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Article

# Rightsizing the Design of a Hybrid Microgrid

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**Abstract:** Selecting the sizes of distributed energy resources is a central planning element when designing a microgrid. Decision makers may consider several important factors, including, but not limited to, capacity, cost, reliability and sustainability. We introduce a method for rightsizing capacity that presents a range of potential microgrid design solutions, allowing decision makers to weigh their upsides and downsides based on a variety of measurable factors. We decouple component-specific modeling assumptions, energy management system logic and objective measurements from our simulation-based nested binary search method for rightsizing to meet power loads. In doing so, we develop a flexible, customizable and extensible approach to microgrid design planning. Aspects which have traditionally been incorporated directly in optimization-centric frameworks, such as resilience and reliability, can be treated as complementary analyses in our decoupled approach. This enables decision makers to gain exposure to a wide range of relevant information and actively participate in the microgrid design assessment process.

**Keywords:** microgrid; battery energy storage; photovoltaic source; diesel generator; design space; load demand; energy management

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## 1. Introduction

This paper addresses the problem of designing a hybrid stand-alone microgrid, a topic that has received significant attention from the research community in recent years. The most common approach to this problem is to define an objective, for example, the least costly, most environmentally friendly, or most reliable metrics, or some weighted combination of similar metrics, and then optimize a design space to identify the best performing microgrid. Such approaches typically provide only one solution—specifically, the best microgrid design with respect to the defined objective. The downside is that by providing only one solution, such approaches may fail to incorporate more subtle preferences in decision making and may fail to leverage expertise of decision makers. In other words, one of the solutions not presented to the decision maker might actually be preferred, but the decision maker might not be made aware of its existence.

A difficult task for an individual is to assess whether a microgrid is under- or over-capacitated to meet varying power loads during a given time horizon. Our approach is constructed to handle this aspect, by presenting a set of potential solutions that are all capacitated to meet given power load demands over time. We refer to this set as *rightsized* microgrid designs, and removing or adding capacity to any of their components would result in an under- or over-capacitated system. To identify rightsized designs, we introduce a nested binary search method for iterating over various microgrid designs and simulating their operation over time.

Our approach can be decoupled, because the set of rightsized designs is agnostic with respect to the set of metrics that may be of interest to a given decision maker. These designs are solely defined by their ability to meet power loads. In other words, we separate the process of identifying solutions and weighing their associated cost, environmental impact, etc. In traditional optimization-centric approaches, these two aspects are combined, which limits the decision makers' access to alternative solutions.

We rely on the decision maker to actually perform the optimization of objectives by ranking solutions, based on the metrics of interest that our methods can provide. The decision maker can and must compare the upsides and downsides of rightsized solutions to select a preferred microgrid design.

### 1.1. Literature Review

Many papers have been written on the topic of selecting the sizes of distributed energy resources (DERs) for both grid-connected and stand-alone microgrids [1,2]. Most propose optimization or heuristic methods focused on financial impact [3–11], environmental impact, resilience and reliability [12] or a multi-objective combinations of these [13–17]. Although each paper proposes interesting analyses and methods, the design space they address is narrowed to the point of limiting their ability to leverage decision makers' expertise in practice.

Some of the literature focuses on optimizing one component of a microgrid, for example, the battery energy storage. Fossati et al. [4] propose a genetic algorithm to identify energy and power capacities of the storage system that minimize operating cost. Bahmani-Firouzi and Azizpanah-Abarghoee [5] optimize battery sizing with an evolutionary algorithm. Chen et al. [7] present a mixed integer programming model for optimally sizing the energy storage with respect to a financial objective. Yang et al. [18] construct a system model to optimize the size of a distributed battery storage system with respect to cost-benefit analysis. Xiao et al. [19] propose a bilevel optimization model to determine both battery capacity and installation site. Liu et al. [8] compare a two-level heuristic approach against mixed integer programming to demonstrate that similar results can be obtained with an increase in computational efficiency. Hussain et al. [20] apply a robust optimization to analyze the impact of battery storage size on the operation of microgrids in the context of demand response programs. Alsaidan et al. [3] introduce a mixed integer programming model for expansion planning to identify a battery energy system with minimal cost given a power distribution capacity. Lai et al. [17] use mixed integer programming to solve a bilevel attacker-defender model, minimizing cost while sizing battery storage to enhance robustness against attacks in islanded microgrids. In the above papers, the design space is narrow and includes only the sizing of the battery.

Other works focus on optimized sizing for two energy sources within a microgrid [9,21,22]. Tabares et al. [21] minimize cost by conducting an exhaustive search over varying quantities of predefined battery and photovoltaic components. Dong et al. [9] apply mixed integer programming to minimize investment cost, while optimizing battery and backup generator size. Zengin et al. [23,24] focus on photovoltaic power and energy storage systems, while also determining an optimal daily power operation plan. Zhang et al. [22] optimize photovoltaic and battery capacity to achieve designs sufficiently robust to be resilient during extreme events. Gan et al. [25] present an empirical approach that considers microgrids with several components, but optimization of the scenario space is limited to batteries and diesel power. Works focusing on a design space with two DERs are limited in their applicability for planning a microgrid from scratch with three or more DER types.

Various methods have been proposed for sizing multiple components of grid-connected or islanded microgrids [6,10,11,13,14,16,26–30], commonly applied to cases in specific locations and with unique requirements, and mostly focused on load demand and cost. Chatterji and Bazilian [6] present a stochastic programming model to optimize energy supply cost in a grid-connected microgrid, accounting for possible grid failures. Chen and Duan [28] present a genetic algorithm framework to address nonsmooth cost functions. Al-Shamma'a and Addoweesh [10] introduce a genetic algorithm to optimize annualized system cost on a stand-alone microgrid located in South Arabia. Zhao et al. [13] apply a genetic algorithm-based method to solve a multi-objective sizing optimization problem that considers operating cost and emissions for a microgrid located on Dongfushan Island, China. Ramli et al. [26] present an evolutionary algorithm with two objectives. Cao et al. [14] search for Pareto efficient points with respect to cost, reliability, emissions

and power balance for a grid-connected microgrid located in Saudi Arabia. Rodríguez-Gallegos et al. [11] focus on the off-grid power system of an Indonesian island and employ a two-stage particle swarm optimization model to identify component sizing with minimum cost. Bukar et al. [15] compare a grasshopper optimization algorithm to particle swarm optimization and Cuckoo search including parameters such as cost of energy for a off-grid microgrid in Nigeria. Lan et al. [16] use multi-objective particle swarm optimization in combination with a genetic algorithm to minimize cost and emissions of a power system on a ship operating in a specific geographical location. Sfikas et al. [27] propose a non-linear programming formulation to optimize capacity, while minimizing either energy losses or cost. Other methods have focused on microgrid design in the context of energy management [31–33]. Siritoglou et al. [30] propose a design method with a wide range of applicability; however the design tool requires a licensed software and furthermore it returns a single solution, depending on the choice made by the designer. In this paper, we expand that design methodology to present a facility energy manager with an entire design space, which can be narrowed down based on various requirements and preferences.

This literature review identifies a multitude of papers presenting optimum DER sizing solutions to selected microgrid requirements; however, all possible specifications are not identified. Optimization and search algorithms typically return a single solution. The implicit or explicit objectives of these methods are defined with the intention of producing the single most effective solution. However, practically any consideration not captured or optimally weighted limits the effectiveness of the solution produced. Moreover, the facility energy manager does not have the opportunity to influence the solution, only to accept or reject it.

### *1.2. Novel Contribution and Paper Organization*

The goal of this paper is to fill the gap identified in the above literature survey by proposing a novel methodology for rightsizing the DERs of a stand-alone microgrid, given the historical load profile of a facility or building. Although a plethora of methods on DER sizing can be found in the literature, as shown in the previous section, all papers present a variety of assumptions necessary to reduce the decision space, limiting their ability to be extended and the ability of decision makers to play a central role in the decision process. Our methods provide a flexible framework, where DER modeling assumptions can be modified without requiring modifications to any of our search and simulation algorithms. Additionally, because we focus on identifying a set of solutions, rather than a single solution, methods can be bootstrapped for further analysis.

