Feasibility of Photovoltaic Energy System to Power Remote Home

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Renewable energy is non-dispatchable and therefore difficult to implement in most residential buildings where energy is required year round. Battery energy storage systems (BESS) can make renewable energy more feasible by storing energy produced when the resource is available and releasing it later when the resource is not available to produce more energy. However, there are numerous BESSs available with different costs, efficiencies, and capacities which correspond to certain strengths and weaknesses that may overwhelm the average individual. Therefore, we developed two models to help individuals decide what BESS they should purchase—an initial model for small households which we apply to a 1600 square-foot remote home and a generalized behavioral model which estimates energy consumption based on the residents' demographic characteristics.

Our first model uses a Monte Carlo method to generate the hourly energy load profile of two residents living in a remote home. We determine the probability distribution of these residents using a given appliance at a given time to calculate the energy demand. Then, we use a charging and discharging battery model and a photovoltaic energy formula to determine the energy supply at any given time. Finally, we calculated the Expected Energy Not Served (EENS), Loss of Load Frequency (LOLF), and levelized cost (LCRES) of each battery system, and we recommended the Sungrow SBP4K8 battery for the residents.

We generalized the energy demand by separating it into occupancy dependent and independent energy demand. For occupancy-dependent demand, we used a Markov chain to model the energy-use related behavior of residents based on data from the ATUS survey. For occupancy-independent demand, we use pre-existing appliance data to estimate energy consumption of a given resident.

Finally, we discuss the implementation of cement batteries. While they are a technology with numerous potential advantages, we will require more information on certain aspects of their performance if we want to incorporate it into daily life.

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1 Introduction

1.1 Battery Energy Storage Systems

Power outages have caused severe economic disadvantages. Power outage accidents will cause $18 billion to $33 billion in economic losses in the US alone annually. Power outage accidents are especially common with renewable energy sources such as solar power and wind power which are not constantly available. As the world is switching to renewable energy, we decided to investigate how batteries could be used to combat this **economic risk**. We considered several batteries in this paper to determine the optimal battery for the issue.

Renewable energy is replenishable, originating from natural forces such as solar radiation, hydropower, and wind. Renewable energy has several benefits. Also known as clean energy, renewable energy is significantly better for the environment than fossil fuels. Additionally, because natural resources abound in rural areas, renewable energy can be used to bring electricity to remote, off-the-grid areas.

However, inconsistent energy supply from renewable sources prevents the widespread implementation of renewable energy. Conventional power systems can produce more or less power on demand. In contrast, renewable sources are non-dispatchable, meaning the energy generated by these sources varies with the availability of the source. For example, a turbine might generate abundant power on a windy day but no power on a windless one.

One solution to mitigate the unreliability of renewable sources is a battery energy storage system (BESS). Batteries in BESSs store excess energy generated by the renewable source and discharge the energy at a later period. This enables them to fulfill energy demands when energy is not actively being generated or insufficient energy is being generated.

There are numerous types of batteries on the market with various advantages and disadvantages, each suited to different scenarios. In this paper, we will begin by designing a model to select the best battery storage for a remote, off-the-grid 1600 square-foot residency. Then, we will generalize our model to select the best battery storage for any home.

1.2 Design Objectives

To model the energy demand profile of our 1600 square-foot residency more accurately, we have set the following characteristics:

1) The home is in McPherson County, Nebraska. There are numerous off-the-grid regions in this county due to its sparse population. Additionally, as this area is located only 200 miles away from the geographical center of the United States, its climate and other characteristics will not be extreme in any way in comparison to the rest of the US.

2) The residence has two bedrooms, two bathrooms, a living room, a kitchen, and an attic, as this is the usual layout of a 1600 square-foot home. A married couple lives in this residence. One bedroom is used as an office. Details on appliances which use electricity in this home are provided in **4.1.1**.

We will base the objectives for a successful model off these characteristics. The objectives are as follows, in order of priority:

1) The model must imitate real life electricity demand and supply as closely as possible. This is the most essential objective as all results will be meaningless if this is not met.
2) The model must select the battery which minimizes the lowest Energy Expected Not Supplied (EENS) and Loss of Load Frequency (LOLF) values.
3) After fulfilling 1) and 2), the model must take secondary factors into consideration such as economic factors.

To fulfill these objectives, our model will consist of two main sub-models which calculate 1) fulfillment of energy demands (ENS, LOLF, LOLD) and 2) economic factors.

The Fulfillment of Energy Demands Model is further split into a model which determines energy demanded and a model which determines energy supplied. The Energy Demand Model will use research on appliance use in United States households and Monte Carlo simulation to generate 8760 data values which correspond to energy demand during every hour in a given year. The Energy Supply Model will calculate photovoltaic power during every hour in a given year and use battery charging and discharging models to determine if energy demand is met in that hour.

The Cost Model will calculate the total cost of the BESS using data generated by the Energy Supply Model and baseline and replacement costs.

After this initial model is applied to the 1600 square foot house, we will provide guidelines for generalization and widespread use.

2 Assumptions

Our model makes the following assumptions due to the absence of data:

Assumption 1: The individuals living in the 1600 square-foot home are average citizens who follow the same patterns of electricity use as individuals living in the United States suburbs. Their lifestyle is diurnal and generally like the rest of the United States except because they live in the remote wilderness, they spend most of their time indoors. They also follow a relatively regular routine, sleeping at 23:00 and waking at 07:00. (This statement allows us to make sub-assumptions about their appliances and electricity use.)

Justification: While those living in a remote setting may have some different needs and routines, there is insufficient data on remote areas in the United States to consider this factor.

Assumption 2: Fulfillment of energy demands is prioritized before economic factors.

Justification: Because insufficient power supply can result in loss of life and legal complications (which can result in greater financial loss), objective 2) is prioritized before objective 3).

Assumption 3: Only commercially available batteries as of November 2021 are considered by the model.

Justification: We assume that we would like to finalize the type of battery storage system for our remote home as soon as possible.

Assumption 4: The battery will not break before the end of its lifetime. Other components of the battery storage system such as the inverter will be replaced if broken with little impact on energy supply.

Justification: Because considerable research is involved in determining the lifetime of batteries, this research is likely trustworthy. It is the duty of our team to replace broken parts in a timely manner.

