery (in kWh) cannot be less than the minimum allowable capacity.

$$W_l^{b^{kWh}} \geq w_l^{\underline{b}} \quad \forall l \in \mathcal{L}$$

A1.16 states that the power capacity of the battery (in kW) cannot be greater than the maximum allowable capacity.

$$W_l^{b^{kW}} \leq b_l^{\bar{b}} \quad \forall l \in \mathcal{L}$$

Production constraints

A1.17 requires that, for all technologies, the rated power supplied in each time step, summed across all loads, be less than or equal to the selected system size.

$$X_{tls}^{\sigma} \geq \sum_{d \in \mathcal{D}, u \in \mathcal{U}} \hat{X}_{dtlhsu}^{q} \quad \forall t \in \mathcal{T} \setminus \mathcal{T}^{CHP^M} \cup \mathcal{T}^{GSHP}, l \in \mathcal{L}, h \in \mathcal{H}, s \in \mathcal{S}$$

Capital cost constraints

A1.18 ensures that each technology operates in exactly one segment of the cost curve.

$$\sum_{s \in \mathcal{S}} \dot{Y}_{tls} = 1 \quad \forall t \in \mathcal{T}, l \in \mathcal{L}$$

A1.19 and A1.20 determine which segment of the piecewise linear cost curve each technology is operating in. This constraint sets the system size to zero if each technology is not in the appropriate segment of the cost curve for a given location, and otherwise sets the size between the appropriate bounds.

$$X_{tls}^{\sigma} \leq c_{ltn^p}^{Kx} \cdot \dot{Y}_{tls} \quad \forall t \in \mathcal{T}, l \in \mathcal{L}, n^p \in \mathcal{S}$$
$$X_{tls}^{\sigma} \geq c_{lt,n^{p-1}}^{Kx} \cdot \dot{Y}_{tls} \quad \forall t \in \mathcal{T}, l \in \mathcal{L}, n^p \in \mathcal{S}$$

A1.21 defines the binary that determines whether a technology is procured or not (this is used in the objective function to apply fixed costs for that technology).

$$\sum_{s \in \mathcal{S}} X_{tls}^{\sigma} \leq b_{lt}^{\overline{\sigma}} \cdot Z_{lt}^{p} \quad \forall t \in \hat{\mathcal{T}}, l \in \mathcal{L}$$

Minimum turndown constraints

A1.22 requires that, for all technologies and time steps, the amount of power supplied across all loads is zero if the technology is not operational in a given time step, and is unlimited otherwise.

$$\sum_{d \in \mathcal{D}, s \in \mathcal{S}, u \in \mathcal{U}} f_{tldh}^{p} \cdot \hat{X}_{dtlhsu}^{q} \leq b_{lt}^{\overline{\sigma}} \cdot Y_{tlh}^{o} \quad \forall t \in \mathcal{T}, l \in \mathcal{L}, h \in \mathcal{H}$$

A1.23 utilizes the binary defined in A1.22 to ensure that, if the technology is operational in that time step, it is operating above the minimum turndown for that technology.

$$\sum_{s \in \mathcal{S}} \underline{m}_t \cdot X_{tls}^{\sigma} - \sum_{d \in \mathcal{D}, s \in \mathcal{S}, u \in \mathcal{U}} \hat{X}_{dtlhsu}^{q} \leq b_{lt}^{\overline{\sigma}} \cdot (1 - Y_{tlh}^{o}) \quad \forall t \in \mathcal{T}, l \in \mathcal{L}, h \in \mathcal{H}$$

A1.24 requires that, for all technologies with a fixed minimum turndown across time steps, the amount of power supplied across all loads is zero if the technology is not operational and is unlimited otherwise.

$$\sum_{d\in\mathcal{D},s\in\mathcal{S},u\in\mathcal{U}} f^{p}_{tldh} \cdot \hat{X}^{q}_{dtlhsu} \leq b^{\overline{\sigma}}_{lt} \cdot \hat{Y}^{o}_{tl} \quad \forall t \in \hat{\mathcal{T}}_{\beta 1} \cup \hat{\mathcal{T}}_{WTE1}, l \in \mathcal{L}, h \in \mathcal{H}$$

A1.25 utilizes the binary defined in A1.24 to ensure that, if the technology is operational, it is operating above the minimum turndown for that technology.

$$\sum_{s\in\mathcal{S}} \underline{m}_t \cdot X^{\sigma}_{tls} - \sum_{d\in\mathcal{D},s\in\mathcal{S},u\in\mathcal{U}} \hat{X}^{q}_{dtlhsu} \leq b^{\overline{\sigma}}_{lt} \cdot \left(1 - \hat{Y}^{o}_{tl}\right) \quad \forall t \in \hat{\mathcal{T}}_{\beta 1} \cup \hat{\mathcal{T}}_{WTE1}, l \in \mathcal{L}, h \in \mathcal{H}$$

Fuel tracking constraints

A1.26 defines the amount of fuel used for each technology and fuel bin by summing over all time steps, loads, and segments the energy produced times the fuel burn rate (M), plus the fixed fuel use per time step (B) for each time step that the technology is operating.

$$\sum_{h\in\mathcal{H},d\in\mathcal{D},s\in\mathcal{S}} f^{p}_{dtlh} \cdot \hat{X}^{q}_{dtlhsu} \cdot f^{M}_{ltdu} + \sum_{h\in\mathcal{H},d\in\mathcal{D}} Y^{o}_{tlh} \cdot f^{B}_{ltdu} = X^{U}_{ltu} \quad \forall h \in \mathcal{H}, t \in \mathcal{T}, u \in \mathcal{U}$$

A1.27 requires that the amount of fuel used must be less than the fuel available for each technology and fuel bin.