In this paper we introduce a simulation-based nested binary search methodology for computing the DER design space for a given load, providing a variety of choices for the energy manager of a facility in which a microgrid is to be installed. Using this design space as a compass, decision makers will be able to select the design(s) most suited to their particular requirements, whether they have cost constraints, environmental specifications or seek to achieve operational resilience. Our method can be used to size DERs for AC or DC microgrids and also for hybrid AC/DC microgrids.

This paper is organized as follows. A nomenclature list is provided in Figure 1. In Section 2, we introduce our simulation framework, including modeling equations and algorithms. We develop our DER rightsizing nested binary search method in Section 3. We apply our methodology to a computational experiment in Section 4, provide further discussion in Section 5 and present our conclusions in Section 6.

Nomenclature	
<b>Acronyms</b>	
BESS	battery energy storage system
DER	distributed energy resource
DG	diesel generator power
EMS	energy management system
PV	photovoltaic power
<b>Load</b>	
$p_l$	power load
<b>All DERs</b>	
$I = \{dg, pv, b\}$	diesel generation ( $dg$ ), photovoltaic ( $pv$ ), BESS ( $b$ )
$q_i$	power rating of $i \in I$
$p_i \in [p_i, \bar{p}_i]$	power output of $i \in I$
$e_i \in [e_i, \bar{e}_i]$	energy output of $i \in I$
$\delta_i$	computed energy difference for $i \in I$
<b>Diesel Generation</b>	
$\lambda \in [0, 1]$	load factor
$f(\lambda)$	fuel consumption rate
<b>Photovoltaic System</b>	
$t$	time
$\alpha_t$	scaling percentage for weather conditions at time $t$
$w$	scaling coefficient for location and season
<b>BESS</b>	
$u_b$	energy rating
$\beta_d$	discharge efficiency
$\beta_c$	charge efficiency
$d$	duration
$\gamma \in [\underline{\gamma}, \bar{\gamma}]$	state of charge
$k$	proportionality constant
<b>EMS</b>	
$s$	state
<b>Simulation</b>	
$g$	microgrid
$P$	power load profile
$h_i$	step size for DER $i \in I$
$h$	current step size
$S$	set of rightsized microgrid designs

Figure 1. Nomenclature list.

## 2. Simulating a Microgrid

We consider stand-alone microgrids with four main components:

1. Diesel generators;
2. Photovoltaic system;
3. Battery energy storage system (BESS);
4. Energy management system.

We present our modeling assumptions for these components below but the methodology we develop for both operating and rightsizing microgrids later in the paper does not rely on these specific component definitions. It has more general applicability. In other words, more detailed DER models can be substituted, as could historical data, if available, and would require no modification to the rightsizing algorithms presented later in this paper.

### 2.1. Diesel Generation

Diesel generators can produce power so long as fuel remains available. A load factor  $\lambda \in [0, 1]$  can be set to adjust the power output:

$$p_{dg}(\lambda) = q_{dg} \cdot \lambda \quad (1)$$

where  $q_{dg}$  is the power rating and where  $\underline{\lambda} \leq \lambda \leq \bar{\lambda}$  specifies an efficient operating range with

$$\underline{p}_{dg} = p_{dg}(\underline{\lambda}) \quad (2)$$

and

$$\bar{p}_{dg} = p_{dg}(\bar{\lambda}) \quad (3)$$

We assume the diesel generation fuel consumption rate  $f$  is proportional to the load factor:

$$f(\lambda) = \lambda \cdot r \quad (4)$$

where  $r$  is the peak consumption rate when  $\lambda = 1$ .

### 2.2. Photovoltaic System

The power generation capability of a photovoltaic system is dependent on solar radiation properties, which vary by location, season, time of day and weather conditions. We model photovoltaic power using the positive part of a sine-wave equation:

$$p_{pv}(t, \alpha_t) = \max \left\{ 0, \frac{q_{pv} \alpha_t}{2w} \left[ 2w - 1 - \sin \left( \frac{\pi(t+6)}{12} \right) \right] \right\} \quad (5)$$

where  $q_{pv}$  is the power rating that sets the base wave amplitude,  $t$  is the time of day in hours,  $\alpha_t$  is a scaling percentage based on weather conditions at time  $t$ , and  $w$  adjusts the magnitude of the wave based on location and season. Details not represented explicitly may be captured implicitly in  $\alpha_t$ , e.g., reduction in solar cell efficiency due to higher temperature and solar resource availability due to clouds.

### 2.3. Battery Energy Storage System (BESS)

The BESS complements primary generation sources by storing excess power when generation exceeds overall loads and meeting load at other times. We model BESS power discharging and charging as positive and negative flows, respectively:

$$p_b = \begin{cases} q_b \cdot \beta_d, & \text{BESS discharging} \\ -q_b \cdot \beta_c, & \text{BESS charging} \end{cases} \quad (6)$$

where  $q_b$  is the power rating,  $0 \ll \beta_d \leq 1$  is the discharge efficiency and  $0 \ll \beta_c \leq 1$  is the charge efficiency. We model the BESS energy discharge capacity over a given duration  $d$  in hours as

$$\bar{e}_b(d, \gamma) = \min\{p_b \cdot d, u_b \cdot (\gamma - \underline{\gamma})\} \quad (7)$$

where  $u_b$  is the BESS energy rating,  $\gamma$  is the BESS state of charge at the start of duration  $d$  and  $\underline{\gamma}$  is the minimum allowable state of charge.

Similarly, we model the BESS energy charge capacity over duration  $d$  as

$$\underline{e}_b(d, \gamma) = \max\{p_b \cdot d, -u_b \cdot (\bar{\gamma} - \gamma)\} \quad (8)$$

where  $\bar{\gamma}$  is the maximum allowable state of charge. The efficiency of the power converter required to interface the BESS to the microgrid is included in the two battery efficiency values defined above.

#### 2.4. Energy Management System

The energy management system includes control logic for operating diesel generators, a photovoltaic system and BESS within a microgrid. Different microgrid structures, AC, DC or hybrid AC/DC, require different energy management algorithms. A facility's operating objectives can be achieved through the energy management system.

We introduce an energy management system with five operating states:

1. Photovoltaic power, BESS charges;
2. Photovoltaic and BESS power;
3. Photovoltaic and diesel power, BESS charges;
4. Photovoltaic, diesel and BESS power;
5. Photovoltaic, BESS and diesel power.

The fourth and fifth operating states differentiate between the priority order of utilizing power sources. In the fourth, diesel generation is maximized, whereas in the fifth, diesel generation is minimized. We can bypass the second and fifth operating states by ensuring that BESS is only discharged when diesel generation is on and, when combined with photovoltaic power, is sufficient to meet the power load. This logic is stated formally in Algorithm 1, where we use a negative value for load and a positive value for generation.

---

#### Algorithm 1 Energy management system control logic.

---

**Input:** power load  $p_l \leq 0$   
**Input:** photovoltaic power  $p_{pv} \geq 0$   
**Input:** max diesel power  $\bar{p}_{dg} \geq 0$   
**Output:** grid operating state  $s$

```

s = 4
if  $p_{pv} + p_l \geq 0$  then
  s = 1
else if  $p_{pv} + \bar{p}_{dg} + p_l \geq 0$  then
  s = 3
end if
return s

```

---

The method we will introduce for rightsizing a microgrid is independent of the energy management system, so it can be flexibly applied with any set of control logic. For example, it might be inefficient to turn diesel generators on and off with a high frequency. We can embed rules in the energy management system to prevent such dynamics: when diesel generation is on, it stays on until either (a) diesel and photovoltaic combined are insufficient for meeting load, but BESS and photovoltaic combined are sufficient, or (b) the BESS is fully charged, load can be met without diesel generation and diesel generation is outside the efficient operating mode. For more on energy management systems, we refer the reader to Raya-Armenta et al. [34].