Assumption 5: All appliances consume energy at a constant rate.

Justification: While this is not true in real life, it significantly simplifies our problem as most electricity consumption models we could find for appliances were highly complex and involved data extraction or algorithms which could not be completed in Excel. Additionally, the power consumption of all appliances which we found online were in units of kw/h.

Assumption 6: The house uses monocrystalline silicon solar panels of 1.6 m^2 and 450 Watt-hours because these are the most popular type of solar panels. The house uses 18 panels because this value allows us to show how some batteries fair significantly better than others in terms of preventing outages. [2]

3 BESS Specifications

Table 1 describes the batteries which will be compared in this paper. Any battery without the Instantaneous Power Rating required to power one of the appliances listed in **4.1.1** was not included in the chart as this would mean that the residents cannot use the appliance at all at night or during other hours without sunlight.

Battery	Usable Capacity	Continuous Power Rating	Charging Efficiency (η_{CHG})	Discharging Efficiency (η_{DCHG})	Unit Price (V_{p_1})	Lifetime (n)
Sungrow SBP4K8	4.5 kWh	2.5 kW	>95%	>95%	$4000	15 years
LG Chem RESU10	8.8 kWh	5kW	94.5%	95%	$6400	10 years

Tesla Powerwall+	12.15 kWh	7kW	90.00%	92.5%	$8500	10 years
Powerplus Energy	3.3 kWh	1.8 kW	>96%	95%	$3375	10 years
Discover AES 7.4 kWh	6.65 kWh	6.65 kW	>95%	90%	$6478	20 years
Red Smart Hybrid System	5kWh – 13kWh	5kW	98%	92%	>$9000	5 years
BYD Premium LVS	4.0 (per battery module)	3.33 kW (per battery module)	≥95%	90%	$3595	10 years
Deka Solar 8GCC2 6V 198	1.18 kWh	0.049 kW (for 20 hrs) 0.017 kW (for 100 hrs)	80-85%	80%	$368	14 years
Trojan L-16 -SPRE	2.5 kWh	0.19 kW (for 10 hrs.) – 0.023 kW (for 100 hrs)	80-85%	Starts out at 100% but regresses	$492	7-9 years
Electriq PowerPod 2	10kWh	7.6 kW	90%	96.6%	$13,000	10 years

Table 1: Specifications of selected batteries.

4 Off-Grid Photovoltaic Energy System Model

4.1 Fulfillment of Energy Demands

The first part of our model will evaluate the ability of various battery storage systems to fulfill energy demands during each hour of a year.

4.1.1 Energy Demand Sub-Model

Energy Demand is modeled by calculating the energy use and times of usage of the following common household appliances retrieved from Jones et al.'s review on household electricity consumption. [1]

Periodic Power Appliance	**Power Consumption**	**Seasonal or Constant Power Appliance**	**Power Consumption**
Washer	0.5 kw/h	Heating	1.5 kw/h
Dryer	4 kw/h	Cooling	3 kw/h
Television	0.234 kw/h	Ventilation	0.05 kw/h
Dishwasher	1.8 kw/h	Hot water heating	4 kw/h
Microwave	1.2 kw/h	Refrigerator	0.225 kw/h
Electric oven	2.3 kw/h	Desktop computer	0.155 kw/h
Stove	1.5 kw/h		
Phone	0.0036 kw/h		
Laptop	0.06 kw/h		
Coffee maker	0.8 kw/h		
Lighting	3 kw/h		

Table 2: Energy consumption profile.

All data was obtained by googling for the power consumption of popular appliance brands and using research and our background knowledge to determine length and frequency of use. (We suggest a more scientific approach to this in our model generalization.)

Next, we must determine when and for how long each appliance will be turned on and consume electricity. Initially, we planned to create a weekly timetable with set times and durations when each appliance would be used. However, we realized that this model failed to meet objective 1 because very few people follow the exact same time table all days of the week. To model spontaneity, we use a Monte Carlo approach. We set time intervals for when various appliances are likely to be used and use random sampling underneath different probability distributions (e.g., random distribution, normal distribution) depending on if the appliance is more likely to be used during certain times than others to determine when the appliance is used. We also use sampling to determine the duration of usage for some appliances.

A column of 8760 units, each representing one hour, labeled t = 1, 2, 3… 8760 was generated in Excel. We assumed that residents will begin living in the house in 2022, and, therefore, used the calendar for 2022 in our data and other values from the year 2021 and 2020 to ensure that our load forecast is as accurate as possible. Columns for each power appliance were generated and populated in the following manner:

1) **Washer and dryer**: Normal washer and dryer cycles last about one hour each. The residents use the washer and dryer twice a week on Wednesday and Sunday. The process begins sometime between 09:00 and 21:00 to ensure that it would be complete before bedtime at 23:00. It is more likely to occur during the middle of the day than very early in the morning, when the residents are just getting ready for the day, and very late at night, when the residents are preparing to go to bed, but these extremes are not impossible. Therefore, we assumed that the start time for washing and drying forms a normal distribution. We used Excel's `=NORMINV(RAND(),A1,B1)` command to generate a value between 9 and 21 for every Wednesday and Sunday in the year 2022. That hour of that day is populated by the number 1 in the washer column, and the hour after it was populated by the number 1 in the dryer column.
2) **Television**: The residents watch television for 0.5 to 2 hours every day between 17:00 and 21:00. We used Excel's random number generator (RNG), the `=RAND` command, to generate the number of hours the residents watch television each day. (It is important to note here that because all computers use algorithms for "random" number generation, the generation can only be called pseudorandom and not truly random. Fortunately, Excel's RAND function is sophisticated and has a very long period that imitates randomness.) We also used the RAND function to generate a value between 17 and 21. This value represents the hour at which the residents start watching TV each day. We placed the RAND value between 0.5 and 2 in the hour of that day. If the value exceeded 1, we placed 1 in the first hour cell and the remainder in the second hour cell.
3) **Dishwasher**: The dishwasher runs for 1 hour every day at 18:00 if it is a weekday and 19:00 if it is a weekend. We put 1 in the appropriate hour cell for each day.
4) **Electric oven**: The residents use the electric oven once every weekend for three hours each time. We used the RAND function to generate either 1 or 2 with 1 representing Saturday and 2 representing Sunday. We put 1 in three hours cells from 12:00 to 15:00 on the appropriate day.
5) **Stove**: The residents use the stove to cook lunch and dinner. On weekdays, lunch is prepared at 12:00 and dinner is prepared at 17:00. On weekends, lunch is prepared at 14:00 and dinner is prepared at 21:00. Because the stove must be turned on for one hour to prepare these meals, the value 1 is placed in these hour cells in the stove column.
6) **Phone and laptop**: The residents own two phones and two laptops in total. They charge their phone and laptop when they go to bed every night at 23:00 which charge four hours each day and stop charging when full. Therefore, 1 is placed in the phone and laptop columns in the hours 23:00, 00:00, 01:00, and 02:00.
7) **Coffee maker**: The residents use the coffee maker for 15 minutes every morning at 08:00. 0.25 is placed in 08:00 every day.