$$X^{U}_{ltu} \leq q^{U}_{ltu} \quad \forall h \in \mathcal{H}, t \in \mathcal{T}, u \in \mathcal{U}$$

A1.28 defines the total fuel cost for each technology and fuel bin, again using the fuel burn rate (M), plus the fixed fuel use per time step (B) for each time step that the technology is operating.

$$\sum_{h\in\mathcal{H},d\in\mathcal{D},s\in\mathcal{S}} f^{p}_{dtlh} \cdot \hat{X}^{q}_{dtlhsu} \cdot f^{M}_{ltdu} \cdot c^{U}_{ltdu} + \sum_{h\in\mathcal{H},d\in\mathcal{D}} Y^{o}_{tlh} \cdot f^{B}_{ltdu} \cdot c^{U}_{ltdu} = X^{U^{c}}_{ltu} \quad \forall l \in \mathcal{L}, t \in \mathcal{T}, u \in \mathcal{U}$$

Storage constraints

A1.29 initializes the state of charge for the battery in each location.

$$X^{b}_{lh} = t^{\underline{b}}_{l} \cdot \sum_{b\in\mathcal{B}} W^{b^{kWh}}_{l} \quad \forall l \in \mathcal{L} | t = 1$$

A1.30 defines the amount of energy being delivered to the battery in each time step by summing energy supplied to the battery across all technologies and applying required storage efficiency derates.

$$X_{hl}^{\check{b}} = \sum_{t \in \mathcal{T}, s \in \mathcal{S}, u \in \mathcal{U}} f_{ldth}^{p} \cdot X_{ldths}^{q} \cdot f_{ltd}^{b} \quad \forall h \in \mathcal{H}, l \in \mathcal{L}, d \in \mathcal{D}^{E^b}$$

A1.31 defines the state of charge of the battery in each location and time step as the energy stored in the battery in the previous time step, plus energy coming in, minus energy going out.

$$X_{lh}^{b} = X_{l,h-1}^{b} + X_{lh}^{\check{b}} - X_{lh}^{\hat{b}} \quad \forall h \in \mathcal{H}, l \in \mathcal{L}$$

A1.32 ensures that the energy coming out of the storage system in each time step is less than the state of charge in the previous time step.

$$X_{lh}^{\hat{b}} \leq X_{l,h-1}^{b} \quad \forall h \in \mathcal{H}, l \in \mathcal{L}$$

A1.33 ensures that the state of charge is maintained above a minimum threshold.

$$t_{l}^{\underline{b}} \cdot W_{l}^{b} \leq X_{lh}^{b} \quad \forall h \in \mathcal{H}, l \in \mathcal{L}$$

A1.34 requires that the inverter size be greater than the amount of electricity taken out of the battery in any time step.

$$X_{lh}^{\check{b}} \leq W_{l}^{b^{kW}} \quad \forall h \in \mathcal{H}, l \in \mathcal{L}$$

A1.35 requires that the inverter size be greater than the amount of electricity delivered to the battery in any time step.

$$X_{lh}^{\hat{b}} \leq W_{l}^{b^{kW}} \quad \forall h \in \mathcal{H}, l \in \mathcal{L}$$

A1.36 requires that the energy capacity of the battery be greater than the amount of electricity stored in the battery in any time step.

$$X_{lh}^{b} \leq W_{l}^{b^{kWh}} \quad \forall h \in \mathcal{H}, l \in \mathcal{L}$$

A1.37 defines whether the battery is charging in a given time step.

$$X_{lh}^{\check{b}} \leq b_{l}^{\bar{b}} \cdot Z_{lh}^{\check{b}} \quad \forall h \in \mathcal{H}, l \in \mathcal{L}$$

A1.38 defines whether the battery is discharging in a given time step.

$$X_{lh}^{\hat{b}} \leq b_l^{\bar{b}} \cdot Z_{lh}^{\hat{b}} \quad \forall h \in \mathcal{H}, l \in \mathcal{L}$$

A1.39 states that in each location and time step, the battery cannot be both charging and discharging.

$$Z_{lh}^{\hat{b}} + Z_{lh}^{\check{b}} \leq 1 \quad \forall h \in \mathcal{H}, l \in \mathcal{L}$$

Demand rate constraints

A1.40 requires that the demand in each demand period be greater than or equal to the grid electricity consumed during the time steps in that demand period.

$$W_{lr}^{D} \geq \sum_{s\in\mathcal{S}, d\in\mathcal{D}, u\in\mathcal{U}} \hat{X}_{dtlhsu}^{q} \quad \forall l \in \mathcal{L}, t \in \mathcal{T}^{grid}, r \in \mathcal{R}, h \in \mathcal{H}_r$$

A1.41 requires that the demand in each demand period be greater than or equal to the look-back demand multiplied by a scaling factor.

$$W_{lr}^{D} \geq f_l^{lb} \cdot W_l^{D^l} \quad \forall l \in \mathcal{L}, m \in \mathcal{M}, r \in \mathcal{R}, h \in \mathcal{H}$$

A1.42 defines the demand in each month as greater than or equal to the grid electricity consumed during the time steps in that month.

$$W_{lm}^{D^m} \geq \sum_{s\in\mathcal{S}, d\in\mathcal{D}, u\in\mathcal{U}} \hat{X}_{dtlhsu}^{q} \quad \forall l \in \mathcal{L}, t \in \mathcal{T}^{grid}, m \in \mathcal{M}, h \in \mathcal{H}_m$$

A1.43 requires that the look-back demand is greater than the monthly demand over the set of months in the look-back.

$$W_l^{D^l} \geq W_{lm}^{D^m} \quad \forall l \in \mathcal{L}, d \in \mathcal{D}, m \in \mathcal{M}^{LB}$$

