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Daily electrical energy consumption characteristics and design implications for off-grid homes on the Navajo Nation

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ABSTRACT

Access to electricity remains elusive for over 700 million people worldwide. Although much attention has been given to solving this vexing problem in the context of communities in Sub-Saharan Africa and South Asia, often overlooked is that in even within so-called developed countries access to electricity might not be universal. It is estimated that more than 200,000 people living in North America do not have a connection to the electric grid. Many of these people live on Native American reservations or other Tribal Lands. Recently, there has been a concerted effort in the public, private, and non-profit sectors to electrify these homes with off-grid solar systems. This paper analyzes the electrical energy usage characteristics of 127 homes on the Navajo reservation in the southwestern United States. The homes have identical 3.8 kW solar arrays, 35.1 kWh 48 V gel lead acid battery banks, and 8 kW inverters. High-resolution inverter data was collected from these systems for a two-year period. Several statistical analyses were conducted on the data, including computing the statistical moments, creating empirical distributions of daily consumption, and analyzing consumption variation across different timescales. The results show average consumption of 2.78 kWh per day, but with a wide range of variation among homes. The implications of the analyses on pre-implementation system design, post-implementation interventions, and comparisons to incipient electricity consumption characteristics elsewhere in the world are discussed. The use of the average daily consumption in data-driven load estimation is evaluated and found to offer promising improvements over survey-based methods.

Introduction

Access to electricity is associated with several positive development outcomes, including those related to education, heath, and economic prosperity (Asghar, Amjad, ur Rehman, Munir, & Alhajj, 2022; Franco, Shaker, Kalubi, & Hostettler, 2017; International Energy Agency, 2014; Kanagawa & Nakata, 2008; Sarkodie & Adams, 2020a, 2020b; Sovacool & Ryan, 2016). Worldwide, 733 million people lack access to a grid connection (The World Bank, 2022). Although this number has been steadily decreasing from over one billion in 2014, universal electricity access is likely decades away (Energy Sector Management Assistance Program, 2022; The World Bank, 2022). The global community's efforts at increasing electricity access have largely focused on Sub-Saharan Africa and South Asia, where energy poverty rates are the highest. Often overlooked, however, are those people without grid-connected electricity access in so-called developed countries.

Presently, tens of thousands of homes – corresponding to perhaps hundreds of thousands of people – living on Tribal Lands in the United States and Canada have no connection to the electricity grid (Gallucci, 2019; Karanasios & Parker, 2018; Mayes, 2000; United States Census Bureau, 2017). Small-scale, standalone, off-grid solar-powered systems have been implemented in some of these homes to provide modest, yet meaningful, access to electricity (Battiest, 2007; Begay, 2018; Pasqualetti, 2011). However, field-collected technical data from these systems have not been systematically analyzed. As a consequence, very little is known about how well these systems operate or how they are used. The absence of this crucial information stifles innovation and design improvements that can enhance performance and increase affordability, which would make off-grid systems available to more people. This research analyzes daily electrical energy consumption data from 127 identical 3.8 kW off-grid residential photovoltaic (PV)

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systems on the Navajo Nation (Navajo reservation). A two-year period is considered. In total, more than one hundred million minutely data points were processed. The systems were implemented and are maintained by the Navajo Tribal Utility Authority (NTUA) (Navajo Tribal Utility Authority, 2022).

The analyses presented in this paper focus on daily electrical energy consumption characteristics of the homes. For the sake of brevity hereafter the term "energy" refers strictly to electrical energy rather than, for example, energy provided by biomass or fossil fuels. Analyzing daily energy consumption is worthwhile for two important reasons. First, it has immediate practical value in improving the designs of off-grid systems in similar conditions. Second, it improves the state-of-knowledge about first-time electricity use in the context of Tribal Lands. This paper is the first to present a dedicated study and analysis of energy consumption characteristics of off-grid users in this important context.