8) **Lighting**: Every day, the residents use lighting between sunset and 23:00, when the family sleeps. The residents also use lighting between 07:00 and sunrise (if 07:00 precedes the sunrise). These hours are assigned the value 0.5 in the lighting column. (The value 1 would represent all lights in the house being turned on, but, realistically, only lights in rooms where residents are turned on.) Data on daylight hours was retrieved from Jan Moesen daylight calculator using primarily 2021 McPherson County data. [2] Additionally, the residents may turn on the lights briefly to use the restroom or to access a room without natural lighting. Therefore, all other cells between sunrise and sunset (or bedtime, depending on which is first) are assigned the value 0.02.

   Cloudy days: There are also stormy or cloudy days when certain lights such as office lights or kitchen lights must be turned on for visibility. Daytime low light periods can be separated into mostly clear/mostly sunny (1/8 – 3/8 opaque cloud coverage), partly cloudy/partly sunny (3/8 – 5/8), mostly cloudy (5/8 – 7/8), and cloudy (7/8 – 8/8). According to Wunderground's historical weather forecast, in 2020 – 2021 in McPherson County, there was a 29% probability of a day being mostly clear/mostly sunny, a 13% probability of a day being partly cloudy/partly sunny, a 12% probability of a day being mostly cloudy, and a 5% chance of a day being cloudy. We used the discrete random number generator, which assigns certain values a probability of being generated, to generate 365 values of either 0.12 (29%), 0.25 (13%), 0.37 (12%), or 0.5 (5%), depending on how cloudy it is and how many lights need to be turned on. Then, these values are assigned to the hours between sunrise and sunset in lieu of 0.02. (We assumed that cloudiness will be consistent throughout the day for simplicity.)

9) **Heating and cooling**: We found recommendations for temperatures below or above which heating and cooling should be used. We assume heating and cooling occurs consistently and uses the same amount of energy per hour throughout the whole day when the low or high for a given day is below or above the value when heating or cooling is recommended and place a 1 in these cells.

10) **Hot water heating**: The residents both take a shower every day. They are most likely to take a shower when they wake up or before they go to bed, but it is not impossible for them to decide to take a shower during the day. To model this, we graphed a parabola and assigned times between 07:00 and 23:00 to x-values in the range [2,2] on the parabola. Each hour equaled 2/7 on the x-axis of the graph. Then, we calculated the square of every y-value which corresponded to a whole hour and divided this number by the sum of all the squares to determine the percentage likelihood of that hour being the hour one of the residents showered. Then, we use the discrete random number generator to generate 365 values between 7 and 23 using the percentages assigned to each hour in the previous step. Finally, we place the value 0.25 in the corresponding hour cell of each day. We repeat the generation

and placement process twice to determine the hours when each resident showers. If we generated the same hour on the same day, we added 0.25 to 0.25 and wrote 0.50 in that cell.

11) **Refrigerator**: The refrigerator is on all year round 24 hours a day. We place a 1 in every hour cell in the column.
12) **Desktop computer**: The desktop computer is on all year round 24 hours a day. We place a 1 in every hour cell in the column.

After the columns are prepared, each column is multiplied by its hourly power consumption value shown in Table 2. Then, rows (or the amount of energy used per hour per appliance) are added up to find the total amount of energy consumed per hour. Without data on energy supply, we can record the average hourly loads for each hour of the day, the average daily load, and the peak load. If we were determining the best battery system for multiple homes at once, these values can help us gain intuition on what type of battery might be best suited for this home.

We will eliminate any battery with a Continuous Power Rating lower than the average load as this means that the battery does not have sufficient power to get through a cloudy day.

4.1.2 Energy Supply Sub-Model

Energy Supply involves the manipulation of three possible energy states: 1) the energy demanded each hour as calculated in the Energy Demand Sub-Model, 2) the photovoltaic (PV) energy column that describes the amount of energy produced by PV panels at the end of each hour, and 3) the energy stored in the battery at the end of each hour. There are several scenarios for the movement of energy into and out of these states:

1) In the optimal case, the energy demanded is subtracted from the energy generated by the PV panels in that hour. The remaining energy is stored in the battery energy storage system according to the charging equation.
2) In the sub-optimal case, the energy demand is greater than the energy generated from the PV panels in that hour but less than the energy generated plus the energy stored. The energy stored is discharged from the battery according to the discharging case.
3) In the worst case, the energy demand is greater than both the energy produced and the dischargeable energy stored. In this case, all energy will be removed from the battery bank, which will go to zero, and the residents will experience an electrical outage until enough energy is produced to run appliances again.