### 2.5. Microgrid Simulation

While power is both generated and consumed continuously, we can discretize time for the purposes of simulating a microgrid. At each time step, we need to compute power and energy availability, identify the state of the energy management system, compute the resulting power profile and update the BESS state of charge. Our simulation method for a single time step is summarized in Algorithm 2, where various energy and power variables are computed using equations governing their behaviors, e.g., Equations (1)–(8). We use a convention on negative values for loads and BESS charging and positive values for generation and BESS discharging.

---

**Algorithm 2** Simulated microgrid operation for one time-step.

---

**Input:** previous energy management state  $s \in \{1, 2, 3, 4, 5\}$

**Input:** microgrid with energy management system  $ems$

**Input:** BESS state of charge  $\gamma \in [0, 1]$

**Input:** power load  $p_l \leq 0$

**Input:** time interval  $(t_a, t_b)$

**Output:** current grid operational status

$$d = t_b - t_a$$

$$e_l = p_l d$$

$$e_{pv} = p_{pv}(t, \alpha_t) \cdot d$$

$$\bar{e}_{dg} = \bar{p}_{dg} \cdot d$$

$$\underline{e}_{dg} = \underline{p}_{dg} \cdot d$$

$$\vec{e} = [e_l, e_{pv}, \bar{e}_{dg}, \underline{e}_{dg}, \bar{e}_b(d, \gamma), \underline{e}_b(d, \gamma)]$$

computer average power  $\vec{p} = \vec{e}/d$

run  $ems$  with input  $\vec{p}$  and previous state  $s$  to update state  $s$

$$e = e_l + e_{pv}$$

**if**  $s == 5$  (BESS discharges, diesel gen. power) **then**

$$e_b = \min\{\bar{e}_b(d, \gamma), \max\{0, -e\}\}$$

$$e_{dg} = \min\{\bar{e}_{dg}, \max\{0, -(e + e_b)\}\}$$

**if**  $e_{dg} < \underline{e}_{dg}$  (wet-stacking) **then**

$$\delta_{dg} = \underline{e}_{dg} - e_{dg}$$

$$\delta_b = \min\{e_b, \delta_{dg}\}$$

$$e_b = e_b - \delta_b$$

$$e_{dg} = e_{dg} + \delta_b$$

**end if**

**else if**  $s == 4$  (diesel gen. power, BESS discharges) **then**

$$e_{dg} = \min\{\bar{e}_{dg}, \max\{0, -e\}\}$$

$$e_b = \min\{\bar{e}_b(d, \gamma), \max\{0, -(e + e_{dg})\}\}$$

**else if**  $s == 3$  (diesel gen. power, BESS charges) **then**

$$e_{dg} = \min\{\bar{e}_{dg}, \max\{0, -(e + \underline{e}_b(d, \gamma))\}\}$$

$$e_b = \min\{-(e + e_{dg}), 0\}$$

**else if**  $s == 2$  (BESS discharges) **then**

$$e_{dg} = 0$$

$$e_b = \min\{\bar{e}_b(d, \gamma), \max\{0, -e\}\}$$

**else if**  $s == 1$  (BESS charges) **then**

$$e_{dg} = 0$$

$$e_b = \max\{\underline{e}_b(d, \gamma), \min\{-e, 0\}\}$$

**end if**

**return** status =  $(e_l, e_{pv}, e_{dg}, e_b, s)$

---

The key decisions, under all five operating states are to determine the energy produced by diesel generation and the energy released or stored in the BESS. When in an energy management state of 5, diesel generation is increased to the minimum level required or as close as possible to avoid wet-stacking, which may occur when running below the minimum specified operating efficiency.



We iterate over all time steps to simulate the microgrid over a given time horizon, updating the BESS state of charge, recording average power generation and tracking whether a power deficit exists at any point in time. This simulation method is formalized in Algorithm 3.

---

**Algorithm 3** Simulated microgrid operation.

---

**Input:** microgrid  $g$   
**Input:** initial BESS state of charge  $\gamma$   
**Input:** power loads  $\vec{p} = [p_1, \dots, p_n]$   
**Input:** time steps  $\vec{t} = [t_0, \dots, t_n]$   
**Output:** deficit boolean  
**Output:** power profile  $P$

```

s = -1
deficit = false
for i = 1; i ≤ n; i = i + 1 do
  (el, epv, edg, eb, s) = run Algorithm 2 w/ s, g, γ, pi, (ti-1, ti)
  if el + epv + edg + eb ≤ 0 then
    deficit = true
  end if
  γ = γ + eb / ub
  Pi = [el, epv, edg, eb] / (ti - ti-1)
end for
return deficit, P

```

---

### 3. Rightsizing the Microgrid

Consider the problem of equipping a microgrid with sufficient energy generation and storage capacity to meet load at all times. We can define microgrid capacity with the following vector:

$$(q_{pv}, q_{dg}, u_b),$$

where  $q_{pv}$  is the total photovoltaic power rating,  $q_{dg}$  is the total diesel generator power rating and  $u_b$  is the BESS energy rating. We assume the BESS energy rating is proportional to its power rating,

$$u_b = k \cdot q_b$$

where  $k$  is the proportionality constant.

#### 3.1. Characterizing Solutions

A range of possible solutions exist, with respect to the singular goal of meeting load. Rightsized solutions, by definition, do not include unutilized resources. For example, load can be met with only diesel generator capacity  $(0, y, 0)$ , where  $y$  is the peak load, so a microgrid with capacity  $(0, y + \epsilon, 0)$  is not rightsized for any  $\epsilon > 0$ . The rightsized point  $(0, 0, z)$  can be identified by computing BESS capacity  $z$  as the integral of load over time—in other words, the energy required to continuously meet load. This assumes the BESS is initially in a fully charged state. However, infinite photovoltaic power  $(\infty, 0, 0)$  is not sufficient to meet load, because power generation would lapse during the night.

While exact analytical solutions exist for the two single-resource rightsized solutions just discussed, in general, no closed-form solution exists. Theoretically, power rating options are continuous, so an infinite number of rightsized solutions exist. Practically, a discrete set of equipment options can be considered. We develop a nested binary search method to identify rightsized solutions within a specified discretization of the continuous problem.

#### 3.2. Photovoltaic Power Rating

For a given  $q_{dg}$  and  $u_b$ , we must first ensure a feasible solution exists by verifying whether a power deficit exists with  $q_{pv} = \infty$ . If so, we can identify the minimum  $q_{pv}$  with

a binary search method. Starting with  $q_{pv} = 0$ , we increase its value and simulate the grid operation, until power load is met over the time horizon. We double the step size at each iteration to ensure a quick convergence. Once a feasible solution is identified with no power deficit, we halve the step size at each iteration. We decrease values of  $q_{pv}$  when no deficit exists and increase them when a deficit exists. Once, we reach the initial step size and obtain a feasible solution  $q_{pv}$ , we have identified the minimum  $q_{pv}$  and the search returns it. This method is summarized in Algorithm 4.

---

**Algorithm 4** Minimum photovoltaic power rating to meet load.

---

**Input:** step size  $h_{pv}$   
**Input:** BESS energy rating  $u_b$   
**Input:** diesel generator power rating  $q_{dg}$   
**Output:** minimum photovoltaic power rating  $q_{pv}$

```

flag = true
h = hpv
qpv = ∞
run Algorithm 3 to simulate grid operation, update deficit
if deficit then
    return qpv
end if
qpv = 0
deficit = true
while deficit or h > hpv or flag do
    if not deficit then
        flag = false
    end if
    if flag then
        h = 2h
    else if h > hpv then
        h = h/2
    end if
    if deficit then
        qpv = qpv + h
    else
        qpv = qpv - h
    end if
    run Algorithm 3 to simulate grid operation, update deficit
end while
return qpv

```

---

### 3.3. Rightsizing for a Given $q_{dg}$

For a given  $q_{dg}$ , we implement a binary search over values of  $u_b$  to identify feasible solutions efficiently. We start with  $u_b = 0$  and increase  $u_b$  at each iteration. We run Algorithm 4 to obtain the minimum  $q_{pv}$  value. If finite, we have identified a feasible solution to meet power load, but it is not necessarily rightsized. We may have overshot the mark on  $u_b$ , so we run another binary search on  $u_b$  with our fixed values of  $q_{dg}$  and  $q_{pv}$ . This inner search is summarized in Algorithm 5.