Production incentive constraints

A1.44 states that the total production incentive realized for each technology in each location must be less than the maximum production incentive for that technology and location if a production incentive is realized, and zero otherwise.

$$I_{tl} \leq \bar{\imath}_{tl} \cdot Z_{tl}^{\bar{\sigma}} \quad \forall t \in \mathcal{T}, l \in \mathcal{L}$$

A1.45 defines the production incentive based on the energy produced and places an upper bound on the production incentive value of the technology accordingly.

$$I_{tl} \leq \sum_{d \in \mathcal{D}, h \in \mathcal{H}, s \in \mathcal{S}, u \in \mathcal{U}} f_{dtlh}^{p} \cdot \hat{X}_{dtlhsU}^{q} \cdot i_{dtl}^{r} \quad \forall t \in \mathcal{T}, l \in \mathcal{L}$$

A1.46 states that for all technologies, if the system size exceeds the maximum system size for production incentive then the production incentives are forfeit (as assessed in the objective function).

$$\sum_{s \in \mathcal{S}} X_{tls}^{\sigma} \leq \bar{\imath}_{tl}^{\sigma} + b^{\overline{\sigma}} \cdot \left(1 - Z_{tl}^{\overline{\sigma}}\right) \quad \forall t \in \mathcal{T}, l \in \mathcal{L}$$

Net metering constraints

A1.47 states that the system must operate in only one net metering regime.

$$\sum_{v \in \mathcal{V}} Y_{lv} = 1 \quad \forall l \in \mathcal{L}$$

A1.48 requires that the sum of system sizes for all technologies that apply towards the net metering level is less than the net metering level if operating in that net metering level, and zero otherwise.≤≤

$$\sum_{t \in \mathcal{T}, s \in \mathcal{S}} f_{t}^{\underline{\sigma}} \cdot X_{tls}^{\sigma} \leq b_{lv}^{cnm} \cdot Y_{lv} \quad \forall l \in \mathcal{L}, v \in \hat{\mathcal{V}}_{t}$$

Appendix 2 – Comparison between electricity modeling in REopt and HOMER for a sample week

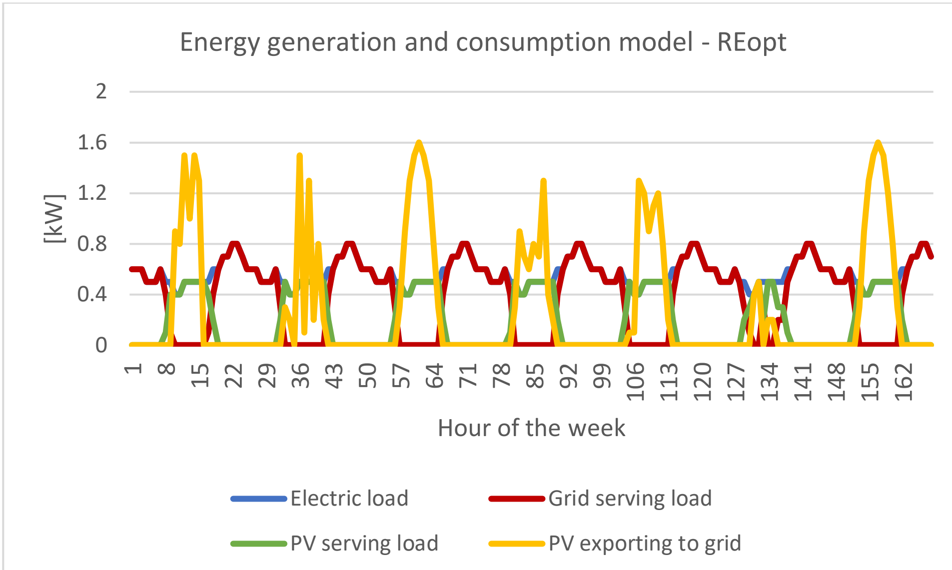

Figure 65. Energy generation and consumption modeled in REopt for a sample week.

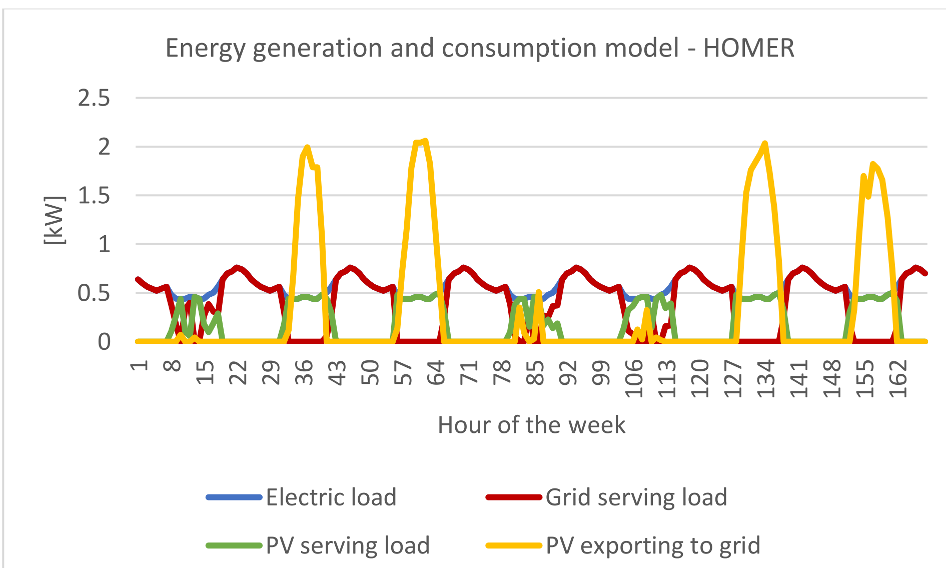

Figure 66. Energy generation and consumption modeled in HOMER for the same sample week.