To determine the values of the three energy states for every hour in the 8760 hours in a year, we use the following models to calculate the energy produced by the PV panels in each of those hours retrieved from HOMER [2]:

$$T_c = \frac{T_a + \left(T_{c,NOCT} - T_{a,NOCT}\right)\left(\frac{G_T}{G_{T,NOCT}}\right)\left[1 - \frac{\eta_{mp,STC}(1-\alpha_p T_{c,STC})}{\tau\alpha}\right]}{1 + (T_{c,NOCT} - T_{a,NOCT})\left(\frac{G_T}{G_{T,NOCT}}\right)\left(\frac{\alpha_p \eta_{mp,STC}}{\tau\alpha}\right)}$$

where T_c is the temperature of the photovoltaic cell, T_a is the ambient temperature, $T_{c,NOCT}$ is the nominal operating cell temperature (46°C), $T_{a,NOCT}$ is the ambient temperature at which the NOCT is defined (20°C), G_T is the solar radiation striking the PV array (1.36 kW/m^2), $G_{T,NOCT}$ is is the solar radiation at which NOCT is defined (0.8 kW/m^2), $\eta_{mp,STC}$ is the maximum power point efficiency under standard test conditions (13.5%), $T_{c,STC}$ is the cell temperature under standard test conditions (25°C), and $\tau\alpha$ is the solar transmittance of any cover over the PV array times the solar absorptance of the PV array (0.9).

$$P_{PV} = Y_{PV} f_{PV}\left(\frac{G_T}{G_{T,STC}}\right)\left[1 + \alpha_p(T_c - T_{c,STC})\right]$$

where P_{PV} is the energy produced by a single PV panel, Y_{PV} is the rated capacity of the PV array (0.325 kW), f_{PV} is the PV derating factor (0.8), G_T is the solar radiation incident on the PV array in the current time step (kW/m^2), $G_{T,STC}$ is the incident radiation at standard test conditions (1 kW/m^2), α_p is the temperature coefficient of power (-0.46), and $T_{c,STC}$ is the PV cell temperature under standard test conditions.

For ambient temperature, we found high and low temperature from historical weather report data for each month and assumed that temperature formed a normal distribution [6] throughout the month to randomly generate average temperatures for each day.

Because solar radiation is only available during the daytime, we use online databases on McPherson County's 2021 daylight hours to determine how many hours a day P_{PV} is calculated for.

Next, we need to model charging and discharging of the battery bank. Suppose there is insufficient energy supplied by the PV panel. We will use Chauhan et al.'s model for the discharging of the battery bank. [7]

$$E_{BATT}(t) = E_{BATT}(t-1) - \left[\frac{E_{Dem}(t)}{\eta_C \times \eta_{DCHG}}\right]$$

where η_{DCHG} is the discharging efficiency of battery, η_C is the converter efficiency, and $E_{Dem}(t)$: energy demand in the current hour.

We use the following model from Chauhan et al.'s paper to model the charging of the battery bank. [7] Because the battery bank can only be charged to usable capacity to prevent harm to the batteries, the charging will be governed by if/then statements in Excel.

$$\text{If } E_{BATT}(t) \le U_C,$$

$$E_{BATT}(t) = (1-\sigma)\times E_{BATT}(t-1) + (P_{PV}(t) - E_{DEM}(t)) \times \eta_{CHG} \times \eta_C$$

$$\text{If } E_{BATT}(t) > U_C,$$

$$E_{BATT}(t) = U_C$$

where t is the time in hours, $E_{BATT}(t)$ is the energy in battery bank currently, $E_{BATT}(t - 1)$ is the energy left in battery bank at the very end of the previous hour, $P_{PV}(t)$ is the energy produced in current hour, $E_{DEM}(t)$ is the demand in current hour, η_{CHG} is the charging efficiency of battery, U_C is the usable capacity, and σ is the hourly self-discharge rate.

The Excel script used for battery charging and discharging is as follows: `=IF(AND(W2<0, X1+W2>0), X1+(W2/(0.8*0.925)), IF(AND(W2<0,X1+W2<0), 0, IF(AND(W2>0, X1<72.9),(1-0.000069)*X1+W2*0.9*0.8,72.9)))`

Only the charging or the discharging equation is applied in each hour so we do not need to worry about the order in which the equations should be applied.

This process is repeated with all ten types of batteries. The number of each type of battery used was determined by the number of batteries needed to produce ~70 kWh continuously as this was the average simulated energy use of our residents.

4.2 Cost

The cost of each battery bank system will be evaluated in two ways: First, we will calculate the cost of using the battery storage system for 100 years using the following equation

$$S_{100} = C_0 \times \frac{100}{n}$$

where C_0 is the cost of purchasing the batteries and n is the number of years in the life span of the batteries.

Next, we will calculate the levelized cost for renewable energy storage (LCRES), also known as the benefit-cost ratio for a battery, measured in cost per kWh storage capacity

$$LCRES = \frac{S_{100}}{E_{S_{100}}}$$

where $E_{S_{100}}$ is the total energy supplied in 100 years. [8]

4.3 Battery Storage System Recommendation

Fig. 1 shows our simulated energy load profile for the year of 2022. We can observe that energy consumption is greater during the winter months possibly due to the burden of heating. Most daytimes are characterized by spikes in demand as individuals are more likely to use appliances during the day while night time is lower.

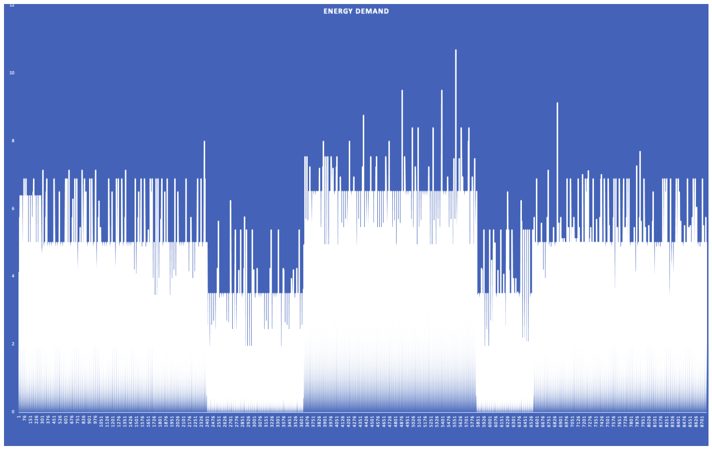


Figure 1: Energy consumption profile. The *x-axis* is hours and the y-axis is energy demand in kWh.

Fig. 2 and **Fig. 3** show energy supply and demand on a typical summer and winter week. Corresponding with the data above, energy demand is higher in the winter. Additionally, energy supply is significantly higher in the summer. This is likely due to lower ambient temperature and shorter daylight hours in the winter.