**Algorithm 5** Minimum BESS energy rating to meet load.

---

```

Input: step size  $h_b$ 
Input: diesel generator power rating  $q_{dg}$ 
Input: photovoltaic power rating  $q_{pv}$ 
Input: maximum BESS energy rating  $u_b$ 
Output: minimum BESS energy rating  $u_b$ 
deficit = false
if  $u_b > h_b$  then
    flag = true
else
    flag = false
end if
 $h = h_b/2$ 
while deficit or  $h_b > h$  or flag do
    if deficit then
        flag = false
    end if
    if flag or  $h < h_b$  then
         $h = 2h$ 
    else if  $h > h_b$  then
         $h = h/2$ 
    end if
    if deficit then
         $u_b = u_b + h$ 
    else if  $u_b \geq h_b$  then
         $u_b = u_b - h$ 
    end if
    run Algorithm 3 to simulate grid operation, update deficit
end while
return  $u_b$ 

```

---

If the design obtained is not dominated by another design previously identified, it is rightsized. The complete method for rightsizing for a Given  $q_{dg}$  is summarized in Algorithm 6.

We can increase the efficiency of the binary search in Algorithm 6 by updating  $q_{pv}$  after a finite value is obtained, using a modified version of Algorithm 5. The required modification is to search  $q_{pv}$  rather than  $u_b$ , but the logic is otherwise the same.

---

**Algorithm 6** Identification of all rightsized designs  $\leq d_g$ .

---

**Input:** step size for BESS energy rating  $h_b$   
**Input:** step size for photovoltaic power rating  $h_{pv}$   
**Input:** diesel generator power rating  $q_{dg}$   
**Input:** set of rightsized solutions  $S$  for  $< q_{dg}$   
**Output:** set of rightsized solutions  $S$  for  $\leq q_{dg}$

```

 $q_{pv} = \infty$ 
 $u_b = 0$ 
 $h = h_b$ 
while  $q_{pv} > h_{pv}$  do
  run Algorithm 4 with inputs  $u_b$  and  $h_{pv}$  to update  $q_{pv}$ 
  if  $q_{pv} < \infty$  and  $h > h_b$  then
    run Algorithm 5 with inputs  $h_b, q_{dg}, q_{pv}, u_b$  to update  $u_b$ 
  end if
  if  $q_{pv} < \infty$  then
    dominated = false
    for all  $(x, q_{dg}, z) \in S$  do
      if  $x \leq q_{pv}$  and  $z \leq u_b$  then
        dominated = true
        break
      end if
    end for
  end if
  if  $q_{pv} < \infty$  and not dominated then
     $S = S \cup (q_{pv}, q_{dg}, u_b)$ 
  else
     $h = 2h$ 
  end if
   $u_b = u_b + h$ 
end while
return  $S$ 

```

---

### 3.4. Iterating over Diesel Generator Ratings

We discretize the diesel generation capacity with a specified step size  $h_{dg}$ , iterating from 0 to the peak load of the system. For each value of  $q_{dg}$ , we run Algorithm 6 to obtain rightsized designs. Our method is summarized in Algorithm 7, illustrated in the flowchart in Figure 2, and is also parallelizable.

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**Algorithm 7** Identify all rightsized solutions.

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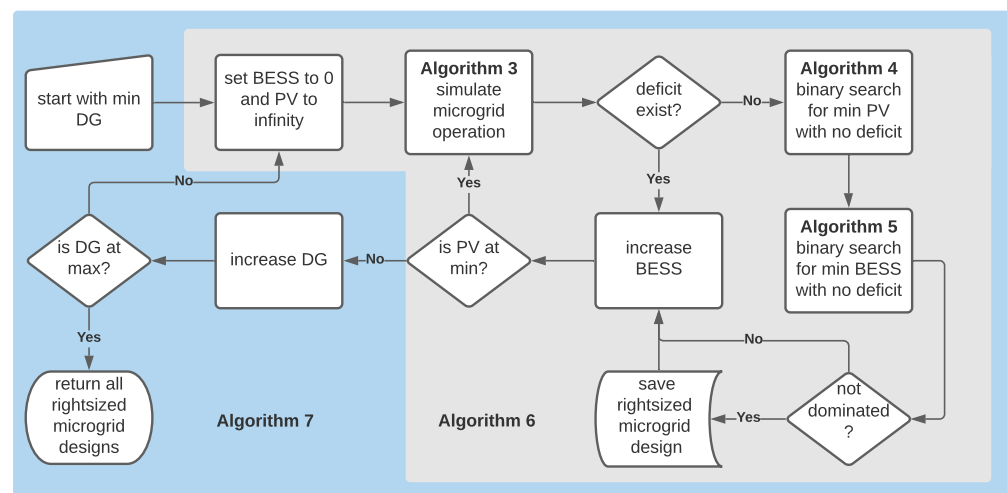
**Input:** step size for diesel generation power rating  $h_{dg}$   
**Input:** step size for photovoltaic power rating  $h_{pv}$   
**Input:** step size for BESS energy rating  $h_b$   
**Output:** set of rightsized solutions  $S$

```

 $S = \emptyset$ 
for  $q_{dg} = 0; q_{dg} < \text{peak load} + h_{dg}; q_{dg} = q_{dg} + h_{dg}$  do
  run Algorithm 6 with inputs  $h_b, h_{pv}$  and  $q_{dg}$  to update  $S$ 
end for
return  $S$ 

```

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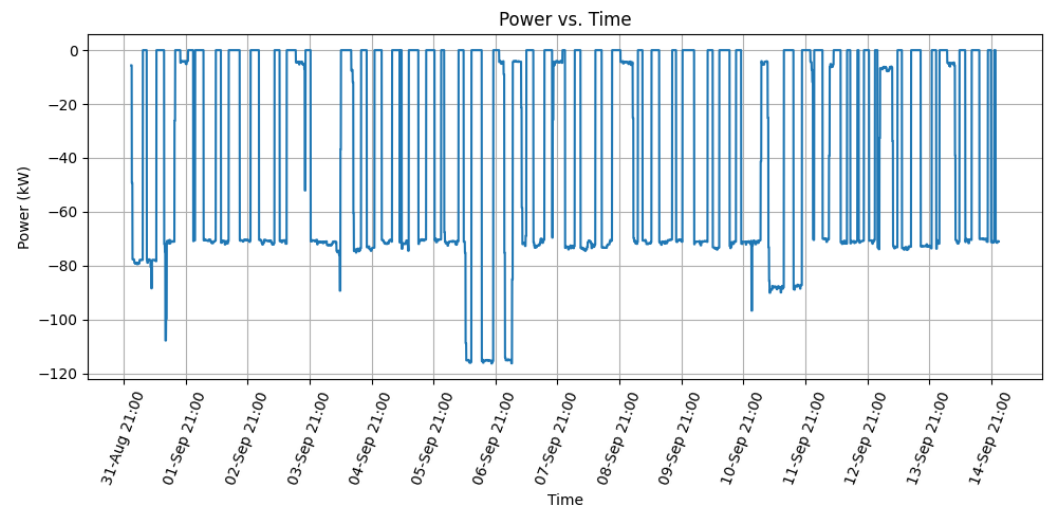
**Figure 2.** This flowchart illustrates the rightsizing procedure, with DG denoting diesel generator power and PV denoting photovoltaic power. The energy management system (Algorithm 1) is run exclusively as a subroutine of single time step simulation (Algorithm 2), which is run exclusively as a subroutine of the microgrid simulation (Algorithm 3). Microgrid simulation (Algorithm 3) is run as a subroutine within the binary search for the minimum photovoltaic power (Algorithm 4), within the binary search for the minimum BESS energy (Algorithm 5), and within the rightsizing search for a given level of diesel generation (Algorithm 6).

