BaSCOT: Battery and Solar Capacity Optimization Tool Using OR-Tools

By
Alton I. Caylor
Department of Environmental Science and Sustainability
Allegheny College
Meadville, Pennsylvania

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Submitted in fulfillment of the senior thesis requirements of the
Department of Environmental Science and Sustainability at Allegheny College
and approved by the senior thesis committee.

	4/26/22		5 May 2022
Dr. Ian Carbone	**Date**	**Dr. Oliver Bonham-Carter**	**Date**

Alton Caylor
Pledge

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Acknowledgements

I would first like to thank my advisor, Dr. Carbone for encouraging me to study this topic, and his patience, advice, and assistance with researching and developing this project.

I would additionally like to thank Dr. Bowden for providing me with the opportunity to work on a manuscript for publication, and for his general guidance over the years with regards to academics.

Name: Alton I. Caylor Date: April, 2022

Major: Environmental Science and Sustainability

Thesis Committee: Dr. Ian Carbone, Dr. Oliver Bonham-Carter

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Abstract

As extreme weather conditions worsen due to climate change, resiliency is becoming an increasingly attractive feature of energy systems. Basic implementation of renewable energy sources such as solar panels causes power production to become more intermittent, resulting in lower resiliency. Battery storage can help to alleviate this problem, but sizing an appropriate solar energy and battery storage system is difficult due to the complexity of the factors involved. Linear programming and mixed-integer linear programming can be used to optimize solar energy and battery storage, but current tools such as REopt do not offer enough flexibility for users to adjust the function of the program. The objective of this project was to develop a tool that is more flexible than existing options, allowing for applications in a wider variety of renewable energy projects. BaSCOT is a tool developed for this project that takes local solar and energy data, and designs systems resilient to 24-hour periods of power failure, optimized for cost savings. In addition to information on the sizes and costs for solar and battery installation, the program also produces several graphics detailing specific information about the 24-hour outage period and the lifetime savings of the system.

Keywords: solar energy, battery storage, linear optimization, resiliency

Introduction

Facing extreme weather as resulting from climate change, and an increasingly limited supply of fuel, resiliency is becoming a greater concern for many organizations with electrical infrastructure. Resiliency is characterized as the ability for an electrical power grid to respond to events that may be disruptive to operation and/or cause shifts in production or demand (Jufri et al., 2019). Power outages caused by extreme weather can have negative impacts on people and business operations within the regions served, resulting in damage to infrastructure and widespread effects on communities (Wilbanks and Fernandez, 2014).

Standard approaches to power production require burning fossil fuels to match power production and energy demand, in order to achieve fairly stable operation. This approach leads to severe environmental ramifications resulting from greenhouse gas emissions (Ram et al., 2018). Implementing renewable energy sources mitigates the impact of greenhouse gases, but introduces intermittent production. This reduces the power grid's resilience and ability to avoid or recover from disruptions in power production (McLellan et al., 2012; Schmietendorf et al., 2017).

Energy storage alleviates the problem of intermittent power production by storing energy produced during periods of excessive production and releasing it when consumption exceeds production (Zsiborács et al., 2019). Energy storage also serves as a buffer, allowing for some duration of operation during power outages. Electro-chemical energy storage systems, composed of primarily lead-acid and lithium-ion battery technologies, are among the most well-developed options for storing energy. These technologies have been demonstrated to be commercially viable for a variety of applications (Nadeem et al., 2018).

Another way to introduce resiliency into an electrical system is through the use of distributed energy production and storage, a system commonly called a microgrid (Lasseter et al., 2002). Renewable-based microgrids are especially important due to their ability to provide self-sufficiency as well as interfacing with other microgrids to provide energy during a period of grid failure (Hussain et al., 2019). Microgrids consisting of solar energy production and battery storage not only improve the energy resilience of the communities in which they are installed, but also do so at a comparably low cost, while providing economic and societal benefits by allowing operation during outages (Laws et al., 2018).

Extreme weather events lead to more frequent unpredictable grid instability, requiring alternative approaches to improving resilience (Panteli and Mancarella, 2015). With declining costs in solar modules and batteries, building owners and managers are increasingly interested in implementing renewable energy sources at a local scale and incorporating energy storage for resiliency (Comello and Reichelstein, 2019). Sizing a solar or battery storage installation can be difficult due to a number of factors impacting system production and operation. The amount of power produced by solar panels is heavily dependent on the conditions of the surrounding environment, including solar irradiance, weather, and shading obstructions (Ghazi and Ip, 2014; Ramli et al., 2016; Bayrak and Oztop, 2020). Additionally, variable energy usage throughout the day produces a major source of strain on electrical grids when peak draw exceeds the ability of the grid to supply power (Cetin et al., 2014). These factors can negatively impact the stability and resilience of the system, necessitating backup energy production or battery storage to ensure the system is able to handle sudden changes in energy demand or production (Baranes et al., 2017; Notton et al., 2018).

Linear Programs

One method of optimizing a renewable energy system is to formulate the system as a linear function, and evaluate an optimal solution mathematically. Linear programming (LP) is a process for maximizing or minimizing a linear function, called an objective function. The objective function is expressed as the linear combination of decision variables modified by coefficients, and is subject to a set of constraints that follow the same form (Vanderbei, 2008).

In the following example, variables denoted by x_n are decision variables. Values denoted by a_{mn} are constraint coefficients, with one coefficient existing per decision variable per constraint. Values denoted by b_m are the values constraining each inequality. Values denoted by c_n are coefficients of the objective function. A given set of values for the set of decision variables is called a solution, which is considered feasible if it satisfies the requirements of every constraint. A feasible solution is considered optimal if it is the maximum solution for the given problem.

LPs can be solved using a process called the simplex method. Given a problem written in standard form maximizing an objective function subject to constraints:

$$\begin{aligned} maximize: \quad & c_1x_1 + c_2x_2 + \cdots + c_nx_n \\ subject\ to: \quad & a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n \le b_1 \\ & a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n \le b_2 \\ & \vdots \\ & a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n \le b_m \\ & x_1, x_2, \dots, x_n \ge 0 \end{aligned}$$

m = no. of constraints, n = no. of decision variables

The problem first can be rewritten in slack form by introducing slack variables to the constraint inequalities. The slack variables are equal to the difference between the two sides of the constraint inequality. For example, the inequality $a_1x_1 + a_2x_2 + a_3x_3 \le b_1$ would be replaced with the variable $w_1 = b_1 - a_1x_1 - a_2x_2 - a_3x_3$, and a constraint requiring each slack variable to be non-negative is added to preserve the meaning of the original constraint:

$$\begin{aligned} maximize: \quad & \zeta = c_1x_1 + c_2x_2 + \cdots + c_nx_n \\ subject\ to: \quad & w_1 = b_1 - a_{11}x_1 - a_{12}x_2 - \cdots - a_{1n}x_n \\ & w_2 = b_2 - a_{21}x_1 - a_{22}x_2 - \cdots - a_{2n}x_n \\ & \vdots \\ & w_m = b_m - a_{m1}x_1 - a_{m2}x_2 - \cdots - a_{mn}x_n \\ & x_1, x_2, \dots, x_n, w_1, w_2, \dots, w_m \ge 0 \end{aligned}$$

m = no. of constraints, n = no. of decision variables

The slack variables are often expressed the same way as the decision variables by adding their constraint index to the subscript of the constraint:

$$x_1, x_2, \dots, x_n, x_{n+1}, x_{n+2}, \dots, x_{n+m} \ge 0$$

After rewriting the problem in slack form, an iterative process is used until it is determined that there is no optimal solution or an optimal solution is found:

- Start with an initial feasible solution where each decision variable is set to zero and calculate the values of the slack variables using the definition equations, and evaluating the resulting objective value.
- Identify the decision variable with the largest positive coefficient, and maximize that variable such that each slack variable is nonnegative.