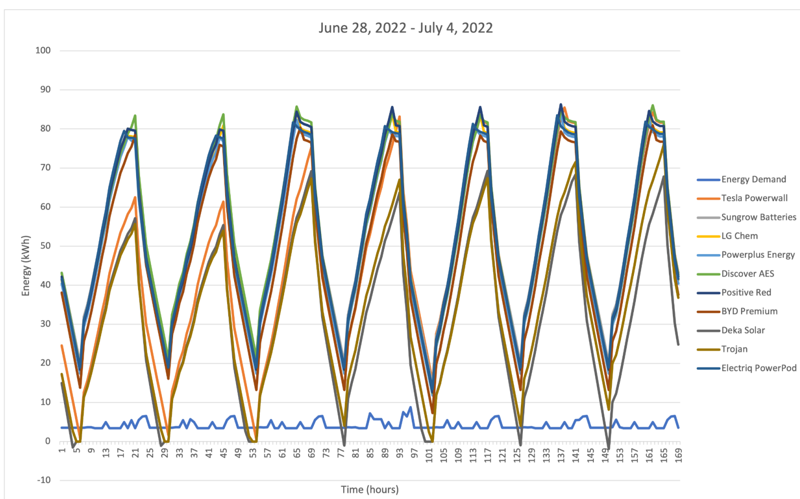


Figure 2: Energy supply and demand on an average summer week.

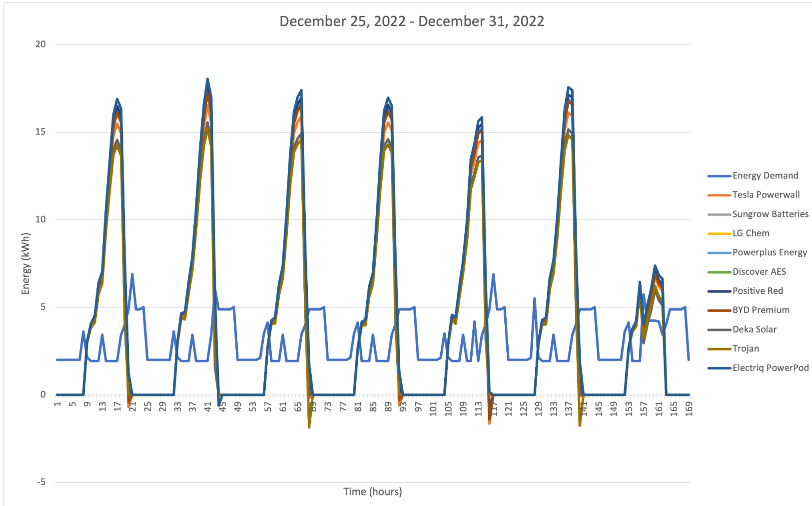
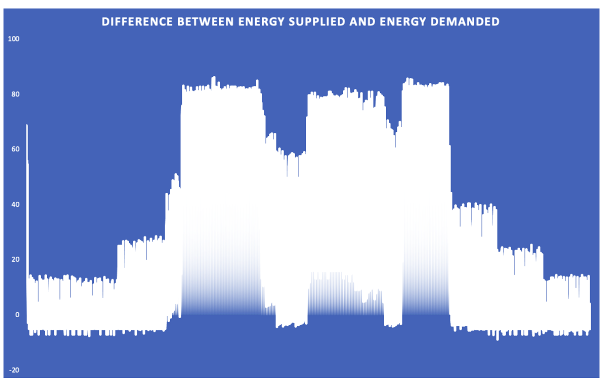
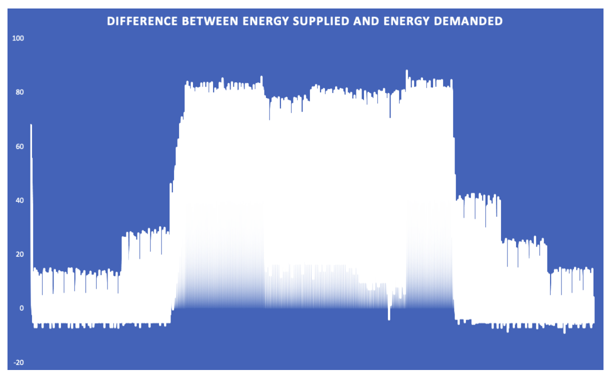


Figure 3: Energy supply and demand on an average winter week.

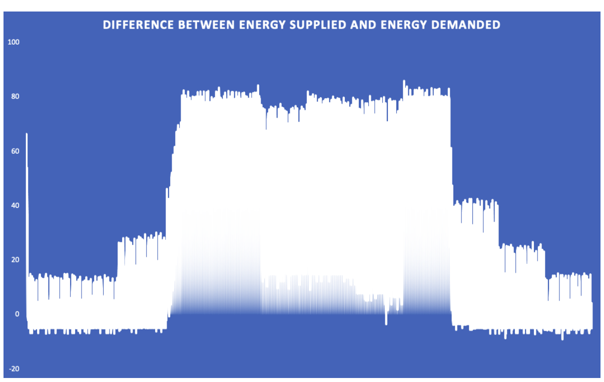
Fig. 4 shows the EENS (Energy Expected Not Served) of each battery.