#### 4. Computational Results

Although the method we propose can be used to rightsize any stand-alone microgrid, whether it is always islanded or it operates in islanding mode when the utility grid is down, in our computational experiments we focus on the design of a back-up microgrid for a facility with loads that are critical to the operation of the facility, such as a hospital or a military facility. When the utility power becomes unavailable, the microgrid must support the critical loads for a number of days specified by the facility's manager.

In the simulation results presented in this section, we focus on an anonymized version of a load profile obtained from an actual facility to which we applied our rightsizing methods. Our aim was to identify microgrid designs capable of fully sustaining loads, while operating exclusively in islanding mode. The time horizon considered is 14 days, discretized in time steps of 4 minutes in duration. The power load profile is shown in Figure 3, and follows our convention of negative power values representing loads and BESS charging, to differentiate from positive-valued power generation and BESS discharging.

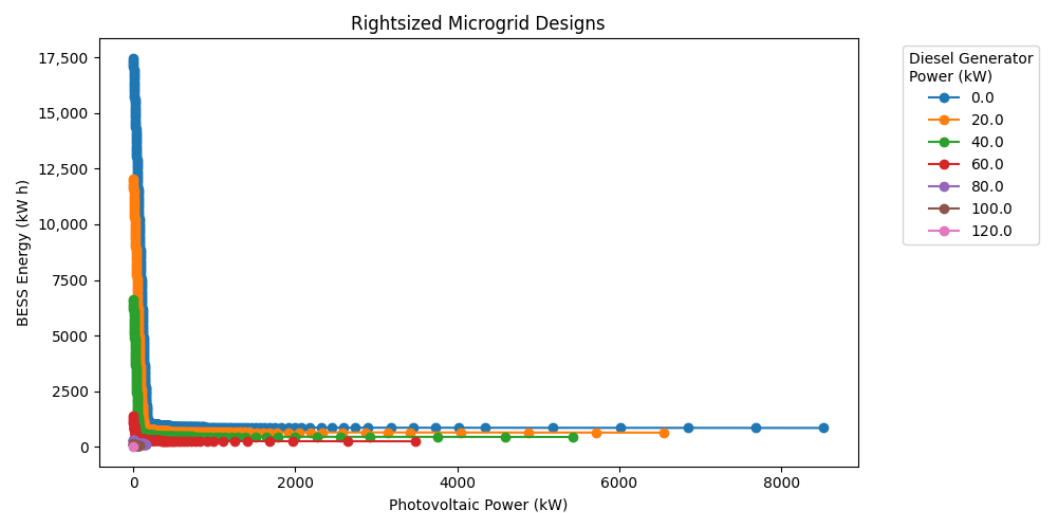
We implemented our approach in Python and ran Algorithm 7 with input step sizes of 20 kW diesel generator power, 1 kW photovoltaic power and 1 kW·h BESS energy. We used the energy management system from Algorithm 1. We initialized the BESS to a fully charged state  $\gamma = \bar{\gamma} = 1$  at the beginning of any simulation call to Algorithm 3 and set the minimum allowable state of charge  $\underline{\gamma} = 0.2$ .



**Figure 3.** Power load profile over two-week time horizon.

#### 4.1. Range of Rightsized Microgrid Designs

We obtained the complete range of potential microgrid designs meeting load requirements, shown in Figure 4. The extreme solutions on both axes are unlikely to be of interest, because the resources required would be orders of magnitude higher than those designs closest to the origin. When introducing diesel generators, these extreme effects are scaled back but their natures are similar, as evidenced by the nested structure of curves.

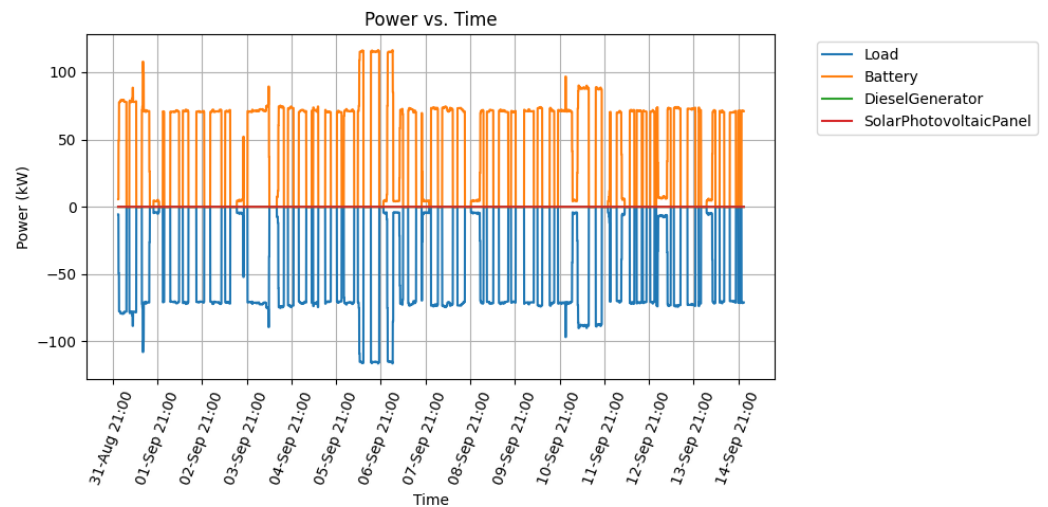


**Figure 4.** Microgrid designs rightsized to meet power load requirements.

To simplify matters, let us first consider designs without diesel generation to understand the dynamics of the extreme solutions.

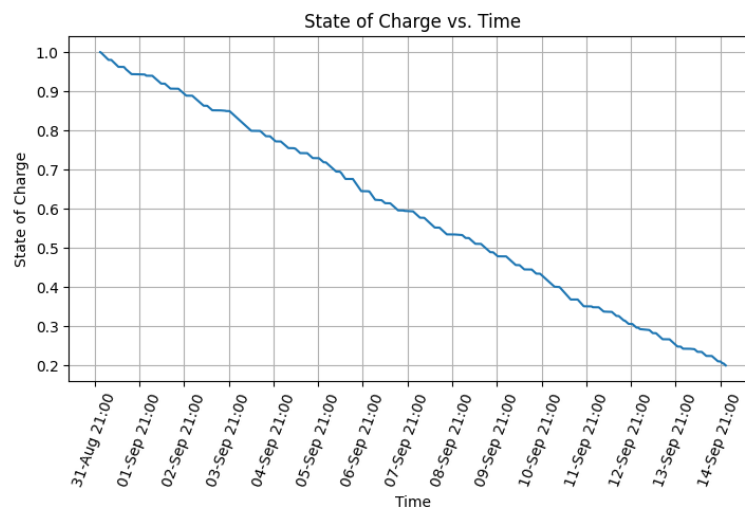
#### 4.2. BESS Max Capacity

Operating solely on a BESS can be achieved with an energy rating  $u_b$  of 17,476 kW·h, while adhering to a 20% minimum state of charge, assuming the BESS was fully charged prior to the time window shown. The power profile in Figure 5 shows the BESS power in the positive  $y$ -axis meeting the power load in the negative  $y$ -axis, one the mirror image of the other.



**Figure 5.** Power profile of microgrid design with 17,476 kW·h BESS.

Without power generation capacity, the state of charge continuously decreases until its minimum allowable value of 20% is reached at the end of the time horizon, as shown in Figure 6.