Analyses of daily energy consumption like those presented in this paper can be used in so-called data-driven load estimation techniques. These techniques use consumption characteristics from similar users to predict consumption characteristics of future users. This method has been shown to substantially reduce load estimation errors by up to 82% (Blodgett, Dauenhauer, Louie, & Kickham, 2017; Yoder & Williams, 2020), allowing the designer to size PV arrays and battery banks that are neither oversized (underutilized) nor undersized (unreliable). Accurate load estimation in the absence of existing energy consumption data is notoriously difficult (Blodgett et al., 2017; Lorenzoni, Cherubini, Fioriti, Poli, Micangeli, & Giglioli, 2020; Weston, Kalhoro, Lockhart, Reber, & Booth, 2019; Williams, Jaramillo, Cornell, Lyons-Galante, & Wynn, 2017; Yoder & Williams, 2020) and is a recognized barrier to wider off-grid system adoption (Booth, Li, Baring-Gould, Kollanyi, Bharadwaj, & Weston, 2018; Weston et al., 2019).

While off-grid energy consumption analyses can be found in the extant literature, they mostly consider rural Sub-Saharan Africa (Africa Minigrid Developers Association, 2020; Few, Barton, Sandwell, Mori, Kulkarni, Thomson, Nelson, & Candelise, 2022; Hartvigsson & Ahlgren, 2018; Hartvigsson, Ehnberg, Ahlgren, & Molander, 2021; Lorenzoni et al., 2020; Louie, 2016, 2016; Mandelli, Merlo, & Colombo, 2016; Mandelli et al., 2016; Prinsloo, Dobson, & Brent, 2016; Williams et al., 2017; Yoder & Williams, 2020). There is abundant literature attempting to estimate daily energy consumption using surveys or statistical regression (Blodgett et al., 2017; Fabini, Baridó, Omu, & Taneja, 2014; Ghafoor & Munir, 2015; Louw, Conradie, Howells, & Dekenah, 2008; Zeyringer, Pachauri, Schmid, Schmidt, Worrell, & Morawetz, 2015). Several studies have been conducted examining the load profiles of different consumer classes, such as businesses and homes (Williams, Jaramillo, Campbell, Musanga, & Lyons-Galante, 2018; Williams et al., 2017). Although many of the studies focus on mini-grid-connected homes, not homes with standalone systems. Generally, it is found that off-grid homes have a strong night-peaking trend, and that there is a wide distribution of average daily consumption, ranging from tens to several hundreds of watthours per day (Blodgett et al., 2017).

There are many reasons to believe the energy use characteristics of off-grid homes on Tribal Lands could be different from the energy characteristics of off-grid homes in Sub-Saharan Africa and elsewhere. Among the potential reasons would be the considerably different demographics between off-grid communities in Sub-Saharan Africa and those on Tribal Lands in terms of age, income, wealth, and education. There are several other differences as well. For example, appliance ownership is often a barrier to higher energy consumption in off-grid homes in Sub-Saharan Africa and elsewhere (Blodgett et al., 2017; Lukuyu, Fetter, Krishnapriya, Williams, & Taneja, 2021; Richmond & Urpelainen, 2019), whereas many off-grid homes on Tribal Lands are manufactured homes that come pre-equipped with hot water heaters and other appliances. The analyses presented in this work highlight the differences these contexts have, as manifested in daily energy consumption.

Other research related to energy issues on Tribal Lands frequently focuses on the cultural, societal, and environmental aspects and considerations of energy development projects (Billy, Heydt, Langness, Laughter, Mann, Rice, & Winslow, 2007; Necefer, Wong-Parodi, Small, & Begay-Campbell, 2018; Pasqualetti, Jones, Necefer, Scott, & Colombi, 2016). The research generally finds that renewable resources such as solar are viewed as compatible with cultural norms, and that off-grid systems reinforce an ethos of independence from external entities (Billy et al., 2007). Much of the literature related to the technical aspects of off-grid systems are feasibility studies with limited generalizability, such as designing a solar power system for a specific home or medical clinic (Cotto & Lee, 2016, 2017). The novelty of the research presented in this paper is it is the only dedicated study and analysis of energy consumption of off-grid users in the context of Tribal Lands.