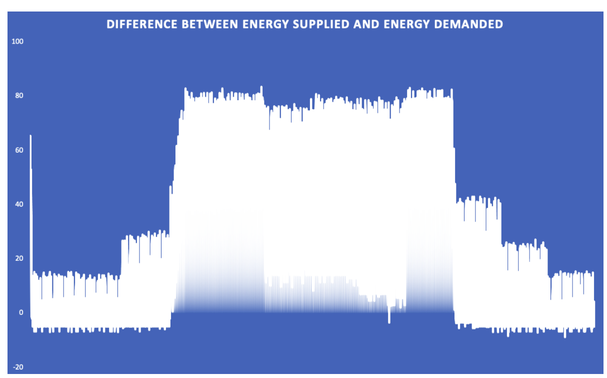
Tesla Powerwall+



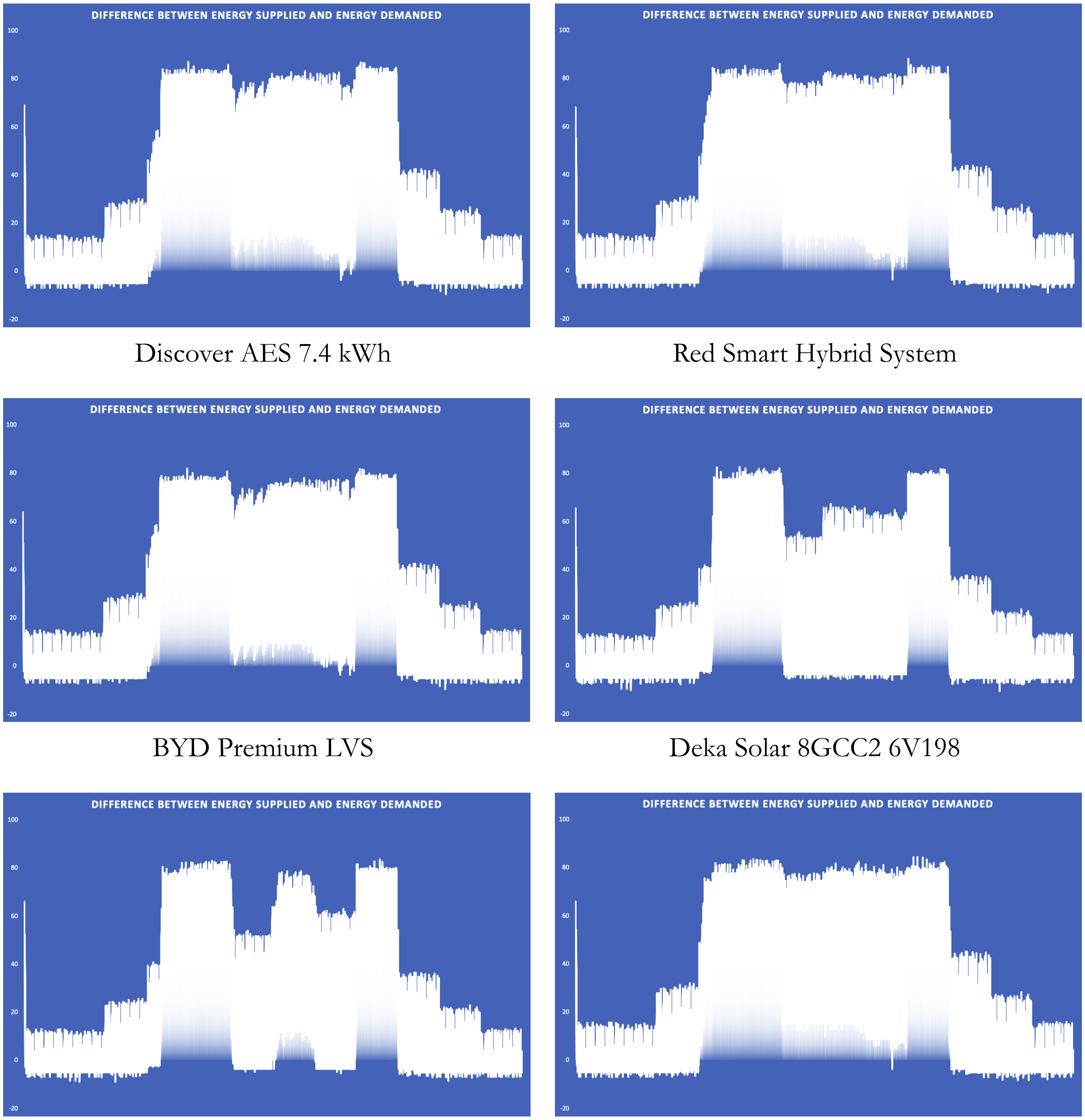
Sungrow SBP4K8



LG Chem RESU10



Powerplus Energy



Discover AES 7.4 kWh — Red Smart Hybrid System

BYD Premium LVS — Deka Solar 8GCC2 6V198

Trojan L-16-SPRE — Electriq PowerPod2

Figure 4: Difference between energy supplied and demanded for various batteries.

In the final step of our analysis, we calculate the EENS (Energy Expected Not Served, or the summation of all negative values when subtracting supply and demand of a given hour), LOLF (Loss of Load frequency, or the number of times when the difference was negative), and LCRES as explained above.

Battery	Units	EENS (kWh)	LOLF	LCRES ($/kWh)
Sungrow SBP4K8	16	6376	6598	0.00152
LG Chem RESU10	8	6395	6592	0.01807
Tesla Powerwall+	6	6745	6492	0.01886
Powerplus Energy	21	6350	6606	0.02436
Discover AES 7.4 kWh	11	6542	6543	0.01300
Red Smart Hybrid System	8	6377	6598	0.04974
BYD Premium LVS	17	6566	6533	0.02309
Deka Solar 8GCC2 6V 198	59	8173	6136	0.00918
Trojan L-16-SPRE	28	7597	6268	0.00576
Electriq PowerPod2	9	6183	6673	0.04022

Table 3: Battery effectiveness and cost.

There are no significant variations in EENS and LOLF, but the cost seems to be a highly distinguishing factor. Sungrow SBP4K8 seems to be significantly less expensive than the other battery options, and it does not have an inferior EENS and LOLF. Therefore, *Sungrow SBP4K8* is our overall choice of battery for the 1600 square-foot home. (However, we would recommend Powerplus Energy if the residents especially fear loss of power.)

5 Energy System Model Generalization

5.1 Overview

In this section, we will generalize our model so that it can simulate the energy consumption of any home using solar energy interested in purchasing a BESS. Our approach to modeling energy supply and cost will remain the same in the generalized model.

Our model for Energy Supply can generally be used on any individual's home and preferences. However, there are a few adjustments which need to be made in certain scenarios. While recording the energy use times for every appliance may have been feasible for our 1600 square-foot home, it is not effective for all scenarios, especially homes with numerous individuals who use hundreds of appliances. This approach is lacking for two additional reasons: 1) self-reporting use schedule may be inaccurate as most individuals do not put much thought into when and for how long they use electrical appliances and 2) this approach somewhat assumes patterns of appliance use (e.g., showering in the morning or at night) when appliance use seldom has such regular patterns.

Additionally, we assumed that the individuals seldom leave their house because they live in the wilderness. However, this assumption does not serve for most scenarios. According to Census data, most individuals in the United States live in suburban or urban areas and hold a job. To accurately model the energy consumption of these individuals, we must take into consideration when they are not inside their house.