- Rewrite the equations, placing the updated decision variable on the left side of the equation such that there are no instances of the variable on the right side, effectively swapping functions with one of the slack variables.
- The value of the new objective function should be greater than the value produced by the basic solution, and the process can be repeated until there are no positive decision variables in the objective function, indicating the solution is optimal.

Mixed-Integer Linear Programs

Mixed-integer linear programs (MILPs) are extensions of LPs with the additional constraint that some or all of the variables are restricted to integer values. These problems can be solved with an algorithm called branch-and-bound. Vanderbei (2008) describes the standard integer programming form as follows:

$$
\begin{aligned}
&maximize: && c^T x \\
&subject\ to: && Ax \le b \\
& && x \ge 0 \\
& && x \text{ has integer components.}
\end{aligned}
$$

The algorithm begins with a naïve approach to solving the problem, by ignoring the constraints requiring integer variables, and checking if the solution contains only integer values. As this will typically not be the result, the algorithm proceeds as follows:

- Starting with the original problem, remove the constraints requiring integer variables, leaving the LP-relaxation. This provides an upper bound on the optimal solution to the MILP problem.
- The LP-relaxation is split into two branches, with constraints that bound the non-integer value of a variable. For example, if the optimal value of a variable in the LP-relaxation is 5/6, then the constraints will be x ≤ 1 and $x \ge 2$.
- Evaluating the first case, find the optimal solution, which will be a feasible solution for the original problem. Record this solution as the best-so-far, and repeat with the next case. If the solution to this case produces a lower objective value than the best-so-far, then the first solution is optimal for the original problem. Otherwise, record the solution to the current case as the new best-so-far, and continue.

- Repeat the process for every branch, splitting into two new cases with constraints surrounding the next non-integer variable, and evaluating both cases for the larger objective value between the two.
- Continue this process of branching and bounding until each branch has been evaluated, and the best-so-far solution that remains is the optimal solution for the integer problem.

The MILP approach has been used in prior models such as REopt, a model developed by NREL for optimizing energy grids for a wide variety of applications (Cutler et al., 2017; Mishra et al., 2021). Within the past years, research into the use of optimization software to evaluate and design renewable energy systems has been developing (Banos et al., 2011). LP and MILP models have been successfully applied in prior research to solve problems related to planning and evaluating renewable energy and energy storage systems (Dicorato et al., 2008; Cai et al., 2009; Ogunmodede et al., 2021). Additionally, MILP models have been applied to the design of renewable energy systems on large time-scales, over each hour in the year (Cosic, 2021).

Customizable code supporting the design of optimized resilient and renewable energy systems is desirable because it allows a program to be applied to a variety of problems and adapt to the specific needs of the user. The code can be modified to solve the specific problem that applies to their situation. Additionally, customizable software prompts users to not only learn to use the software as designed, but encourages innovation and collaboration in methods and adaptations of its use (Mackay, 1990).

Considering the environmental risks of traditional energy systems and the benefits of improving grid resilience, implementing solar energy production and battery storage is an appealing endeavor. These systems must be designed to minimize the cost to install solar energy production, while including enough battery storage to account for intermittency and power failure. The purpose of this project was to 1) produce BaSCOT, a customizable tool that uses a LP/MILP model to optimize a grid-tied solar with battery backup system for a site based on location-specific data; 2) test the program using data from a local house in Meadville, PA; 3) develop scripts for interpreting and visualizing model output; and 4) produce a report summarizing and explaining the inputs/outputs of the tool, and how they can be modified to extend or adapt the tool.

Methods

BaSCOT was designed to size an optimal solar energy and battery storage system based on user-inputted data. The goal of the program is to optimize a grid-tied system with solar energy production and battery backup over a 25-year time span, and resilient to periods of 24-hour grid failure on battery power. To calculate the size of this system, several pieces of data were compiled:

- Cost of solar installation per kilowatt of capacity
- Cost of batteries per kilowatt-hour of capacity
- Cost of energy per kilowatt-hour
- Solar panel area usage in square meters per kilowatt of capacity
- Local energy production data values
- Energy consumption data for a Meadville house
- Available roof space in square meters
- Federal income tax credit

Data on current costs of photovoltaic solar technology is based on the results of reports compiled by Althoff and Altenburg (2018) and Feldman et al. (2021). These sources indicated that 2.71 dollars per watt or 2710 dollars per kilowatt is a fair estimate of the cost of installing solar energy production. Battery system costs were based on reports from Feldman et al. (2021) and Cole et al. (2021). A cost of 341 dollars per kilowatt-hour was estimated for battery systems based on these reports.

Energy costs at the site were acquired from the owner's electrical bill, and were estimated at 0.134 dollars per kilowatt-hour. Area usage per kilowatt of capacity was roughly estimated to be 5.181 square meters per kilowatt based on common sizes and production capacities of solar panels, and available area was estimated to be 30 square meters using aerial photographs of the site.

Production data was generated using PVWatts, supplying data about the location of the Meadville house, and using a 1-kilowatt system to later scale by the actual system size (Dobos, 2014). Usage data was acquired from Green Button, which provided smart meter data collected from the site (Henderson and Fowler, 2015).

Software

BaSCOT is written for Python (3.9.6) making use of several libraries to carry out its function. Google's library OR-Tools (9.0.9048) is used to implement optimization tools in Python (Perron and Furnon, 2019). The program uses SCIP (8.0) to solve MILP problems (Bestuzheva et al., 2021). Matplotlib (3.5.1) (Hunter, 2007) is used to generate figures and graphs from the data produced by the software, and Numpy (1.21.2) is used to streamline mathematical operations and data structure (Harris et al., 2020). The program runs from the command line without a GUI, and should be able to run on platforms supporting modern versions of Python.

Problem

$$
\begin{array}{ll}
maximize\colon & (SC_E P_{tot} - TC_A)x_A - C_B x_B \\
subject\ to\colon & P_{tot}x_A \leq U_{tot} \\
& Dx_A \leq A \\
& B_0 \leq x_B \\
& B_n \leq B_{n-1} + \Delta_n^{in} - \Delta_n^{out} \\
& \Delta_n^{in} \leq P_n x_A - U_n d_n^{in} \\
& U_n - P_n x_A \leq \Delta_n^{out} \\
& B_{min} x_B \leq B_n \\
& B_n \leq x_B \\
& \Delta_n^{out} \leq B_{n-1} \\
& \Delta_n^{out} \leq M d_n^{out} \\
& \Delta_n^{in} \leq x_B - B_{n-1} \\
& \Delta_n^{in} \leq M d_n^{in} \\
& d_n^{in} + d_n^{out} \leq 1 \\
& \qquad x_A, x_B, B_n, \Delta_n^{in}, \Delta_n^{out}, d_n^{in}, d_n^{out} \geq 0
\end{array}
$$

Definitions for values and decision variables in the objective function and constraints can be found in Table 1 and Table 2 respectively. Constraint explanations can be found in Table 3.

Objective function

The objective function is designed to maximize the money saved over the lifetime of the system. The value for gross lifetime energy costs offset by solar production is represented by $SC_E P_{tot}$, from which the upfront cost of installing solar panels after tax credit (TC_A) is subtracted. Both of these values are scaled by the total capacity of solar production that is installed. From the resulting value, the upfront cost of installing batteries ($C_B x_B$) is subtracted, leaving the difference between offset energy costs and upfront installation costs, or the lifetime savings.