Appendix 3 – Cash flows of the residential case

Table 17. Nominal cash flows of the least-cost and base scenarios.

	Nominal cash flows					
	Least-cost		Base		Difference	
Year	**Annual**	**Cumulative**	**Annual**	**Cumulative**	**Annual**	**Cumulative**
0	-7000	-7000	0	0	-7000	-7000
1	-33	-7033	-1046	-1046	1013	-5987
2	-33	-7066	-1046	-2092	1013	-4974
3	-33	-7099	-1046	-3138	1013	-3961
4	-33	-7132	-1046	-4184	1013	-2948
5	-33	-7165	-1046	-5230	1013	-1935
6	-33	-7198	-1046	-6276	1013	-922
7	-33	-7231	-1046	-7322	1013	91
8	-33	-7264	-1046	-8368	1013	1104
9	-33	-7297	-1046	-9414	1013	2117
10	-33	-7330	-1046	-10460	1013	3130
11	-33	-7363	-1046	-11506	1013	4143
12	-33	-7396	-1046	-12552	1013	5156
13	-33	-7429	-1046	-13598	1013	6169
14	-33	-7462	-1046	-14644	1013	7182
15	-383	-7845	-1046	-15690	663	7845
16	-33	-7878	-1046	-16736	1013	8858
17	-33	-7911	-1046	-17782	1013	9871
18	-33	-7944	-1046	-18828	1013	10884
19	-33	-7977	-1046	-19874	1013	11897
20	-33	-8010	-1046	-20920	1013	12910
21	-33	-8043	-1046	-21966	1013	13923
22	-33	-8076	-1046	-23012	1013	14936
23	-33	-8109	-1046	-24058	1013	15949
24	-33	-8142	-1046	-25104	1013	16962
25	-33	-8175	-1046	-26150	1013	17975
26	-33	-8208	-1046	-27196	1013	18988
27	-33	-8241	-1046	-28242	1013	20001
28	-33	-8274	-1046	-29288	1013	21014
29	-33	-8307	-1046	-30334	1013	22027
30	-33	-8340	-1046	-31380	1013	23040

Table 18. Discounted cash flows of the least-cost and base scenarios.

	Discounted cash flows					
	Least-cost		Base		Difference	
Year	**Annual**	**Cumulative**	**Annual**	**Cumulative**	**Annual**	**Cumulative**
0	-7000	-7000	0	0	-7000	-7000
1	-31	-7031	-970	-970	939	-6061
2	-28	-7059	-899	-1869	871	-5190
3	-26	-7085	-834	-2703	808	-4382
4	-24	-7110	-773	-3477	749	-3633
5	-23	-7132	-717	-4194	694	-2939
6	-21	-7153	-665	-4859	644	-2295
7	-19	-7173	-617	-5475	597	-1698
8	-18	-7191	-572	-6047	554	-1144
9	-17	-7207	-530	-6577	513	-630
10	-16	-7223	-492	-7069	476	-154
11	-14	-7237	-456	-7525	441	287
12	-13	-7251	-423	-7947	409	696
13	-12	-7263	-392	-8339	380	1076
14	-11	-7275	-363	-8703	352	1428
15	-123	-7398	-337	-9040	214	1642
16	-10	-7408	-313	-9352	303	1944
17	-9	-7417	-290	-9642	281	2225
18	-8	-7425	-269	-9911	260	2485
19	-8	-7433	-249	-10160	241	2726
20	-7	-7441	-231	-10391	224	2950
21	-7	-7447	-214	-10605	207	3158
22	-6	-7454	-199	-10804	192	3350
23	-6	-7459	-184	-10988	178	3528
24	-5	-7465	-171	-11159	165	3694
25	-5	-7470	-158	-11317	153	3847
26	-5	-7474	-147	-11464	142	3989
27	-4	-7479	-136	-11600	132	4121
28	-4	-7483	-126	-11726	122	4244
29	-4	-7486	-117	-11844	113	4357
30	-3	-7490	-109	-11952	105	4462

Table 19. Nominal cash flows of the resilient and base scenarios (accounting for VoLL).

	Nominal cash flows					
	Resilient		Base inc. VoLL		Difference	
Year	**Annual**	**Cumulative**	**Annual**	**Cumulative**	**Annual**	**Cumulative**
0	-9225	-9225	0	0	-9225	-9225
1	-103	-9328	-1282	-1282	1180	-8045
2	-103	-9431	-1282	-2565	1180	-6866
3	-103	-9533	-1282	-3847	1180	-5686
4	-103	-9636	-1282	-5130	1180	-4507
5	-103	-9739	-1282	-6412	1180	-3327
6	-103	-9842	-1282	-7694	1180	-2148
7	-103	-9945	-1282	-8977	1180	-968
8	-103	-10048	-1282	-10259	1180	212
9	-103	-10150	-1282	-11542	1180	1391
10	-2628	-12778	-1282	-12824	-1345	46
11	-103	-12881	-1282	-14106	1180	1225
12	-103	-12984	-1282	-15389	1180	2405
13	-103	-13087	-1282	-16671	1180	3584
14	-103	-13190	-1282	-17954	1180	4764
15	-453	-13642	-1282	-19236	830	5594
16	-103	-13745	-1282	-20518	1180	6773
17	-103	-13848	-1282	-21801	1180	7953
18	-103	-13951	-1282	-23083	1180	9132
19	-103	-14054	-1282	-24366	1180	10312
20	-2628	-16682	-1282	-25648	-1345	8966
21	-103	-16784	-1282	-26930	1180	10146
22	-103	-16887	-1282	-28213	1180	11326
23	-103	-16990	-1282	-29495	1180	12505
24	-103	-17093	-1282	-30778	1180	13685
25	-103	-17196	-1282	-32060	1180	14864
26	-103	-17299	-1282	-33342	1180	16044
27	-103	-17401	-1282	-34625	1180	17223
28	-103	-17504	-1282	-35907	1180	18403
29	-103	-17607	-1282	-37190	1180	19582
30	-103	-17710	-1282	-38472	1180	20762

Table 20. Discounted cash flows of the resilient and base scenarios (accounting for VoLL).