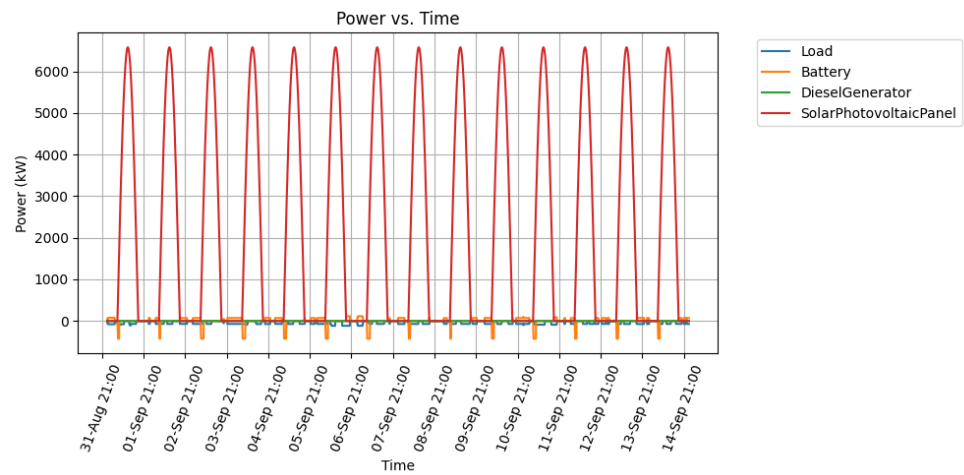
**Figure 6.** State of charge of microgrid design with 17,476 kW·h BESS.

#### 4.3. Photovoltaic Max Capacity

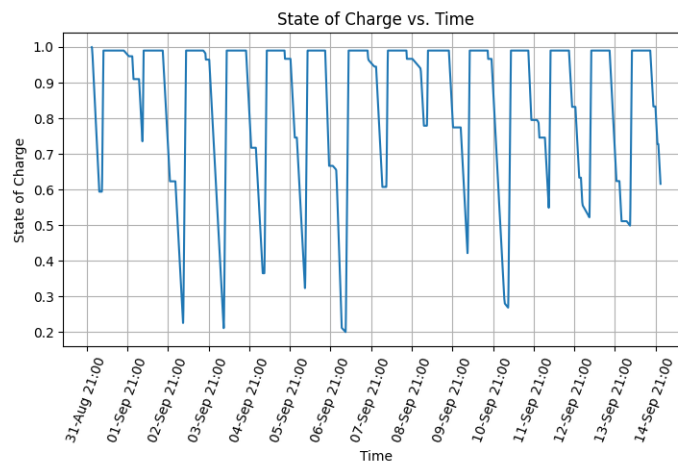
Operating solely on solar energy is not possible, because power loads exist at night. The most extreme photovoltaic power rating  $q_{pv}$  identified is 8520 kW, accompanied by a 851 kW·h BESS rating  $u_b$ . The power profile is shown in Figure 7.

Further reducing the BESS capacity would result in an inability to meet power loads before peak sun hours, as can be seen in Figure 8 when the 20% minimum allowable state of charge is reached.

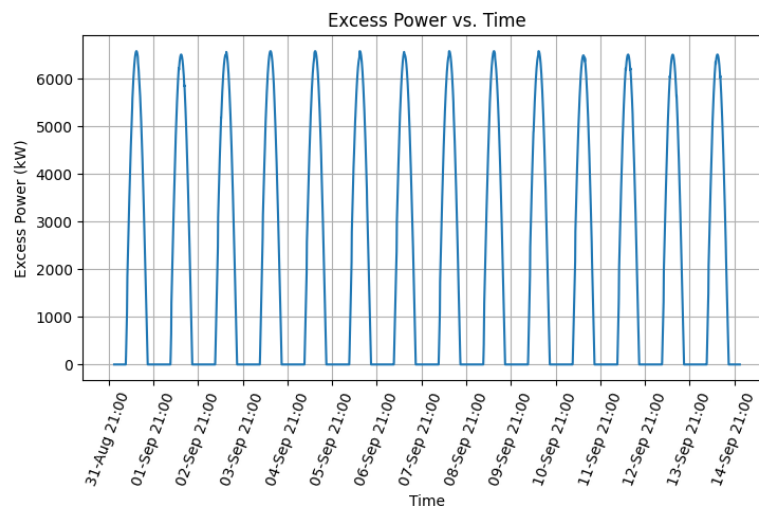
Including photovoltaic power capacity that is orders of magnitude higher than the power load allows a sustainable level of power production to be output, just as the sun is beginning to rise. However, the power production then becomes severely underutilized for the remainder of the day, as is observable in Figure 7 and is further highlighted in Figure 9.



**Figure 7.** Power profile for a microgrid with 8520 kW photovoltaic power rating and 851 kW·h BESS. Daytime photovoltaic power is orders of magnitude greater than load and other DER capacity.



**Figure 8.** BESS state of charge for a microgrid with 8520 kW photovoltaic power rating and 851 kW·h BESS.



**Figure 9.** Excess power generation for an extreme microgrid design with 8520 kW photovoltaic power rating and 851 kW·h BESS.



#### 4.4. Microgrid Design Region of Interest

Now that we have seen the microgrid designs with extreme BESS and photovoltaic capacities, let us hone in on the region of interest that is closer to the origin, shown in Figure 10.

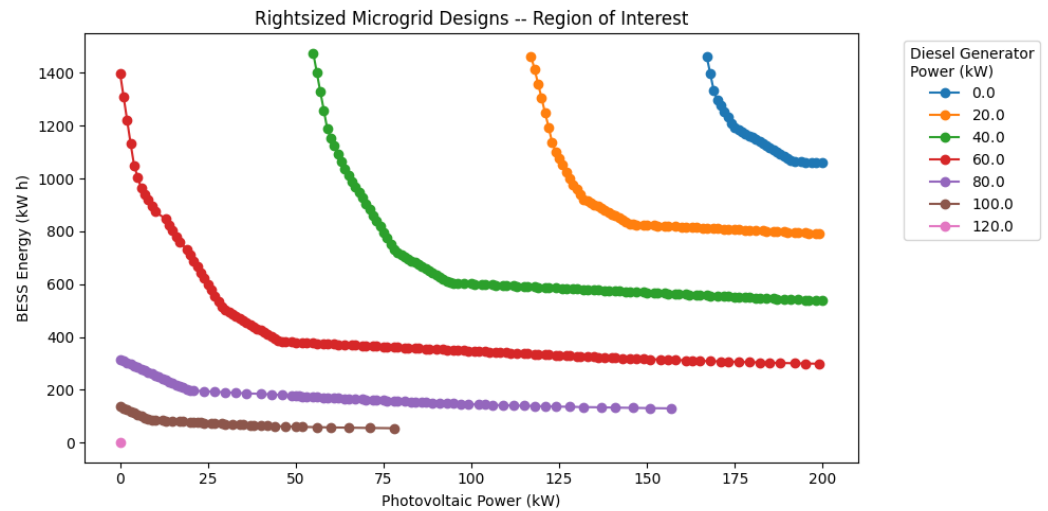


Figure 10. Microgrid designs rightsized to meet power load requirements.

For any diesel generation power rating  $q_{dg}$ , we can observe inflection points, to the left of which BESS capacity increases rapidly and to the right of which photovoltaic power increases rapidly. Microgrid designs with a high utilization of both their photovoltaic system and BESS will be close to these inflection points.

#### 4.5. Well-Utilized Photovoltaic System and BESS

A microgrid with 174 kW photovoltaic power rating  $q_{pv}$  and 1211 kW·h BESS energy rating  $u_b$  is able to meet power loads with the power profile shown in Figure 11.