For our generalized model, we employ an occupancy-based approach inspired by Yao et al. We ask all residents to report 1) their gender, occupation status, and age, 2) what appliances they use on a regular basis from a comprehensive list of appliances, and 3) when they are inside the house (their schedule). [8]

Then, we will separate the list of appliances used into occupancy-dependent appliances and occupancy-independent appliances. Occupancy-dependent appliances are typically only used when residents which use the appliance are inside the house and include stove, washer, oven, and so forth. Occupancy-independent appliances include HVAC and refrigerator.

We will use separate approaches to calculate the energy consumed through use of these two categories of appliances. For occupancy-dependent appliances, we will use survey data and a Markov chain to determine the likelihood of the use of a certain appliance at a certain point during the day. For occupancy-independent appliances, we will generate scalable equations based on factors such as the square foot size of the house.

While this model sacrifices some accuracy, it will allow us to rapidly determine the best battery system for many households without too much inconvenience to our clients.

5.2 Energy Consumption Generalization — Occupancy Dependent Behavioral Model

Individuals typically transition from activity to activity throughout the day. We used a Markov chain procedure inspired by Muratori et al. to determine the likelihood of an individual, based on their demographic characteristics, to be doing any common household activity involving an appliance at any given time. [9] We downloaded our data from the American Time Use Survey (ATUS), a survey conducted annually in a subsample of participants in the Consumer Preferences Survey (CPS) administered by the U.S. Bureau of Labor Statistics. We selected demographic characteristics and time-use data in our data extract.

First, we assigned each activity in the ATUS survey an energy consumption per hour value summed from all energy-consuming appliances the individual uses when doing that activity.

Then, we created two transition matrices in Excel of all household activities using the pivot tables function which approximated the likelihood of an individual transitioning from one activity to another for each age/gender/occupation group. The first transition matrix did not consider an individual's proximity to leaving the house and was used for all times that were not within an hour of inoccupancy. The second matrix was used for times within an hour of inoccupancy and assigned likelihoods which were calculated from the data values within an hour of inoccupancy from the ATUS survey.

Once the transition matrices were complete, we created a 1,440-row column in Excel and marked off all minutes of the day when the individual would not be in the house with the value 0. Then, we used the `=MMULT()` function in Excel to generate the individual's activity state for the rest of the minutes, using the appropriate matrices based on whether the individual was within an hour of leaving the house. We repeated the process of creating this column 1,000 times. Then, we calculated the average appearance of each activity in a given minute to determine the typical schedule of the individual.

Then, we repeated this process with all residents in the house. After constructing their typical daily energy profiles, we placed them onto a household energy profile to calculate the total energy consumption at any given moment during the simulated day.

Because individuals typically give their occupancy schedule as weekday vs weekend or a 7-day week, this process will likely need to repeat this process multiple times to determine the typical energy load for each individual on each type of day.

Next, we would calculate occupancy-independent energy consumption and create a year's worth of data on energy consumption. Then, we would graph energy supply and calculate EENS and LOLF as in our un-generalized model. Finally, we will present the clients with the graph so that they may choose whether they are more interested in a lower cost or no outages.

5.3 Energy Consumption Generalization — Occupancy Independent Model

The energy consumption of occupancy-independent appliances will be calculated in the same manner as in the earlier model. However, we must consider that larger homes may require more energy for certain services such as HVAC. Unfortunately, we were unable to find sufficient data to determine how home size, ambient temperature, etc affects HVAC expenditures. However, if we were a reputable company, we could reach out to databases such as the Comprehensive Energy Use Database to obtain data on the effect of various factors on energy expenditure. For example, we can run a regression which considers climate and space size as factors to model the energy consumption of furnace heating and use the regression line to predict the amount of energy consumed by these appliances. For now, we will assume the energy consumption provided in **Table 2** for the purposes of demonstration.

5.4 Model Application and Sensitivity Analysis

In **Fig. 5**, we apply our model to analyze the first 12 hours of a male doctor living in a 1000-square foot flat in New York City, New York in the absence of specific appliance data. This figure also shows our model's sensitivity to age.

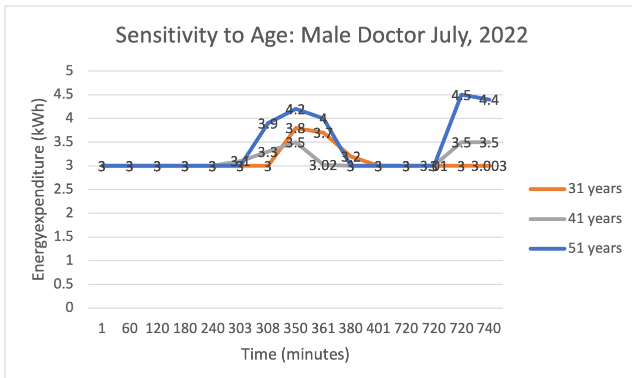


Figure 5: Model sensitivity to age.

As our model places relatively large emphasis on correctly predicting the load profile of the client residents, we wanted to test whether load affected the electricity supplied by each battery greatly. We tested sensitivity to load using the Sungrow batteries recommended for the 1600-square foot home by the previous model. As seen in **Fig. 6** below, load size does not actually significantly impact the amount of energy supplied (or efficiency) by the battery (given that the number of batteries used stays the same). Therefore, factors such as house size or energy consumption may not greatly affect which battery is the most favorable option, and small errors such as overlooking the size of the house or the ambient temperature in HVAC calculations will not significantly affect the model accuracy.

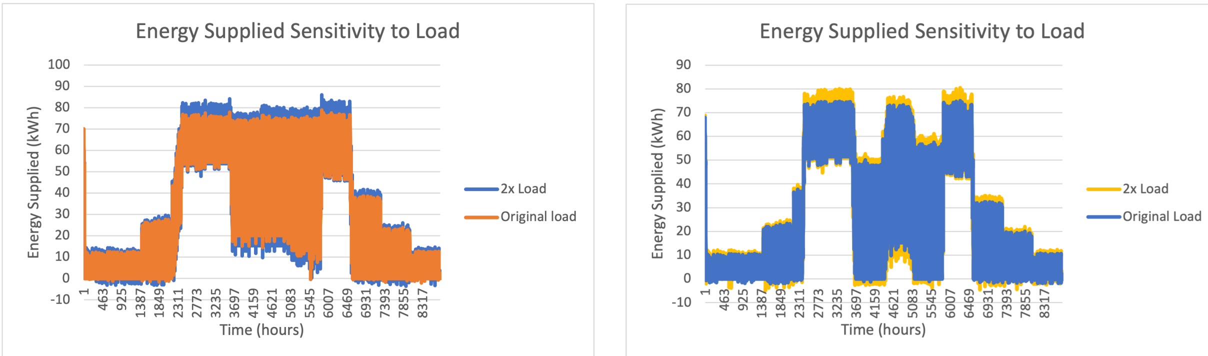


Figure 5: Model sensitivity to age. Left is Sungrow batteries and right is Trojan batteries.