NAME	DEFINITION
$\boldsymbol{T}$	Federal income tax credit fraction
$\boldsymbol{C_A}$	Cost of solar panels per kW of capacity
$\boldsymbol{C_B}$	Cost of batteries per kWh of capacity
$\boldsymbol{C_E}$	Cost of energy per kWh produced
$\boldsymbol{P_{tot}}$	Total annual energy production
$\boldsymbol{S}$	Lifespan of array in years
$\boldsymbol{D}$	Area used by solar panels in m^2 per kW
$\boldsymbol{U_{tot}}$	Total annual energy usage
$\boldsymbol{P_n}$	Production during hour n of the outage period
$\boldsymbol{U_n}$	Usage during hour n of the outage period
$\boldsymbol{A}$	Available installation area
$\boldsymbol{B_{min}}$	Minimum charge fraction
$\boldsymbol{M}$	Arbitrarily large number for linearizing constraints
$\boldsymbol{n_0, n_1, \ldots, n_{23}}$	Set of hours during outage period

Table 1: Constant values used in the objective function and constraints.

Variables

The primary decision variables found in the objective function, $\mathrm{x_A}$ and x_B, are used to represent the capacities of the final solar array and battery system respectively. Each other variable contains a temporal element, based on the number of hours in the outage period. Each variable with a subscript n is used as a shorthand representation of a set of variables for each hour in the outage period. The level of charge of the system at each time step is represented by B_n. The amounts of energy entering and leaving the battery are represented by Δ_n^{in} and Δ_n^{out}. Two of the variables, d_n^{in} and d_n^{out}, are restricted to binary integer values, representing the battery's status as charging or discharging respectively.

VARIABLE	DEFINITION
$\boldsymbol{x_A}$	Solar array capacity
$\boldsymbol{x_B}$	Battery storage capacity
$\boldsymbol{B_n}$	Battery charge value at time step n
$\boldsymbol{\Delta_n^{in}}$	Incoming energy at time step n
$\boldsymbol{\Delta_n^{out}}$	Outgoing energy at time step n
$\boldsymbol{d_n^{in}}$	Binary variable for charging status at time step n
$\boldsymbol{d_n^{out}}$	Binary variable for discharging status at time step n

Table 2: Decision variables used in the objective function and constraints for the optimization problem.

Constraints

The constraints are configured to place restrictions on the values of variables, representing physical or economic limitations of the system. Constraints 1 and 2 are non-temporal constraints, the rest of the constraints are duplicated for each hour of the simulated outage (Table 1). These constraints contain variables denoted with a subscript n, the relevant hour of the outage period.

The letter M represents an arbitrarily large number (for this application, the value 10^6 was used). This is used to transform a non-linear constraint in which several variables are multiplied into separate linear constraints. Constraints 9-12 are linearized forms of two constraints:

$$\Delta_n^{out} \leq B_{n-1} d_n^{out}$$
$$\Delta_n^{in} \leq (x_B - B_{n-1}) d_n^{in}$$

These constraints are intended to limit the energy entering or leaving the battery based on whether the system is charging or discharging. For sufficiently large values of M, the constraints meanings are preserved in the linearized form, limiting charging or discharging to zero when the corresponding variable is equal to zero, and leaving them unrestricted when the variable is equal to one.

CONSTRAINTS	**PURPOSE**
1. $\boldsymbol{P_{tot}x_A \leq U_{tot}}$	Projected annual production of the array must not exceed annual usage.
2. $\boldsymbol{Dx_A \leq A}$	Size of the array must not exceed the area available for installation.
3. $\boldsymbol{B_0 \leq x_B}$	Initial state of charge for the battery cannot exceed the size of the battery.
4. $\boldsymbol{B_n \leq B_{n-1} + \Delta_n^{in} - \Delta_n^{out}}$	State of charge at each time step n must not exceed charge of the previous step plus incoming energy, less outgoing energy.
5. $\boldsymbol{\Delta_n^{in} \leq P_n x_A - U_n d_n^{in}}$	Amount of incoming energy must not exceed the difference between production and usage at each time step n.
6. $\boldsymbol{U_n - P_n x_A \leq \Delta_n^{out}}$	The difference between usage and production must not exceed the amount of outgoing energy at each time step n.
7. $\boldsymbol{B_{min}x_B \leq B_n}$	Minimum allowable amount of charge must exceed the state of charge at each time step n.
8. $\boldsymbol{B_n \leq x_B}$	The state of charge at each time step n must not exceed the capacity of the battery.
9. $\boldsymbol{\Delta_n^{out} \leq B_{n-1}}$	Outgoing energy at time step n must not exceed charge of the previous time step.
10. $\boldsymbol{\Delta_n^{out} \leq M d_n^{out}}$	Outgoing energy at time step n must not exceed 0 if the battery is not discharging.
11. $\boldsymbol{\Delta_n^{in} \leq x_B - B_{n-1}}$	Incoming energy at time step n must not exceed the difference between capacity of the battery and charge of the previous step.
12. $\boldsymbol{\Delta_n^{in} \leq M d_n^{in}}$	Incoming energy at time step n must not exceed 0 if the battery is not charging.
13. $\boldsymbol{d_n^{in} + d_n^{out} \leq 1}$	The status of the battery must not be both charging and discharging.

Table 3: Descriptions of constraints.

Results

BaSCOT sizes an optimal solar energy and battery storage system based on locational data. The program optimizes a grid-tied system with solar and battery backup over a 25-year time span, for a 24-hour period of operation on battery storage during grid failure.

Algorithm

The program parses two main sets of data stored in CSV files: solar production estimates from PVwatts are stored in pvwatts_hourly.csv, and energy usage data from the utility is stored in usage.csv. This data is processed to remove unnecessary information, and used to generate 24-hour sets of usage and production data starting from each hour in the year. The program processes these with user-inputted data to dynamically generate the variables and constraints. Variables and constraints are generated for each hour in the outage period. For each 24-hour set of data, a MILP problem is generated and solved, producing an optimal solution for every 24-hour span over the course of a year. The program then uses the resulting values of the objective function to evaluate the best-case, worst-case, and median scenarios. These scenarios are summarized graphically in three charts each, depicting the state of charge over the 24-hour period, the usage versus production over the 24-hour period, and the net savings over the 25-year expected lifetime of the system.

Output

The program calculates three scenarios for the Meadville house based on potential 24-hour periods of outages throughout the year:

- Worst-case: the period during which consumption most exceeds production. This period represents the largest battery size required for a 24-hour outage period in a given year.
- Best-case: the period during which production most exceeds consumption. This period represents the smallest battery size required for a 24-hour outage period in a given year.
- Median-case: the median period within the year based on the optimal battery sizes for each possible period. This period represents a typical 24-hour outage period in a given year.

Worst-case

In the worst-case 24-hour outage scenario, BaSCOT produces a negative result for the net savings, indicating a $8133.83 overall cost after 25 years. The system includes 4.542 kilowatts of solar panel capacity for a cost of $12,307.64, and 51.508 kilowatt-hours of battery storage for a cost of

$17,564.38. The combined cost of installation after tax credits is $26,672.03, and the total cost of energy offset by the system is $18,538.20.

Best-case

In the best-case 24-hour outage scenario, BaSCOT indicates overall savings of $8883.87 after 25 years. The system consists of 4.542 kilowatts of solar panel capacity for a cost of $12,307.64, and 1.603 kilowatt-hours of battery storage for a cost of $546.67. The combined cost of installation after tax credits is $9654.32, and the total cost of energy offset by the system is $18,538.20.

Median-case

In the median-case 24-hour outage scenario, BaSCOT indicates overall savings of $3934.65 after 25 years. The system consists of 4.542 kilowatts of solar panel capacity for a cost of $12,307.64, and 16.117 kilowatt-hours of battery storage for a cost of $5495.89. The combined cost of installation after tax credits is $14,603.55, and the total cost of energy offset by the system is $18,538.20.