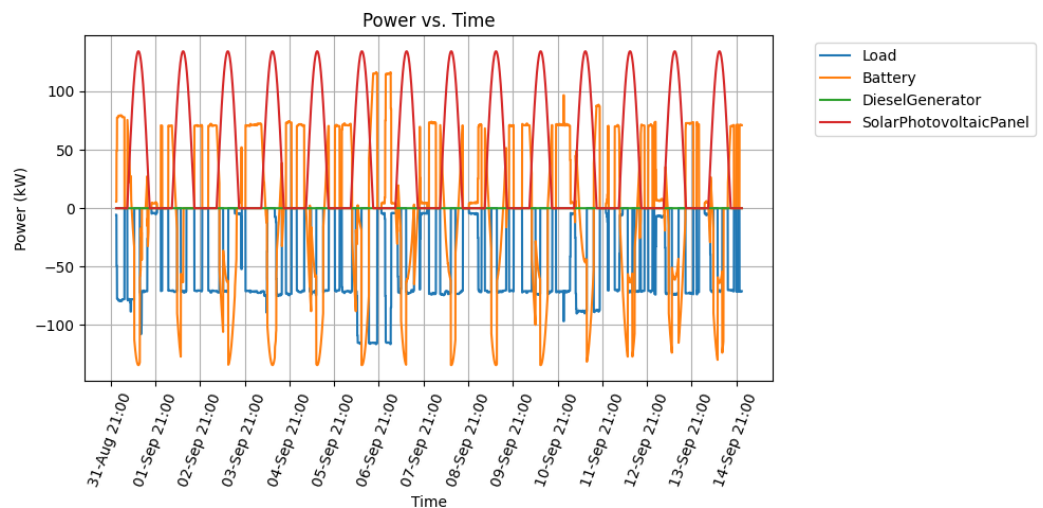
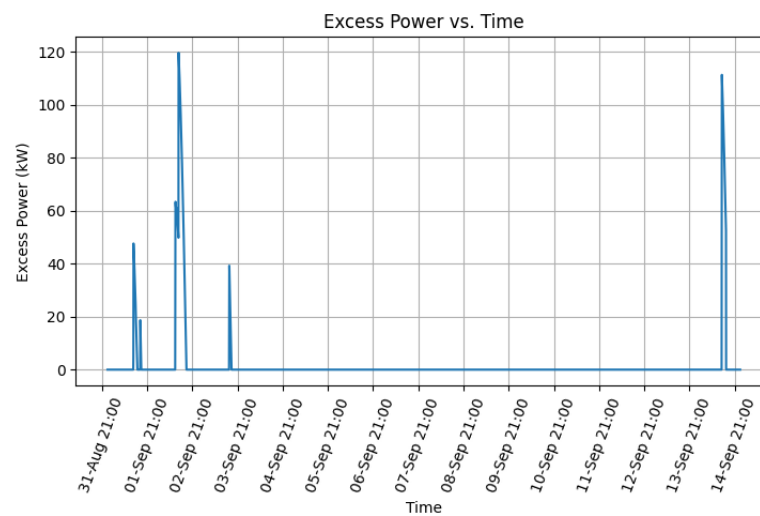
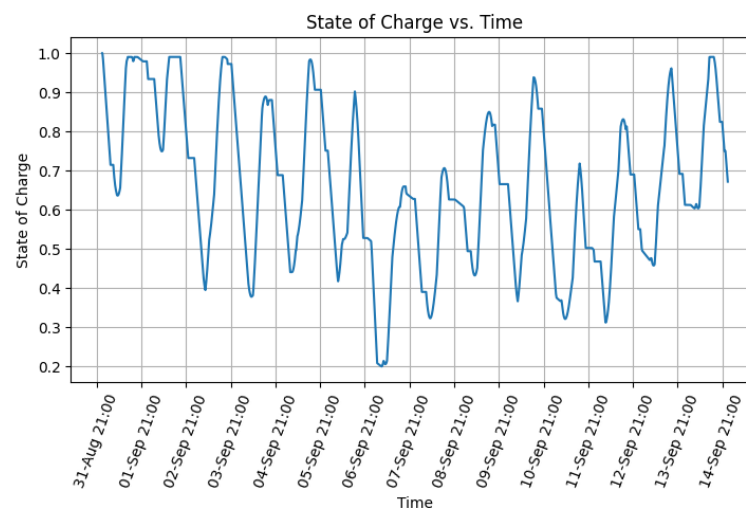


Figure 11. Power profile for a microgrid with 174 kW photovoltaic power rating and 1211 kW·h BESS.

Excess capacity is rarely available, which is more easily seen in Figure 12. In the absence of extreme power excess spikes, such as those in Figure 9, excesses will tend to occur when the BESS is at a fully charged state, as is confirmed in Figure 13. The combination of Figures 11–13 illustrates that both the photovoltaic system and BESS are well-utilized.



**Figure 12.** Excess power for a microgrid with 174 kW photovoltaic power rating and 1211 kW·h BESS.



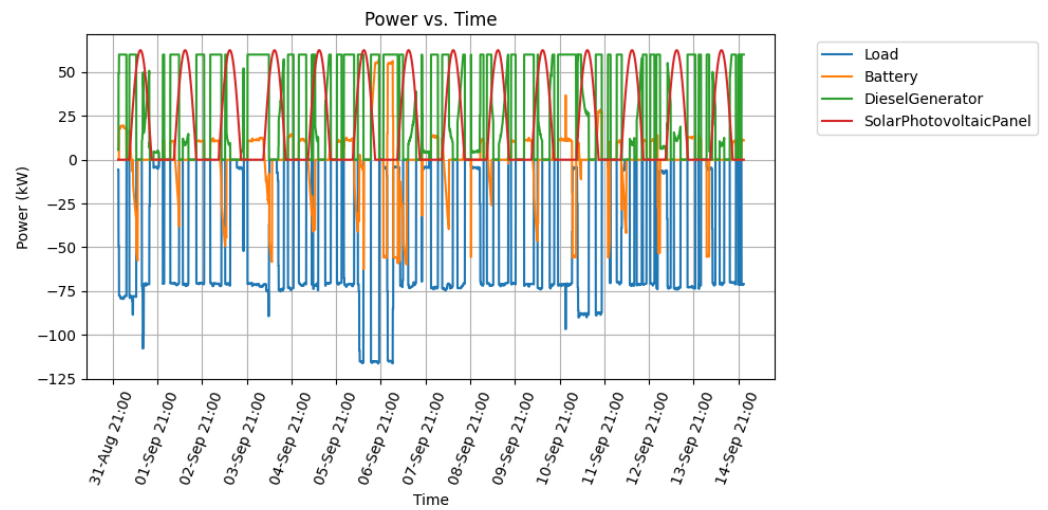
**Figure 13.** State of charge for a microgrid with 174 kW photovoltaic power rating and 1211 kW·h BESS.

Note that by increasing the BESS energy rating  $u_b$  42% from 851 to 1211 kW·h, we were able to reduce the photovoltaic power rating  $q_{pv}$  by 98% from 8520 to just 174 kW. Similarly, when compared to the BESS-only microgrid with 17,476 kW·h, we were able to reduce the BESS energy rating  $u_b$  by 93% to 1211 kW·h, with the addition of only a 174 kW photovoltaic power rating  $q_{pv}$ . This again highlights why the region of rightsized microgrid designs of greatest interest may exclude extreme solutions.