	Discounted cash flows					
	Resilient		Base inc. VoLL		Difference	
Year	**Annual**	**Cumulative**	**Annual**	**Cumulative**	**Annual**	**Cumulative**
0	-9225	-9225	0	0	-9225	-9225
1	-95	-9320	-1189	-1189	1094	-8131
2	-88	-9409	-1103	-2292	1014	-7117
3	-82	-9491	-1022	-3314	940	-6177
4	-76	-9567	-948	-4262	872	-5304
5	-70	-9637	-879	-5141	809	-4496
6	-65	-9703	-815	-5957	750	-3746
7	-61	-9763	-756	-6713	695	-3051
8	-56	-9819	-701	-7414	645	-2406
9	-52	-9872	-650	-8064	598	-1808
10	-1235	-11107	-603	-8666	-632	-2440
11	-45	-11151	-559	-9225	514	-1926
12	-42	-11193	-518	-9743	477	-1450
13	-39	-11231	-481	-10224	442	-1008
14	-36	-11267	-446	-10669	410	-598
15	-146	-11413	-413	-11083	267	-331
16	-31	-11444	-383	-11466	352	22
17	-28	-11472	-355	-11821	327	349
18	-26	-11499	-329	-12150	303	652
19	-24	-11523	-305	-12456	281	933
20	-580	-12104	-283	-12739	-297	635
21	-21	-12125	-263	-13002	242	877
22	-20	-12144	-244	-13245	224	1101
23	-18	-12162	-226	-13471	208	1309
24	-17	-12179	-209	-13681	193	1501
25	-16	-12195	-194	-13875	179	1680
26	-14	-12209	-180	-14055	166	1846
27	-13	-12223	-167	-14222	154	1999
28	-12	-12235	-155	-14377	142	2142
29	-12	-12246	-144	-14520	132	2274
30	-11	-12257	-133	-14653	122	2396

Appendix 4 – Cash flows of the commercial case

Table 21. Nominal cash flows of the least-cost and base scenarios.

	Nominal cash flows					
	Least-cost		Base		Difference	
Year	**Annual**	**Cumulative**	**Annual**	**Cumulative**	**Annual**	**Cumulative**
0	-100000	-100000	0	0	-100000	-100000
1	-576	-100576	-16117	-16117	15541	-84459
2	-576	-101152	-16117	-32234	15541	-68918
3	-576	-101728	-16117	-48351	15541	-53377
4	-576	-102304	-16117	-64468	15541	-37836
5	-576	-102880	-16117	-80585	15541	-22295
6	-576	-103456	-16117	-96702	15541	-6754
7	-576	-104032	-16117	-112819	15541	8787
8	-576	-104608	-16117	-128936	15541	24328
9	-576	-105184	-16117	-145053	15541	39869
10	-576	-105760	-16117	-161170	15541	55410
11	-576	-106336	-16117	-177287	15541	70951
12	-576	-106912	-16117	-193404	15541	86492
13	-576	-107488	-16117	-209521	15541	102033
14	-576	-108064	-16117	-225638	15541	117574
15	-5476	-113540	-16117	-241755	10641	128215
16	-576	-114116	-16117	-257872	15541	143756
17	-576	-114692	-16117	-273989	15541	159297
18	-576	-115268	-16117	-290106	15541	174838
19	-576	-115844	-16117	-306223	15541	190379
20	-576	-116420	-16117	-322340	15541	205920
21	-576	-116996	-16117	-338457	15541	221461
22	-576	-117572	-16117	-354574	15541	237002
23	-576	-118148	-16117	-370691	15541	252543
24	-576	-118724	-16117	-386808	15541	268084
25	-576	-119300	-16117	-402925	15541	283625
26	-576	-119876	-16117	-419042	15541	299166
27	-576	-120452	-16117	-435159	15541	314707
28	-576	-121028	-16117	-451276	15541	330248
29	-576	-121604	-16117	-467393	15541	345789
30	-576	-122180	-16117	-483510	15541	361330

Table 22. Discounted cash flows of the least-cost and base scenarios.

	Discounted cash flows					
	Least-cost		Base		Difference	
Year	**Annual**	**Cumulative**	**Annual**	**Cumulative**	**Annual**	**Cumulative**
0	-100000	-100000	0	0	-100000	-100000
1	-534	-100534	-14945	-14945	14411	-85589
2	-495	-101029	-13858	-28803	13363	-72227
3	-459	-101489	-12850	-41653	12391	-59836
4	-426	-101914	-11916	-53568	11490	-48346
5	-395	-102309	-11049	-64617	10654	-37692
6	-366	-102675	-10245	-74863	9879	-27813
7	-340	-103015	-9500	-84363	9161	-18652
8	-315	-103330	-8809	-93172	8495	-10157
9	-292	-103622	-8169	-101341	7877	-2281
10	-271	-103893	-7575	-108916	7304	5023
11	-251	-104144	-7024	-115939	6773	11796
12	-233	-104376	-6513	-122452	6280	18076
13	-216	-104592	-6039	-128492	5823	23899
14	-200	-104792	-5600	-134092	5400	29299
15	-1764	-106557	-5193	-139284	3428	32728
16	-172	-106729	-4815	-144099	4643	37371
17	-160	-106888	-4465	-148564	4305	41676
18	-148	-107036	-4140	-152704	3992	45668
19	-137	-107173	-3839	-156544	3702	49370
20	-127	-107301	-3560	-160103	3433	52803
21	-118	-107419	-3301	-163404	3183	55986
22	-109	-107528	-3061	-166465	2952	58937
23	-101	-107629	-2838	-169304	2737	61674
24	-94	-107723	-2632	-171935	2538	64212
25	-87	-107811	-2440	-174376	2353	66565
26	-81	-107892	-2263	-176639	2182	68747
27	-75	-107967	-2098	-178737	2023	70771
28	-70	-108036	-1946	-180683	1876	72647
29	-64	-108101	-1804	-182487	1740	74387
30	-60	-108160	-1673	-184160	1613	76000