The remainder of this paper is organized as follows. Section "Electricity access on Navajo Nation" provides a brief background of the historical and present context of electricity access on the Navajo Nation. Section "Off-grid system description" details the off-grid systems considered in this research. The data collection, pre-processing, and analysis methodology are described in Section "Data set description". Temporal characteristics of the daily energy use are described in Section "Temporal analysis". Section "Daily energy use statistics" provides the statistical analysis of the data. Section "Discussion" discusses the implications of this research. Conclusion and future work are provided in Section "Conclusions and future work".

Electricity access on Navajo Nation

The Navajo Nation is a sovereign nation located in the southwestern region of the United States. It is the largest and most populous Tribal Land in the continental United States. Approximately 300,000 people live on the Navajo Nation, spread over 70,000 square kilometers in Arizona, New Mexico, and Utah. The Navajo Nation, which can be described as high desert plains with mesas and deep canyons, is rich with natural resources. The Navajo Nation has an excellent solar resource, with over 270 sunny days per year and an average insolation exceeding 6 kWh/m^2/day. This has made photovoltaics the preferred choice for powering off-grid systems. The Köppen climate classification ranges from BWk (Cold Dessert Climate) to BSk (Cold Semi-Arid Climate).

Although resilient and rich in tradition and culture, 40 percent of those living in Navajo Nation live below the poverty line (United States Census Bureau, 2017). It is also the least electrified of all Tribal Lands within the United States; one-third of its people are without grid access (Begay, 2018). The difficult terrain and low population density, along with Tribal Lands largely being excluded from rural electrification efforts by the United States government have been barriers to grid extension. Some homes are as far as 70 km from the grid. There is little expectation that the grid will be extended to reach all the homes, with the estimated cost exceeding $350 million (Bain, Ballentine, DeSouza, Majure, Smith, & Turek, 2004). At the present rate of grid extension, it will be 40 years before every home is connected (Gallucci, 2019).

Still, concerted efforts have been made to increase access to electricity on Navajo Nation. Public, private, non-profit, and individual actors have implemented off-grid systems throughout the years and at different scales. Some have targeted individual homes, others have prioritized community services such as schools and health facilities.

Off-grid system description

The off-grid systems considered in this work were implemented by the Navajo Tribal Utility Authority (NTUA). NTUA is a tribally-owned utility that provides electrical, water, and communication services to the Navajo Nation (Navajo Tribal Utility Authority, 2022). NTUA

Fig. 1. Image of the Sol-Ark off-grid electrical system. The inverter, charge controller, battery bank and data acquisition system are in the enclosures in the foreground. The bi-facial 3.8 kW PV array tilted at 35 degrees in the background.

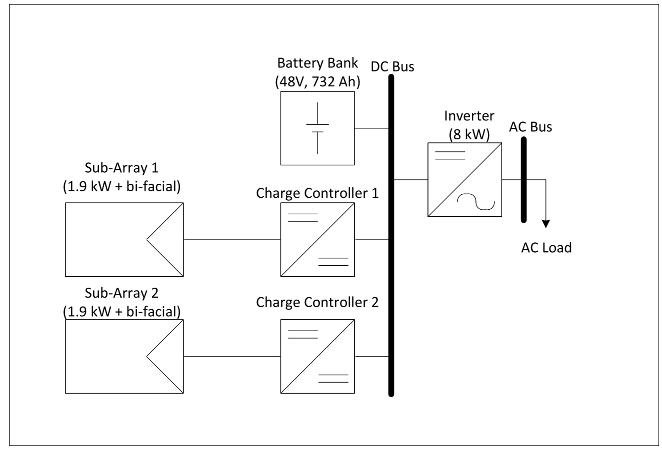

Fig. 2. Schematic of off-grid electrical system considered in this research.