#### 4.6. The Impact of Diesel Generation

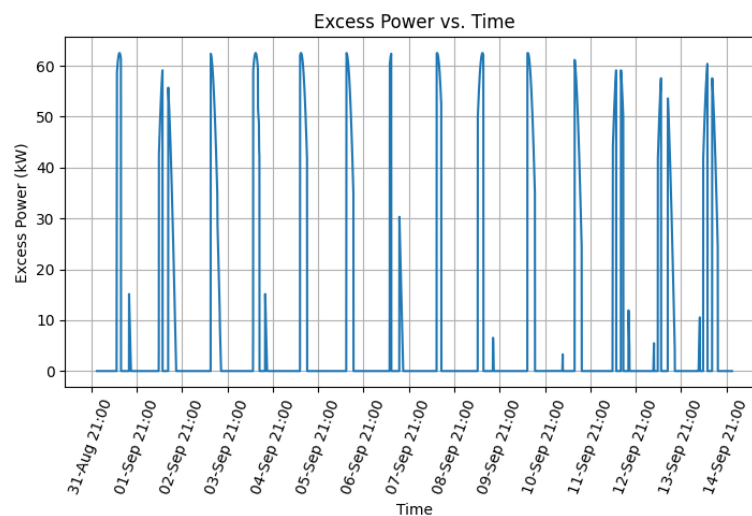
Unlike photovoltaic power, diesel generators can provide a consistent level of power at all times. So, with sufficient capacity to meet peak loads and a reliable fuel supply, diesel generators can operate as a sole source of power. When operating in tandem with a photovoltaic system and BESS, we aim to rightsize the latter components.

A microgrid with 60 kW diesel generation  $q_{dg}$ , 81 kW of photovoltaic power  $q_{pv}$  and 360 kW·h BESS energy rating  $u_b$  is rightsized. The power profile is shown in Figure 14.



**Figure 14.** Power profile for a microgrid with 60 kW diesel generation power rating, 81 kW photovoltaic power rating and 360 kW·h BESS.

Excess power is available, primarily during peak sun hours after the BESS reaches a full state of charge, as shown in Figure 15.

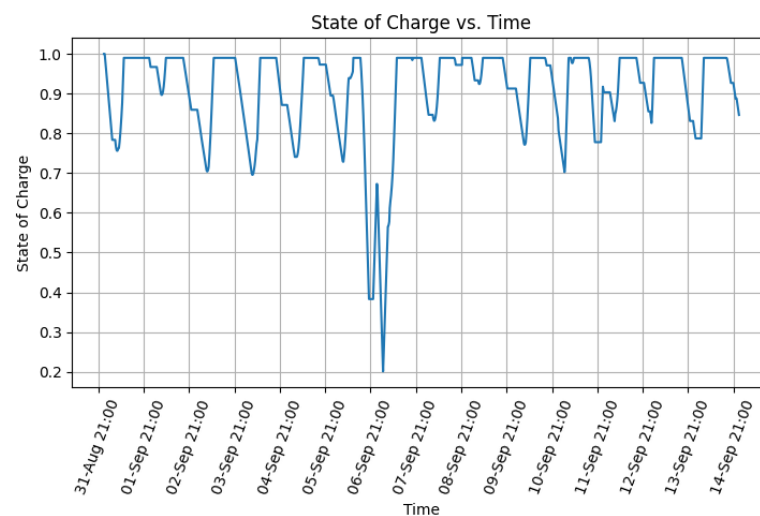


**Figure 15.** Excess power for a microgrid with 60 kW diesel generation capacity, 81 kW photovoltaic power rating and 360 kW·h BESS.

When compared to the previous microgrid design that did not include diesel generation, this one maintains a higher average BESS state of charge, as observed in Figure 16.

Designing the microgrid with 60 kW diesel generation power rating  $q_{dg}$  reduces the required photovoltaic power rating  $q_{pv}$  from 174 to 81 kW and BESS energy rating  $u_b$  from 1211 to 360 kW·h, when compared with the prior design.

A decision maker can weigh additional considerations, such as cost, environmental impact, maintenance, etc., to select the ideal design.



**Figure 16.** State of charge for a microgrid with 60 kW diesel generation capacity, 81 kW photovoltaic power rating and 360 kW·h BESS.

## 5. Discussion

### 5.1. Metrics and Optimization

Our rightsizing method is intended to be used early in the microgrid design process, before an initial design is selected, refined and finalized. Optimization is performed by a decision maker, such as a facility energy manager, who is empowered to rank preferences, after our rightsizing method supplies a set of potential solutions with associated metrics. For example, a decision maker can select a preferred design based on one or more criteria, such as life cycle or maintenance cost, CO<sub>2</sub> emissions, resilience, etc.

Our computational results illustrate the variety of rightsized designs produced by our method. To focus and simplify the presentation, we do not include various metrics that may be computed for each design, e.g., cost and emissions. A decision maker will need these additional metrics to weigh trade-offs between microgrid design options and they can be calculated in a straightforward manner. For example, by tracking fuel consumption in Algorithm 2, we can compute emissions and fuel cost within the rightsizing method. Alternatively, we can post-process these metrics from the underlying data used to generate the power profiles in Figures 5, 7, 11 and 14. Investment and maintenance costs are similarly straightforward to compute for any rightsized microgrid design generated. Presented with these metrics, decision makers are then empowered to select designs that they deem optimized for their requirements and preferences.

### 5.2. Limitations

Our method does have certain limitations. Most notably, the set of rightsized microgrid designs is identified based off a single power load profile. In practice, power loads vary and additional capacity is needed to function in a reliable and robust manner. Assessing sensitivity to load increases or varying weather conditions throughout the year requires bootstrapping additional methods, a subject of future research. Another limitation is the rightsizing algorithms are designed for exactly three DER types. Adding a fourth dimension, e.g., wind turbines, while maintaining computational tractability is nontrivial. A third limitation is that our DER models introduced in Section 2 and used in our computations in Section 4 are simplified. However, more detailed DER models can be substituted without requiring modification to the rightsizing methods presented in Section 3, an advantage of the decoupled design of our approach.

## 6. Conclusions

This paper developed a simulation-based modeling framework for rightsizing hybrid microgrids that are composed of diesel generators, a photovoltaic system, a battery energy

storage system and an energy management system. We have decoupled many factors to maximize flexibility when applying our methodology both in practice and in future research. For example, while we modeled photovoltaic power generation using the positive part of a sine function, this could be replaced with a model based on historical weather data without modification to any of the algorithms we present. Similarly, while we introduce a simple energy management system for use in our computational experiments, more complex control logic could be incorporated without requiring any other modifications.

Our aim is for practitioners to utilize our methods when designing hybrid microgrids. We focused on the complicated dynamics of aiming to satisfy a given power load over a time horizon, a task that requires a simulation model. We identified a full range of microgrid options that are rightsized to meet the specified loads. Even with a simulation model, this task would be onerous if it is not impossible for an individual to complete. In theory, one could iterate over every single set of options, but this would be computationally intractable in practice. By constructing a nested binary search method, we introduce a computationally efficient approach for identifying all rightsized solutions.

Decision makers can then expend their efforts on analyzing other aspects of importance, e.g., cost and environmental considerations. These aspects need only be measured and associated with each potential microgrid design, which is readily output from our simulation model, given the necessary input information, e.g., purchasing costs. While optimization methods may incorporate some aspects of importance, in doing so they exclude potential suboptimal solutions. However, rarely is it possible to incorporate all factors of importance for decision makers, so an unintentional consequence is lost information. In contrast, our method empowers decision makers to consider trade-offs and logically narrow down the set of potential solutions of interest.

In practice, a decision maker is not limited to a rightsized solution. A solution deemed desirable is a starting point. Increasing capacity by a modest amount, for example, 10%, would make such a solution robust to different but similar load profiles. Analyzing the sensitivity of rightsized solutions can be decoupled from the methods presented in this paper and handled in post-processing. Such analyses could be the subject of future work.

**Author Contributions:** Conceptualization, D.R. and G.O.; methodology, D.R.; software, D.R. and G.O.; validation, D.R. and G.O.; formal analysis, D.R.; writing—original draft preparation, D.R.; writing—review and editing, D.R. and G.O.; visualization, D.R.; funding acquisition, D.R. and G.O. All authors have read and agreed to the published version of the manuscript.

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## Abbreviations

The following abbreviations are used in this manuscript:

BESS	battery energy storage system
DER	distributed energy resource
DG	diesel generator power
EMS	energy management system
PV	photovoltaic power

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