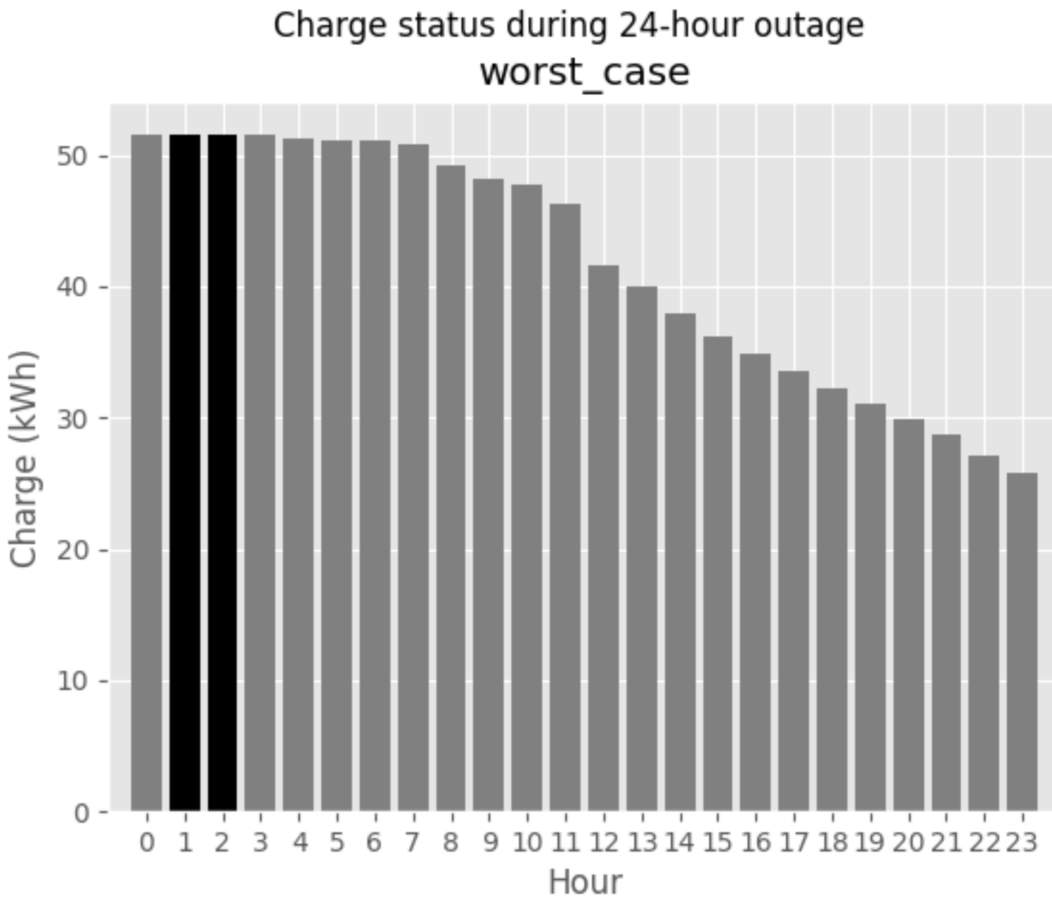

Figure 1: Graph of charge status over the worst-case 24-hour period. The black bars represent periods where the battery is charging, and the grey bars represent periods where the battery is discharging.

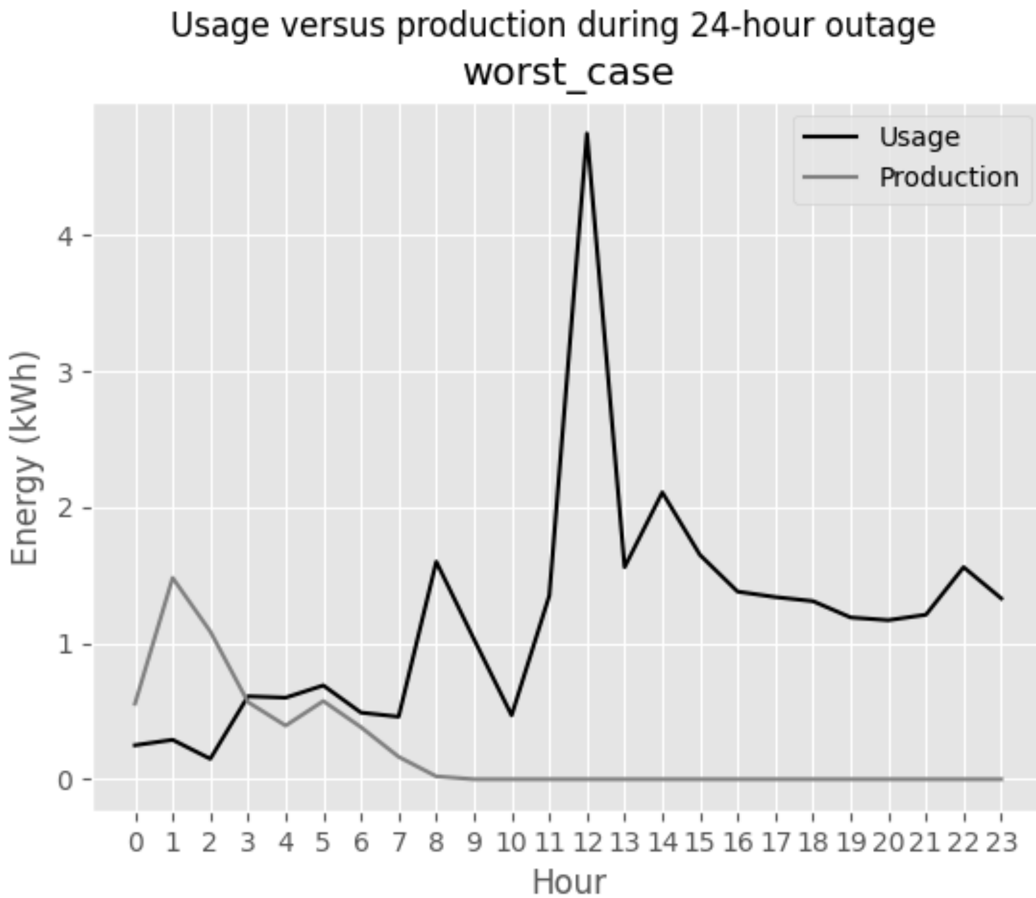

Figure 2: Graph of energy usage versus production over the worst-case 24-hr period. The black line represents the energy usage of the site, while the grey line represents the estimated production.