Table 23. Nominal cash flows of the resilient (without diesel backup) and base scenarios (accounting for VoLL).

	Nominal cash flows					
	Resilient		**Base inc. VoLL**		**Difference**	
Year	**Annual**	**Cumulative**	**Annual**	**Cumulative**	**Annual**	**Cumulative**
0	-178950	-178950	0	0	-178950	-178950
1	-4064	-183014	-131979	-131979	127914	-51036
2	-4064	-187079	-131979	-263957	127914	76879
3	-4064	-191143	-131979	-395936	127914	204793
4	-4064	-195207	-131979	-527915	127914	332707
5	-4064	-199272	-131979	-659893	127914	460621
6	-4064	-203336	-131979	-791872	127914	588536
7	-4064	-207401	-131979	-923850	127914	716450
8	-4064	-211465	-131979	-1055829	127914	844364
9	-4064	-215529	-131979	-1187808	127914	972278
10	-4064	-219594	-131979	-1319786	127914	1100193
11	-4064	-223658	-131979	-1451765	127914	1228107
12	-4064	-227722	-131979	-1583744	127914	1356021
13	-4064	-231787	-131979	-1715722	127914	1483935
14	-4064	-235851	-131979	-1847701	127914	1611850
15	-4064	-239916	-131979	-1979679	127914	1739764
16	-4064	-243980	-131979	-2111658	127914	1867678
17	-4064	-248044	-131979	-2243637	127914	1995592
18	-4064	-252109	-131979	-2375615	127914	2123507
19	-4064	-256173	-131979	-2507594	127914	2251421
20	-4064	-260237	-131979	-2639573	127914	2379335
21	-4064	-264302	-131979	-2771551	127914	2507249
22	-4064	-268366	-131979	-2903530	127914	2635164
23	-4064	-272431	-131979	-3035508	127914	2763078
24	-4064	-276495	-131979	-3167487	127914	2890992
25	-4064	-280559	-131979	-3299466	127914	3018906
26	-4064	-284624	-131979	-3431444	127914	3146821
27	-4064	-288688	-131979	-3563423	127914	3274735
28	-4064	-292752	-131979	-3695402	127914	3402649
29	-4064	-296817	-131979	-3827380	127914	3530563
30	-4064	-300881	-131979	-3959359	127914	3658478

Table 24. Discoounted cash flows of the resilient (without diesel backup) and base scenarios (accounting for VoLL).

	Discounted cash flows					
	Resilient		**Base inc. VoLL**		**Difference**	
Year	**Annual**	**Cumulative**	**Annual**	**Cumulative**	**Annual**	**Cumulative**
0	-178950	-178950	0	0	-178950	-178950
1	-3769	-182719	-122380	-122380	118611	-60339
2	-3495	-186213	-113480	-235860	109985	49647
3	-3241	-189454	-105227	-341087	101986	151633
4	-3005	-192459	-97574	-438661	94569	246202
5	-2786	-195245	-90478	-529138	87691	333893
6	-2584	-197829	-83897	-613036	81314	415207
7	-2396	-200225	-77796	-690831	75400	490607
8	-2222	-202446	-72138	-762969	69916	560523
9	-2060	-204506	-66892	-829861	64832	625355
10	-1910	-206416	-62027	-891887	60117	685471
11	-1771	-208188	-57516	-949403	55744	741216
12	-1642	-209830	-53333	-1002736	51690	792906
13	-1523	-211353	-49454	-1052190	47931	840837
14	-1412	-212765	-45857	-1098047	44445	885282
15	-1310	-214075	-42522	-1140569	41213	926495
16	-1214	-215289	-39430	-1179999	38215	964710
17	-1126	-216415	-36562	-1216561	35436	1000146
18	-1044	-217459	-33903	-1250464	32859	1033005
19	-968	-218427	-31437	-1281901	30469	1063474
20	-898	-219325	-29151	-1311052	28253	1091728
21	-832	-220157	-27031	-1338083	26198	1117926
22	-772	-220929	-25065	-1363148	24293	1142219
23	-716	-221645	-23242	-1386390	22526	1164746
24	-664	-222309	-21552	-1407942	20888	1185634
25	-615	-222924	-19984	-1427927	19369	1205003
26	-571	-223495	-18531	-1446458	17960	1222963
27	-529	-224024	-17183	-1463641	16654	1239617
28	-491	-224515	-15934	-1479574	15443	1255060
29	-455	-224970	-14775	-1494349	14320	1269380
30	-422	-225391	-13700	-1508049	13278	1282658

Table 25. Nominal cash flows of the resilient (with diesel backup) and base scenarios (accounting for VoLL).