has been implementing residential off-grid systems since 1993 (Begay, 2018). The off-grid systems considered in this work were funded through the U.S. government CARES Act (Coronavirus Aid, Relief, and Economic Security Act) (Navajo Tribal Utility Authority, 2021). In total, US$13 million was allocated for off-grid solar systems, with a total of 300 systems installed. A caveat to the funds, however, was the very short time frame in which they had to be spent, from August 2020 to December 2020. A motivation for the off-grid systems was to reduce COVID-19 exposure to off-grid households by providing them with electricity to power refrigerators, thereby reducing the frequency of trips to grocery stores, and allowing the residents to work-from-home and study-from-home during the pandemic.

The use-it-or-lose-it nature of the funds added pressure on NTUA to implement the systems quickly and to use on contractors to assist in the installation. Two solar contractors were used to install the systems, each installing 150. The 150 systems considered in this research are the Sol-Ark 8 K All-in-One model (Sol-Ark, 2022). Fig. 1 shows one such system. The systems are powered by a 3.8 kW bi-facial array, arranged into two sub-arrays, and tilted nominally at latitude (35 degrees). A schematic is shown in Fig. 2 The battery bank consists of sixteen 183 Ah (20-h rate) lead-acid gel batteries arranged in four strings of four batteries, for a total energy capacity of 35.1 kWh at 48 V. The inverter is rated at 8 kW. NTUA provided wiring to and within the homes connected to the off-grid systems.

NTUA services the systems approximately twice per year. The homes were provided an energy efficient refrigerator and an orientation describing how the systems function and to discourage wasteful consumption.

Data set description

Scope

This research analyzes time-stamped inverter AC output power data, expressed in watts. The data are collected by Samsara (Samsara, Inc., 2020) industrial data acquisition systems and are transmitted via a cellular network to a cloud-based database. The data acquisition systems measure the inverter power at irregular intervals, with a sampling frequency as high as several times per minute. The data period considered spanned from 1 January 2021 to 31 December 2022. It should be noted that not all systems were installed or fully functional during this window. Some systems were installed somewhat before 1 January 2021, and some began transmitting data later. The data were accessed through an API using a customized Python script. Data from 150 homes were considered for analysis, but this was reduced to 127 after data cleaning, as described next.

Pre-processing

As with any real world data set, omissions and errors in the collected data are possible. The data set overall was found to be of high quality. However, approximately half of the systems experienced data outages for a three-month period from September through October 2021. This was due to a backend data acquisition system error. The collected inverter data underwent several pre-processing stages to clean it and to organize it into a more conveniently analyzable form. The pre-processing methodology is described in the following.

The data were first down-sampled to reduce the data set into a more manageable size. The down-sampling was performed in two stages. First, the data for each home were down-sampled to minutely resolution. Any data for a home that had timestamps occurring within the same minute were averaged. Any minute without data was flagged as missing. Second, a ten-minutely data set was created by averaging the minutely data. Any ten-minute interval with no minutely-data was flagged as missing.

The ten-minutely data for each home were then screened in several ways. Any day that was missing more than 48 (eight hours) of the possible 144 ten-minute values was discarded from further analysis. The missing values need not occur consecutively for the day to be discarded. Therefore, any day remaining in the data set had least 16 h of data. Next, linear interpolation was used to “fill-in” any missing 10-minute values in days still in the data set.

Since the primary objective of this research is concerned with daily energy consumption, the 10-minutely time-series values of inverter power for each home were averaged for each day. The average power for a day is multiplied by 24 and then divided by 1000 to convert from power in watts to daily energy in kilowatthours.

The daily energy values were then filtered to remove likely erroneous values. Specifically, daily energy values were considered invalid if they were negative or they exceeded 50 kWh. Consumption of 50 kWh in a single day is implausible given the PV array and battery bank sizes, inverter low voltage disconnect settings, and typical daily insolation. This filtering removed very few days from the analysis. Next, if the filtering process removed more than 330 days of data for a home, that home was removed from further analysis. The data from 16 homes were removed during this stage.