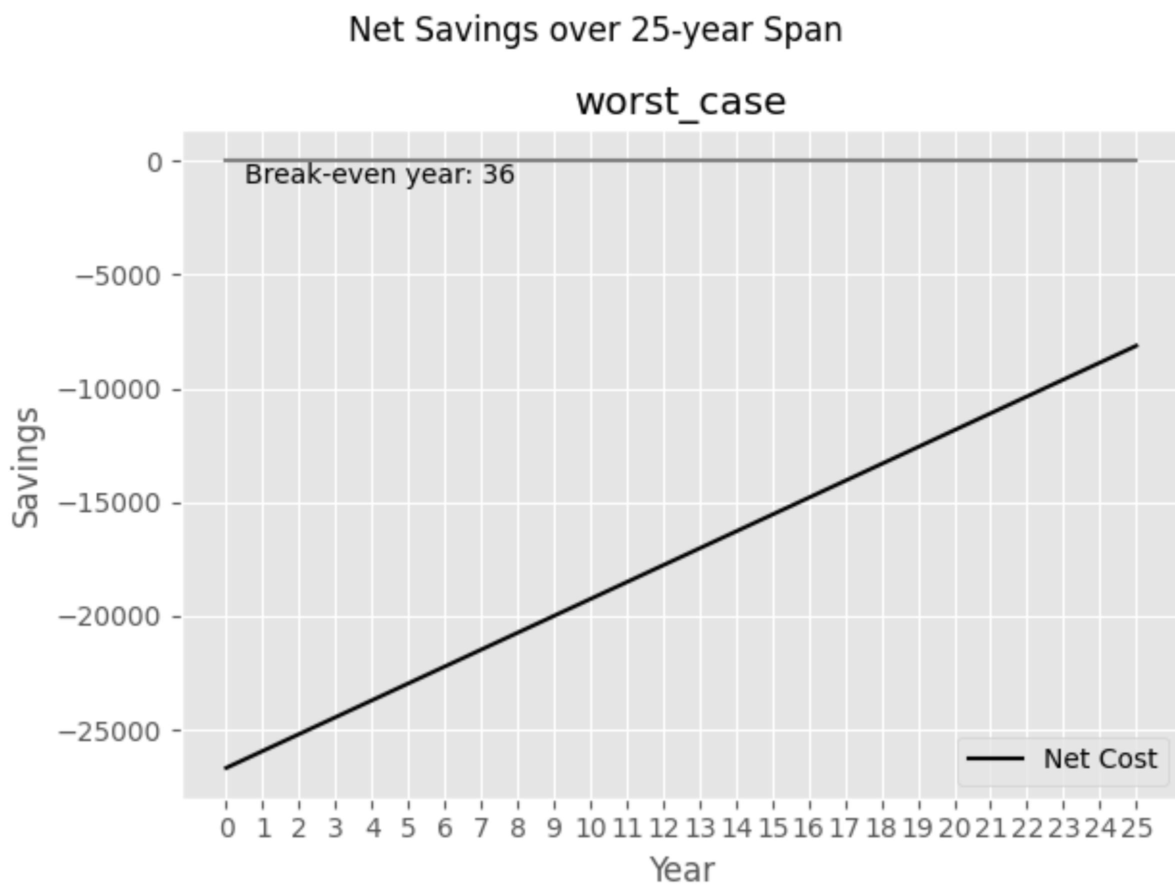

Figure 3: Graph of net energy savings over the lifespan of the worst-case system. The grey line is at $0, and the black line represents the projected net-savings over the lifetime of the system.

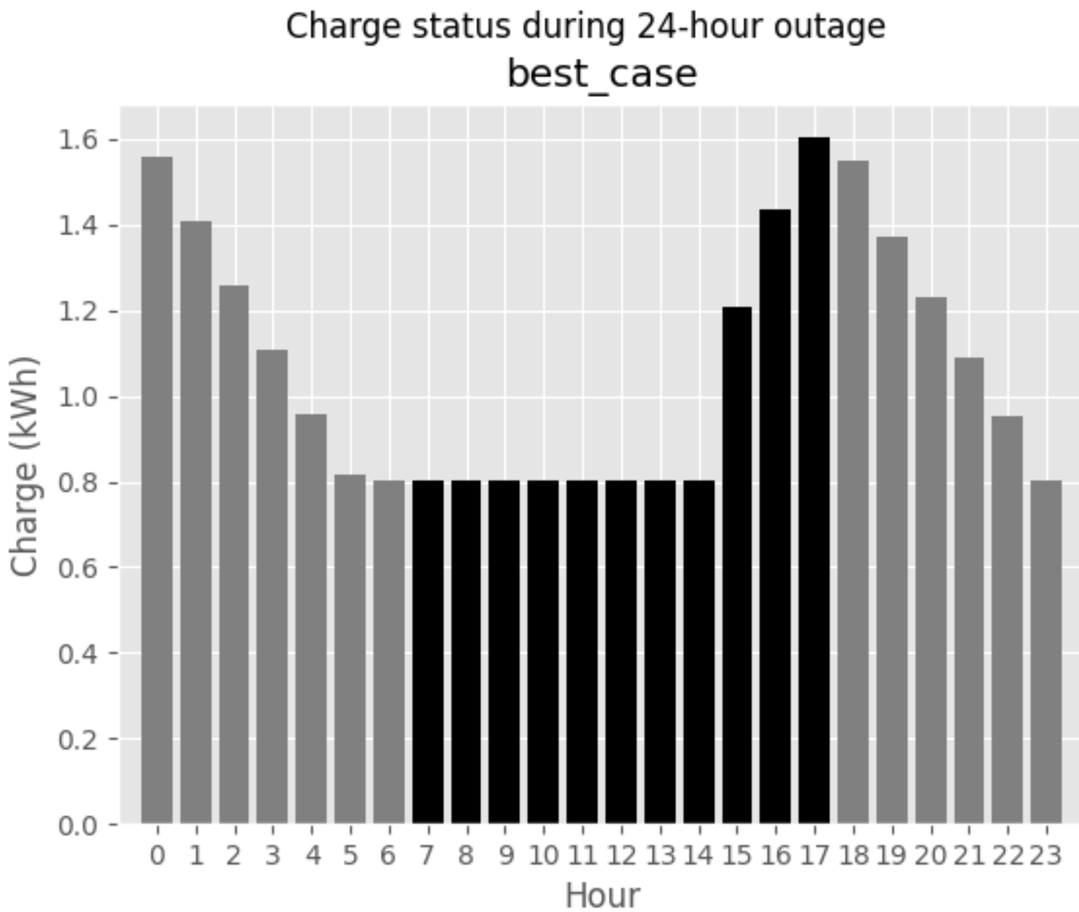

Figure 4: Graph of charge status over the best-case 24-hr period. The black bars represent periods where the battery is charging, and the grey bars represent periods where the battery is discharging.

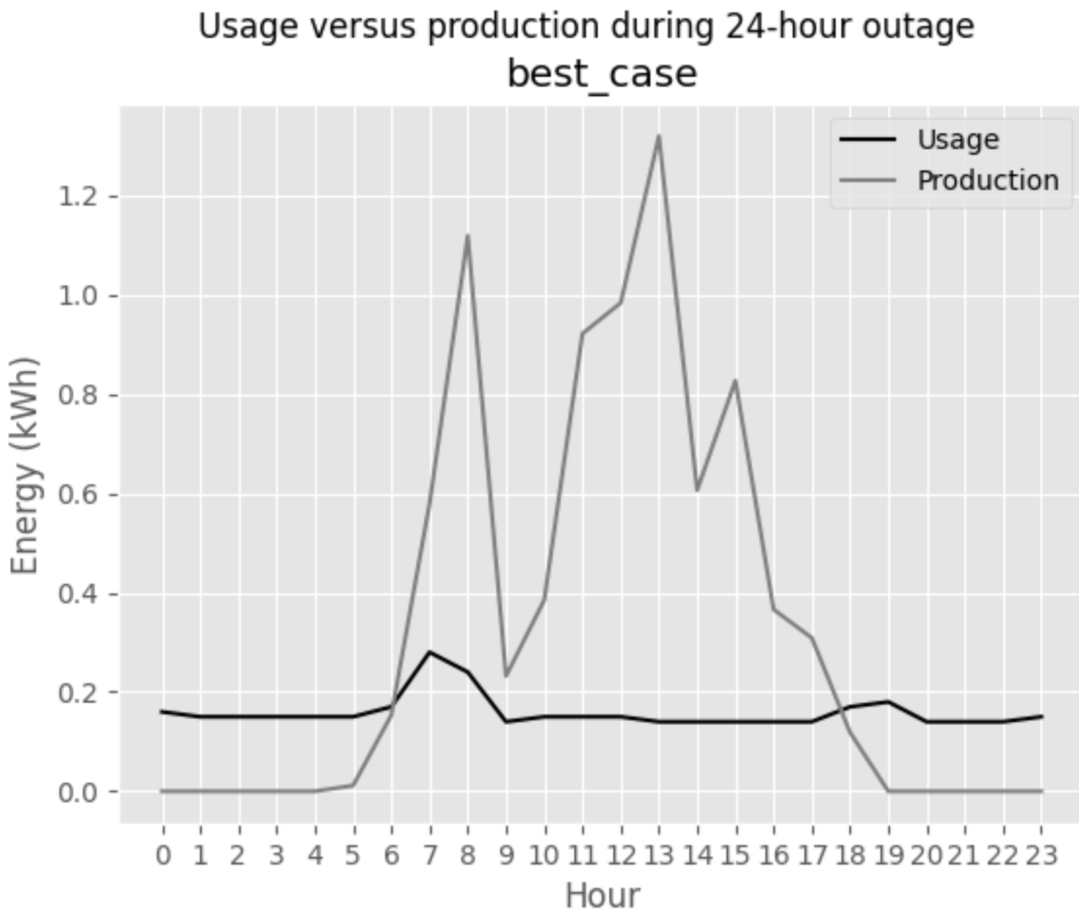

Figure 5: Graph of energy usage versus production over the best-case 24-hr period. The black line represents the energy usage of the site, while the grey line represents the estimated production.