	Nominal cash flows					
	Resilient		**Base inc. VoLL**		**Difference**	
Year	**Annual**	**Cumulative**	**Annual**	**Cumulative**	**Annual**	**Cumulative**
0	-118910	-118910	0	0	-118910	-118910
1	-2703	-121613	-131979	-131979	129276	10366
2	-2703	-124316	-131979	-263957	129276	139641
3	-2703	-127019	-131979	-395936	129276	268917
4	-2703	-129722	-131979	-527915	129276	398193
5	-2703	-132425	-131979	-659893	129276	527468
6	-2703	-135128	-131979	-791872	129276	656744
7	-2703	-137831	-131979	-923850	129276	786020
8	-2703	-140534	-131979	-1055829	129276	915296
9	-2703	-143236	-131979	-1187808	129276	1044571
10	-2703	-145939	-131979	-1319786	129276	1173847
11	-2703	-148642	-131979	-1451765	129276	1303123
12	-2703	-151345	-131979	-1583744	129276	1432398
13	-2703	-154048	-131979	-1715722	129276	1561674
14	-2703	-156751	-131979	-1847701	129276	1690950
15	-2703	-159454	-131979	-1979679	129276	1820225
16	-2703	-162157	-131979	-2111658	129276	1949501
17	-2703	-164860	-131979	-2243637	129276	2078777
18	-2703	-167563	-131979	-2375615	129276	2208052
19	-2703	-170266	-131979	-2507594	129276	2337328
20	-2703	-172969	-131979	-2639573	129276	2466604
21	-2703	-175672	-131979	-2771551	129276	2595880
22	-2703	-178375	-131979	-2903530	129276	2725155
23	-2703	-181078	-131979	-3035508	129276	2854431
24	-2703	-183781	-131979	-3167487	129276	2983707
25	-2703	-186483	-131979	-3299466	129276	3112982
26	-2703	-189186	-131979	-3431444	129276	3242258
27	-2703	-191889	-131979	-3563423	129276	3371534
28	-2703	-194592	-131979	-3695402	129276	3500809
29	-2703	-197295	-131979	-3827380	129276	3630085
30	-2703	-199998	-131979	-3959359	129276	3759361

Table 26. Discounted cash flows of the resilient (with diesel backup) and base scenarios (accounting for VoLL).

	Discounted cash flows					
	Resilient		Base inc. VoLL		Difference	
Year	**Annual**	**Cumulative**	**Annual**	**Cumulative**	**Annual**	**Cumulative**
0	-118910	-118910	0	0	-118910	-118910
1	-2506	-121416	-122380	-122380	119874	964
2	-2324	-123740	-113480	-235860	111156	112120
3	-2155	-125895	-105227	-341087	103072	215191
4	-1998	-127894	-97574	-438661	95576	310767
5	-1853	-129747	-90478	-529138	88625	399391
6	-1718	-131465	-83897	-613036	82179	481571
7	-1593	-133058	-77796	-690831	76203	557773
8	-1477	-134536	-72138	-762969	70661	628434
9	-1370	-135906	-66892	-829861	65522	693955
10	-1270	-137176	-62027	-891887	60756	754711
11	-1178	-138354	-57516	-949403	56338	811049
12	-1092	-139446	-53333	-1002736	52240	863290
13	-1013	-140459	-49454	-1052190	48441	911731
14	-939	-141398	-45857	-1098047	44918	956649
15	-871	-142269	-42522	-1140569	41651	998300
16	-808	-143077	-39430	-1179999	38622	1036922
17	-749	-143825	-36562	-1216561	35813	1072736
18	-694	-144520	-33903	-1250464	33209	1105944
19	-644	-145163	-31437	-1281901	30794	1136738
20	-597	-145761	-29151	-1311052	28554	1165292
21	-554	-146314	-27031	-1338083	26477	1191769
22	-513	-146827	-25065	-1363148	24552	1216321
23	-476	-147303	-23242	-1386390	22766	1239087
24	-441	-147745	-21552	-1407942	21110	1260197
25	-409	-148154	-19984	-1427927	19575	1279773
26	-380	-148534	-18531	-1446458	18151	1297924
27	-352	-148886	-17183	-1463641	16831	1314755
28	-326	-149212	-15934	-1479574	15607	1330363
29	-303	-149514	-14775	-1494349	14472	1344835
30	-281	-149795	-13700	-1508049	13420	1358254

Appendix 5. Sensitivity analysis tables – residential case

Table 27. Sensitivity analysis - net present cost.

	Sensitivity variable				
Multiplier	**PV**	**BESS**	**VoLL**	**Annual load**	**Discount rate**
0.5	9574	11317	12829	6866	16709
0.6	10622	11794	13007	8191	16016
0.7	11460	12270	13172	9494	15352
0.8	12232	12746	13330	10907	14727
0.9	12945	13222	13487	12060	14146
1	**13645**	**13645**	**13645**	**13645**	**13645**
1.1	14345	14016	13785	14699	13214
1.2	15020	14395	13858	16285	12823
1.3	15670	14785	13932	17380	12461
1.4	16320	15181	14005	18888	12146
1.5	16970	15578	14078	20047	11869

Table 28. Sensitivity analysis - optimal size of PV.

	Sensitivity variable				
Multiplier	**PV**	**BESS**	**VoLL**	**Annual load**	**Discount rate**
0.5	5.75	3.5	3.25	1.75	5
0.6	4.5	3.5	3.25	2	4.25
0.7	4	3.5	3.5	2.5	4
0.8	3.75	3.5	3.5	2.75	3.75
0.9	3.5	3.5	3.5	3	3.5
1	**3.5**	**3.5**	**3.5**	**3.5**	**3.5**
1.1	3.5	3.5	3.5	3.75	3.5
1.2	3.25	3.5	3.5	4	3.25
1.3	3.25	3.5	3.5	4.5	3.25
1.4	3.25	3.5	3.5	4.75	3.25
1.5	3.25	3.5	3.5	5	3.25

Table 29. Sensitivity analysis - optimal size of storage.