6 Model Evaluation

- **Strength**: We simulate the energy load profile to provide "real" data we can base decisions on instead of using a weighting method which only compares variables.
- **Strength**: Our un-generalized model imitates randomness and creates all reasonable combinations of energy use, thus covering all possible scenarios.
- **Strength**: Our generalized model requires minimal information from clients and pulls from a large database to minimize inaccuracy.
- **Weakness**: Our un-generalized model calculates variables in discrete hour-long intervals instead of continuously. Therefore, we may have missed small outages which occur within the hour.
- **Weakness**: Our un-generalized model does not consider holidays, spontaneous outings, etc.
- **Weakness**: Our generalized model is based on the activities of a certain demographic in the US population and not the specific residents.
- **Weakness**: Our LCRE model did not take inflation into consideration. (However, as each cost inflates at the same rate, this should not affect results.)
- **Weakness**: Neither of our models were unfortunately able to achieve the level of sophistication and accuracy that could be achieved through machine learning methods based on the individual's electricity use historical data.
- **Weakness**: Our models both assume constant energy consumption and fail to consider sudden spikes in power use from certain appliances such as HVAC which may lead to outages.

7 Cement Batteries

7.1 Use of Cement Batteries

7.1.1 Incorporation Into Buildings

Another type of battery we analyzed was cement batteries. For decades, engineers have envisioned buildings which have mechanisms to collect and store. Such a concept would be revolutionary because it could solve energy shortage through increasing storage capacity significantly. One potential design for such a building are cement batteries. Cement batteries are created by adding electrically conductive components to cement, giving it conductor properties. [10] This discovery is significant because various structures such as building walls and sidewalks are largely composed of cement.

Should cement batteries become a mature, stable, and affordable technology, we can implement them in our off-the-grid home. Because many buildings are made of concrete, which is 10-15% cement, we can easily incorporate many of these batteries into all walls of the home. With more batteries, we are able to store more solar energy, and we are less likely to experience energy shortages. If we find that the cement batteries are insufficient in some way, we can supplement them with existing battery technologies by connecting them in parallel or in series with other batteries. Cement batteries can also be incorporated into large office buildings which were previously unable to use renewable energy because they did not have sufficient room for the batteries required to store enough solar energy to power the building during periods without sunlight.

Unfortunately, cement batteries are a relatively new technology which has yet to achieve a market-ready form. Below we analyze some advantages and disadvantages of current cement battery technologies with information obtained from Zhang et al.'s pioneer study on cement batteries. [10]

7.1.2 Advantages

1) One of the primary advantages of cement batteries is the conservation of storage space. Some batteries, such as the Electriq PowerPod 2, have volumes of over seven cubic feet. While this may not seem overwhelmingly large, dozens or even hundreds of these batteries may be needed to power some buildings without outages, and the space can add up quickly.
2) Cement batteries could potentially be cheaper than the rare minerals which are required for other types of batteries.
3) Cement is a relatively sturdy material with a long life cycle that is not easily damaged. Unlike other batteries, they will not break as easily if dropped.

7.1.3 Disadvantages

1) Cement is harmful for the environment. According to a Chatham House Report, its production accounts for around 6% of global carbon dioxide emissions. Other types of batteries are not correlated to increase in carbon dioxide emissions.
2) Unlike other batteries such as lithium ion batteries, cement (and, therefore, cement batteries) are not biodegradable.

3) Currently, cement batteries store significantly less energy than most batteries, with an average energy density of 7 Watthours per square meter. (For comparison, lithium-ion batteries store about 36 Watt-hours.) However, this drawback could be ameliorated by the large amount of cement that can be stored in a single building.
4) Cement batteries have significantly higher resistance (0.9 $\Omega \cdot m$) than other batteries (for example, lithium ion has a resistance of 0.320 $\Omega \cdot m$).

7.2 Suggestions for Further Evaluation

Currently, there is insufficient information on cement batteries for us to obtain a conclusion about what situations they can best be implemented in. First, further information about the usable capacity, charging efficiency, and discharging efficiency are needed to fit cement batteries into our model and determine how efficiently they can store and release energy.

While providing sufficient energy is the most important factor, secondary factors also play a role in determining the most suitable battery, primarily cost and safety. Cost involves unit price and lifetime duration. While most batteries are equally safe, it is important to ensure that proper testing has been done with cement batteries before suggesting it to clients.

8 How To Pick the Best Battery for Your Sustainable Home

So you've decided to switch to solar panels as the main energy source for your house. Congratulations! Solar panels are a renewable source, meaning they are probably significantly better for the environment than what your house was running on before. However, powering a home on solar panels is a little tricky. As you might guess, solar panels cannot provide energy when the sun is not out… but you might still need electricity on a cloudy day!

Fortunately, we have the perfect solution: a battery energy storage system. A battery energy storage system is exactly what the name suggests—a storage system that stores solar energy for when the sun isn't out. There are a lot of solar battery energy storage systems out there. How can you choose the one that is perfect for you? Fortunately, we have just the system!

First, you must let us know if you live in a big family or a small one. If you have a small family that is aware of their electricity use, we will ask you to record the appliances you use regularly and the times you typically use them. Then, we will forecast one year of your electricity use. We will compare your usage patterns with the amount of energy different batteries can store and release, and we will present you with the cheapest battery that still covers all your needs!

However, this might not be possible if you live in a bigger family with lots of appliances. No worries, we have an option for that too! We will ask you for some basic demographic characteristics and when you and your family are typically inside the house. Then, we will use data from individuals similar to you to estimate your appliance use. We will also compare your usage patterns to various batteries to determine the best battery option for you.

We're super excited for you to begin your renewable energy journey, and we wish you the best of luck!

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