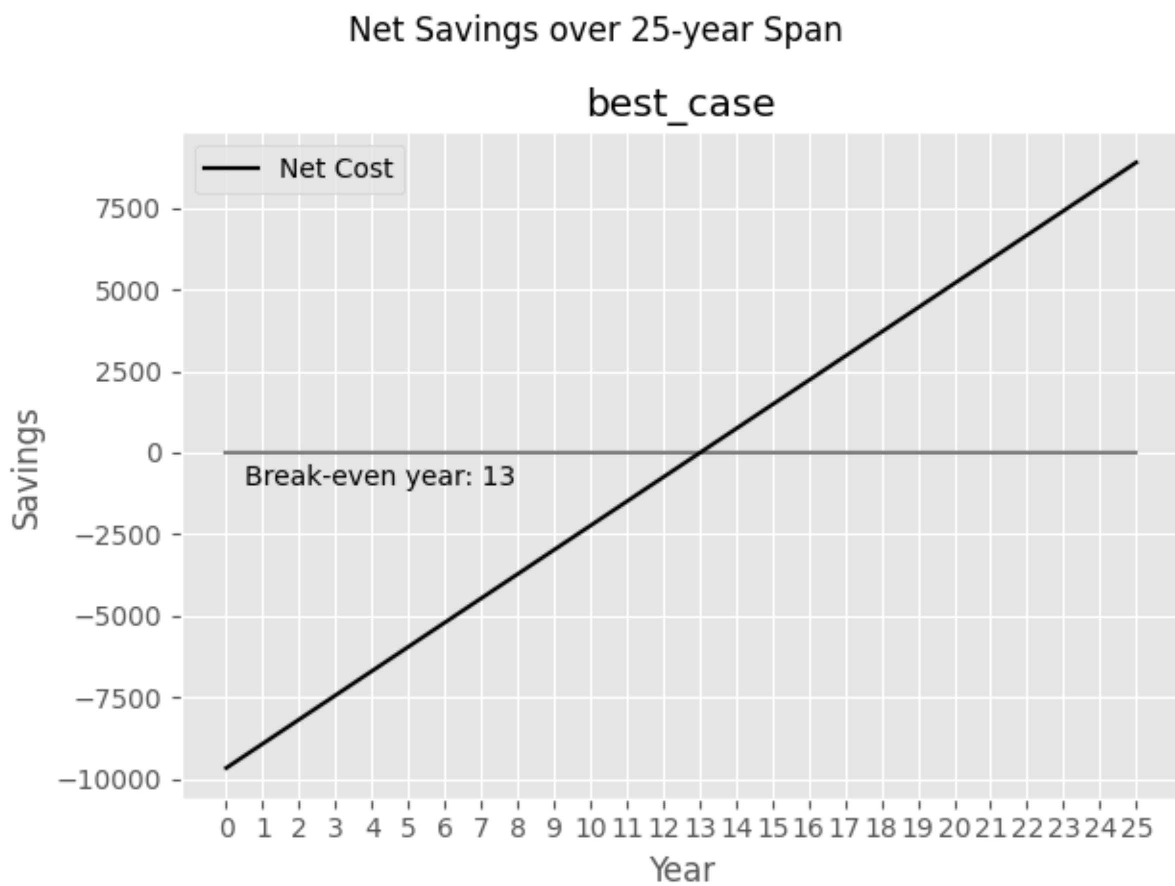

Figure 6: Graph of net energy savings over the lifespan of the best-case system. The grey line is at $0, and the black line represents the projected net-savings over the lifetime of the system.

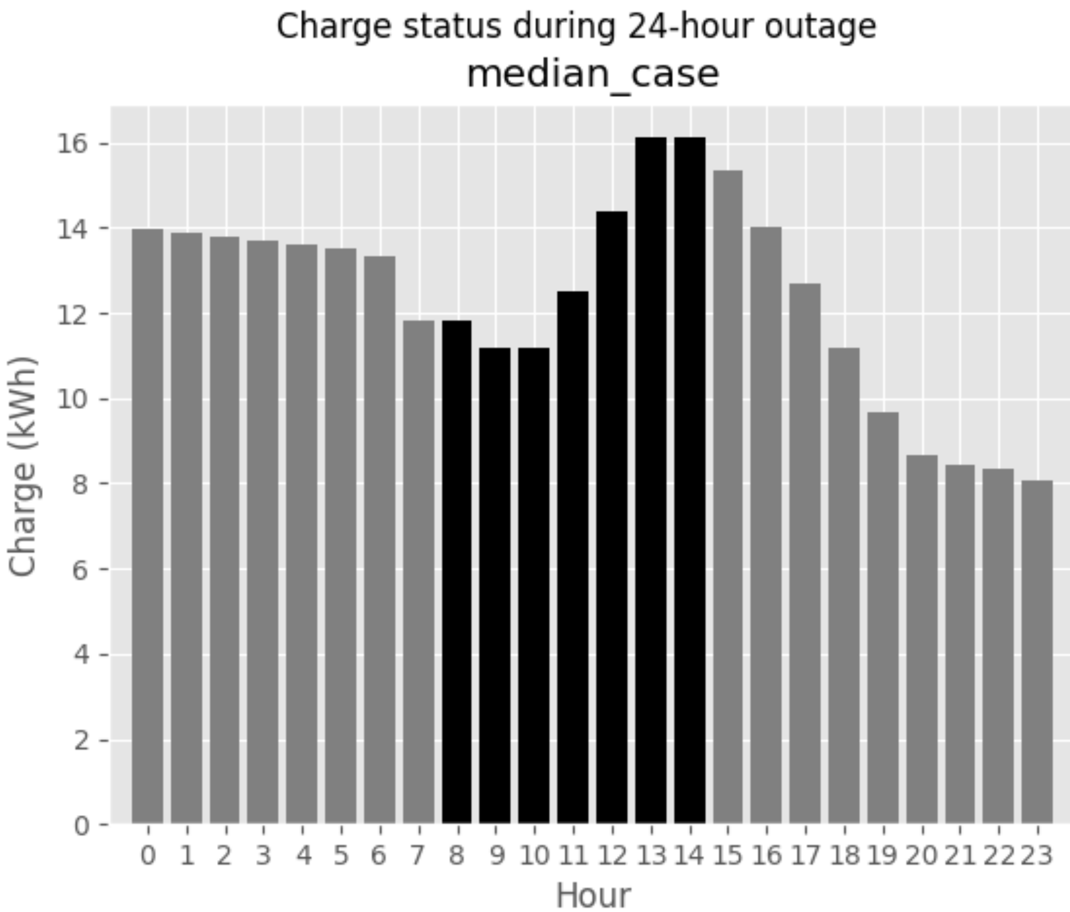

Figure 7: Graph of charge status over the median-case 24-hr period. The black bars represent periods where the battery is charging, and the grey bars represent periods where the battery is discharging.