	Sensitivity variable				
Multiplier	**PV**	**BESS**	**VoLL**	**Annual load**	**Discount rate**
0.5	5	6	5	3	5
0.6	5	6	5	3	5
0.7	5	6	5	4	5
0.8	5	6	5	4	5
0.9	5	6	5	5	5
1	**5**	**5**	**5**	**5**	**5**
1.1	5	5	6	6	5
1.2	5	5	6	7	5
1.3	5	5	6	7	5
1.4	5	5	6	8	5
1.5	5	5	6	8	5

Table 30. Sensitivity analysis - unmet load.

	Sensitivity variable				
Multiplier	**PV**	**BESS**	**VoLL**	**Annual load**	**Discount rate**
0.5	20	24	59	12	27
0.6	34	24	59	34	37
0.7	41	24	53	18	41
0.8	46	24	53	43	46
0.9	53	24	53	29	53
1	**53**	**52**	**53**	**53**	**53**
1.1	53	52	24	36	53
1.2	59	52	24	35	59
1.3	59	52	24	43	59
1.4	59	52	24	41	59
1.5	59	52	24	57	59

Table 31. Sensitivity analysis - outage cost.

	Sensitivity variable				
Multiplier	**PV**	**BESS**	**VoLL**	**Annual load**	**Discount rate**
0.5	52	64	78	32	71
0.6	88	64	94	90	98
0.7	108	64	97	47	108
0.8	121	64	110	114	121
0.9	138	64	124	76	138
1	**138**	**138**	**138**	**138**	**138**
1.1	138	138	71	94	138
1.2	156	138	77	92	156
1.3	156	138	83	113	156
1.4	156	138	90	107	156
1.5	156	138	96	150	156

Appendix 6. Sensitivity analysis tables – commercial case

Table 32. Sensitivity analysis - net present cost.

	Sensitivity variable				
Multiplier	**PV**	**BESS**	**VoLL**	**Annual load**	**Discount rate**
0.5	121040	156736	171040	101421	209072
0.6	131140	161102	171040	117337	199846
0.7	141040	165291	171040	133213	191225
0.8	151040	168525	171040	148909	183407
0.9	161040	170191	171040	164345	176741
1	**171040**	**171040**	**171040**	**171040**	**171040**
1.1	180474	171164	171040	194460	165669
1.2	189474	171851	171040	209859	160655
1.3	198474	172384	171040	225052	156304
1.4	207474	173112	171040	237921	152510
1.5	214894	173710	171040	250773	148233

Table 33. Sensitivity analysis - optimal size of PV.

	Sensitivity variable				
Multiplier	**PV**	**BESS**	**VoLL**	**Annual load**	**Discount rate**
0.5	50	50	50	25	50
0.6	50	50	50	30	50
0.7	50	50	50	35	50
0.8	50	50	50	40	50
0.9	50	50	50	45	50
1	**50**	**50**	**50**	**50**	**50**
1.1	45	50	50	50	45
1.2	45	50	50	55	45
1.3	45	50	50	60	45
1.4	45	50	50	65	45
1.5	30	50	50	70	30

Table 34. Sensitivity analysis - optimal size of storage.

	Sensitivity variable				
Multiplier	**PV**	**BESS**	**VoLL**	**Annual load**	**Discount rate**
0.5	10	55	10	5	40
0.6	10	55	10	10	40
0.7	10	45	10	15	20
0.8	10	40	10	10	10
0.9	10	10	10	10	10
1	**10**	**10**	**10**	**10**	**10**
1.1	10	10	10	10	10
1.2	10	10	10	10	10
1.3	10	10	10	10	10
1.4	10	10	10	10	10
1.5	10	5	10	10	10

Table 35. Sensitivity analysis - unmet load.

	Sensitivity variable				
Multiplier	**PV**	**BESS**	**VoLL**	**Annual load**	**Discount rate**
0.5	0	0	0	0	0
0.6	0	0	0	0	0
0.7	0	0	0	0	0
0.8	0	0	0	0	0
0.9	0	0	0	0	0
1	**0**	**0**	**0**	**0**	**0**
1.1	0	0	0	0	0
1.2	0	0	0	0	0
1.3	0	0	0	0	0
1.4	0	0	0	0	0
1.5	0	0	0	0	0

Table 36. Sensitivity analysis - outage cost.

	Sensitivity variable				
Multiplier	**PV**	**BESS**	**VoLL**	**Annual load**	**Discount rate**
0.5	0	0	0	0	0
0.6	0	0	0	0	0
0.7	0	0	0	0	0
0.8	0	0	0	0	0
0.9	0	0	0	0	0
1	**0**	**0**	**0**	**0**	**0**
1.1	0	0	0	0	0
1.2	0	0	0	0	0
1.3	0	0	0	0	0
1.4	0	0	0	0	0
1.5	0	0	0	0	0

Table 37. Sensitivity analysis - fuel cost.

	Sensitivity variable				
Multiplier	**PV**	**BESS**	**VoLL**	**Annual load**	**Discount rate**
0.5	2446	475	2446	1509	1114
0.6	2446	475	2446	1541	1114
0.7	2446	907	2446	1573	1984
0.8	2446	1114	2446	2106	2446
0.9	2446	2446	2446	2376	2446
1	**2446**	**2446**	**2446**	**2648**	**2446**
1.1	2483	2442	2446	2938	2483
1.2	2483	2438	2446	3215	2483
1.3	2483	2429	2446	3477	2483
1.4	2483	2427	2446	3625	2483
1.5	2483	2773	2446	3799	2649