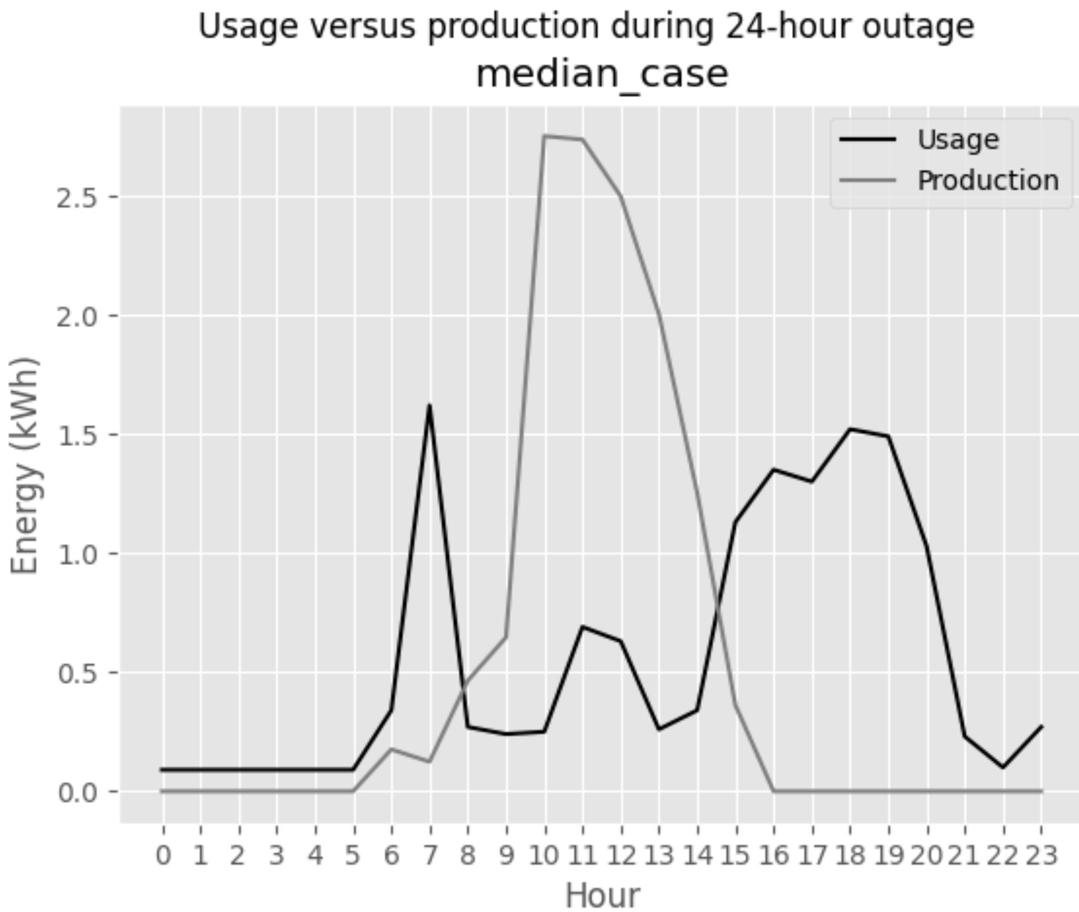

Figure 8: Graph of energy usage versus production over the median-case 24-hr period. The black line represents the energy usage of the site, while the grey line represents the estimated production.

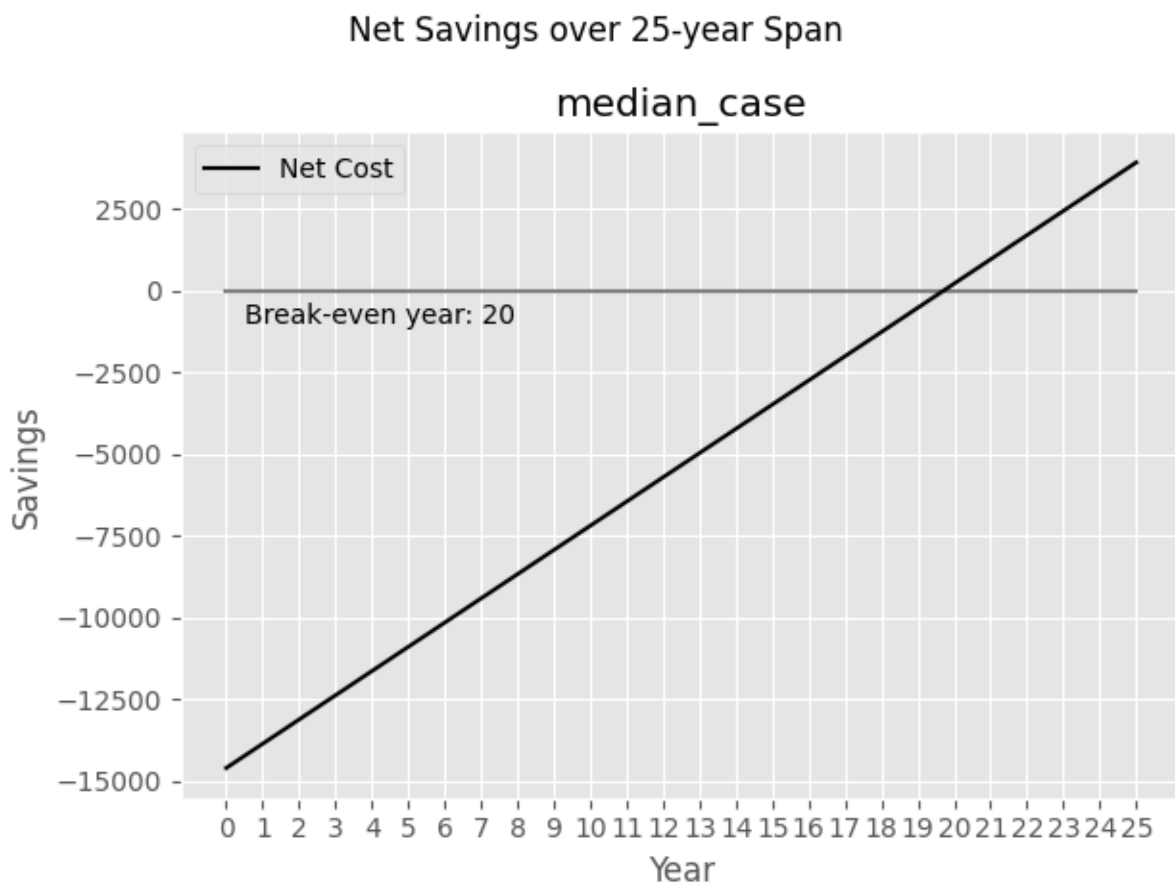

Figure 9: Graph of net energy savings over the lifespan of the median-case system. The grey line is at $0, and the black line represents the projected net-savings over the lifetime of the system.

Discussion

Program capabilities

BaSCOT is designed to provide flexibility in the parameters of the scenarios it simulates. The data used in the objective function and constraints can be modified by the user, and changed according to the desired specifications for the individual site. For example, the available area for solar panels is highly dependent on the type of installation and space available at each site, and could often have a direct impact on the capacity of solar panels that are appropriate to install. Every piece of data used by the program can be modified to suit the needs of the site and the user. Modifying the number of years in the lifespan of the system or the number of hours during the outage period are two major factors that could be changed to simulate different scenarios. Changing the number of years could account for components with a shorter expected lifetime, and the span of hours can be changed to consider longer or shorter outage periods. Other pieces of data, such as the cost of energy, or the projected growth rate for the cost can be changed to predict different economic scenarios, or be updated to reflect actual observed growth. These changes are simple to make by changing the value of the data in code (Figure 10).

```
MIN_CHARGE = 0.5
ARRAY_COST = 2710  # $/kW
TAX_MODIFIER = 0.74
BATTERY_COST = 341  # $/kWh
ENERGY_COST = 0.134  # current $/kWh
SYSTEM_LIFESPAN = 25  # yrs
ROOF_AREA = 30  # m^2
AREA_USAGE = 5.181  # m^2/kW
OUTAGE_LENGTH = 24  # hrs
```

Figure 10: Data declarations in code.

In addition to control over the data, BaSCOT solves MILP problems for each hour in the year, allowing for the highest granularity of detail in the output that is afforded by the inputted data. By default, the program produces figures for the worst-case, best-case, and median-case 24-hour periods, accounting for the extreme and average cases, but could be modified to output figures and reports for each of the 8760 possible 24-hour periods in the year of data available. The general overview of the year provided by the best, worst, and median cases is enough for the purposes of this report, but results for an entire year, or several years could be used to produce more complex analyses or predictions.

Output interpretation

BaSCOT's output is the raw, optimal solutions for the amount of solar energy production capacity and battery storage for given time periods. While the output is useful on its own, it becomes useful in more ways when carefully analyzed and interpreted.

In each of the three highlighted cases (worst, best, and median), the optimal capacity of solar panels to install is identical. This indicates that the same constraint is limiting each of the cases and that it must be independent of the temporal constraints, because the same value is shared between each set of hours. The limiting constraint can be inferred by strategically tweaking or removing constraints and observing how the output changes. This limits the constraints that could be controlling the capacity of solar panels in this case to two: the annual energy usage, or the available installation space. In this case, the limiting factor is the annual energy usage. This indicates that the installation could benefit from installing a larger capacity of solar panels, but only if the annual usage increased. If the limiting factor were the available installation space, that would indicate that increasing the amount of available space for solar panels would produce a better overall system.

The graphical outputs of the program can be used to visually assess the systems. The shape of the charge graphs reflects the hourly status of charging/discharging over the 24-hour period in question. Figure 1 shows the charge of the battery dropping from 100% to 50% over the 24-hour span, discharging nearly the entire time. Such a graph indicates that the energy production rarely exceeds usage, and that the system is relying entirely on stored energy to supply power during the 24-hour period. In the worst-case scenario for the house in Meadville, the battery must be sized to store around twice the difference between usage and production over the period to maintain a minimum charge of fifty percent of the total capacity. Graphs that depict charging and discharging such as Figures 4 and 7 demonstrate how more time spent charging reduces the overall required size of the battery for the period. The graphs depicting production versus usage (Figs. 2, 5, and 8) mirror the graphs showing charge status; when the production line exceeds the usage line, the battery status is charging, and when the usage line exceeds the production line, the battery status is discharging. The graphs depicting net savings over the lifetime of the system can be interpreted to gauge the potential savings or premium costs of installing the optimal system. Figure 3 shows the net savings starting below zero and remaining negative over the lifetime of the system. Note the break-even year is beyond the 25-year expected lifespan at year 36, indicating that the system is not capable of offsetting more energy costs than the upfront cost of installation. Both Figures 6 and 9 show break-even years within the 25-year lifespan, at 13 and 20 years respectively, indicating that these systems should save more in offset energy costs than the initial upfront cost of the system.

Strengths and weaknesses

Overall, while BaSCOT produces mathematically optimal solutions for the capacities of solar panels and battery storage, the actual "best" amount of solar capacity depends on the goals of the shareholder and installer. While the "worst-case" scenario is optimized to provide battery storage for the worst possible 24-hour period, the upfront cost of installing the high capacity of batteries far exceeds the savings from offsetting energy costs. The inverse is true for the "best-case" scenario, although the lifetime savings are high, the small amount of installed battery capacity would only be enough to last through mild outages. Both of these scenarios represent opposite extremes, and the shareholder can use their individual priorities regarding savings and resiliency to select their ideal system size. For example, if the shareholder's priority is to maximize their resilience to electrical grid failure, they may be willing to pay a premium over the lifetime of the system for this purpose. Likewise, if the sole goal of the shareholder is to simply maximize lifetime savings by offsetting energy costs, they may not be particularly interested in a higher upfront cost for greater resilience. The variability of solutions over a year emphasizes the importance of having clear priorities for an installation. Designing the inputs to the problem to achieve specific goals will allow for more accurate and applicable system designs that better reflect real needs.

Due to the number of optimization problems BaSCOT solves to produce its results, the program takes a substantial amount of time to execute. Additionally, the program was designed solely prioritizing the accuracy of output and flexibility of inputs over usability for the end-user. The result is that the program is moderately inconvenient to use. Although the program allows for all of the data used to calculate its results to be adjusted by the user, most of the changes have to be made directly to the code. Despite the program's flexibility, it is not immediately obvious that this is the case. Accessing the program through the command-line obfuscates the level of control that is available, and limits the ability to achieve granular control over the program. Given the intention to develop a program that is more flexible in its use than other existing software, this is a clear drawback of the program.

NREL's REopt Lite software, accessed through a web interface, allows the user to input data and change the parameters of the program to solve for different priorities. For example, the user can select between prioritizing resilience and clean energy in addition to cost savings. As a result of its design, despite sharing many of the same input categories as BaSCOT, REopt Lite is much more accessible as a tool for the end user. In other capacities, REopt also allows for more freedom, such as allowing the user to select other energy technologies than solar, or different methods of energy storage. BaSCOT is currently limited in this regard, but additional technologies could be added without fundamentally changing the function of the program. The ability to directly modify the parameters of the program to solve different problems is the main advantage over using an existing program such as REopt.

Threats to validity

BaSCOT relies on a variety of data to calculate solutions. Any of these data may be subject to change based on the details at the installation site, local prices of installation, and a variety of other factors. The validity of the output is directly correlated to the accuracy of the input data; inaccurate data is likely to produce invalid and unusable results. Additionally, any biases in methods of collecting or inputting data will be reflected in the output of the program. To produce valid optimal system designs using BaSCOT, users should take steps to eliminate any bias in the methods used to collect data, ensure that data is up-to-date and accurate, and ensure that it is input into the program correctly. If the program is to be used for multiple separate simulations, care should be taken to update all relevant information that changes for the different cases.

Further research

Currently, the program solves 8760 MILP problems to produce its output, but only summarizes three results as cases. Since the rest of the results are already calculated, it would be fairly trivial to implement more analysis of trends in battery sizes and patterns in charge status. This would allow for more in-depth analysis of a site without changing or adding any new features to the program.

Most of the economic data collected is subject to change over time as a result of falling costs of technology, changing tax credits, and inflation. These economic considerations can be accounted for with fairly minor changes to the design of the code, but would exceed the scope of this project to ensure accuracy. As such, the program considers economic data to be static over the lifetime of the system.

With regards to its merit as a piece of software, there are a number of improvements that could be made. The solving algorithm takes up the bulk of the runtime of the program, making it a prime candidate for improvements. Techniques such as multithreading or CUDA processing are well-suited to doing separate calculations in parallel, and as such would likely result in great improvements to the execution speed. Additionally, general optimizations could be made to the code to streamline the processing of data leading up to the solving algorithm.

As it stands, BaSCOT is capable of executing its primary functions as a tool for optimizing solar capacity and battery storage. Due to the aforementioned usability issues, an obvious next step for the program is to implement a user-friendly interface, allowing the user to more easily modify the input data, and control the output as desired. This could consist of a graphical user interface, or a method of importing a list of parameters from a spreadsheet or text file. Additionally, implementing more modularity into the objective function, variables, and constraints could allow for a deeply customizable optimization suite that could be adapted for different technologies, applications, and goals. The ability to add additional energy technologies to the optimization, complete with different variables and constraints to represent the real-life limitations of those technologies would allow for a much closer feature parity with existing software such as REopt.

BaSCOT was not developed with the intent to replace any such software as REopt, nor does it achieve that goal. Rather, the intention of the project is to provide a platform for approaching energy system optimizations in general, by developing software that is customizable and flexible for different needs. To this end, despite its weaknesses, BaSCOT is a starting point for future projects based on similar technology, and provides insight into one method of optimization that is available.

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Appendix

The full source code for BaSCOT, its version history, example data, and other information related to the project can be found at the following repository: https://github.com/caylora/BaSCOT

More information about REopt and NREL can be found at their website: https://reopt.nrel.gov/

Use-cases, demonstrations, and documentation for OR-Tools can be found at Google's developer resources: https://developers.google.com/optimization

Information about SCIP, its background and development, and related projects can be found at their website: https://www.scipopt.org/