Finally, the time-series plots of the daily energy values were individually inspected to filter out homes whose consumption was anomalous. The data for seven homes were removed at this stage, usually for persistent zero consumption or implausible consumption patterns that suggest errors in the data acquisition system. After data pre-processing, a total of 74,610 days corresponding to 127 homes remained for inclusion in the analyses. Implications and possible biases introduced by the data cleaning process are discussed in detail in Section “Discussion”.

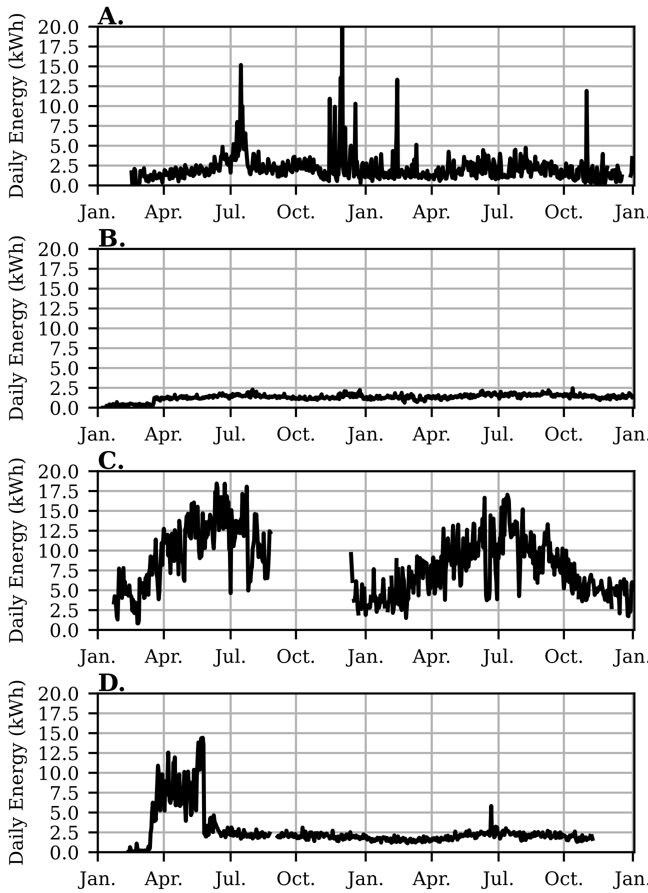

Fig. 3. Examples of daily energy time series showing A. high and variable consumption, B. low and consistent consumption, C. pronounced seasonal trend, D. change in consumption pattern.

Temporal analysis

A common first step in data analysis is to inspect the data as a time-series. The time-series of energy consumption are explored in daily, monthly, and yearly timescales in the following.

Daily energy

When exploring the data as a time-series with daily resolution, several features become apparent. These are exemplified in the curated subset of plots provided in Fig. 3. Each plot corresponds to a particular home. Taken together, the plots in Fig. 3 show the diversity and range of consumption that can occur amongst the off-grid homes. Fig. 3A illustrates the range of daily consumption that can occur within even the same home—on some days the consumption is several times the average. Fig. 3B, however, illustrates that some of the homes exhibit consistent, steady consumption throughout the data set. Other homes, like that in Fig. 3C, exhibit a pronounced seasonal trend. Some homes had notable changes in consumption, as exemplified by the home in Fig. 3D.

Collectively, these observations indicate that despite the homogeneity in the systems' technical capabilities and their application on the Navajo Nation, there is variation with the energy consumption patterns, and that there is no universal energy consumption profile.

Monthly energy

We next explore the longer-term temporal trends of energy consumption. In particular, we explore if there is a seasonal trend in the consumption. Seasonal trends are common in electricity consumption characteristics in many parts of the world, including the southwestern United States. Grid-connected homes in this region tend to have summer-peaking load (Energy Information Administration, 2022). Whether this characteristic applies to off-grid systems on Tribal Lands has not been studied in the extant literature, and are considered for the first time here.

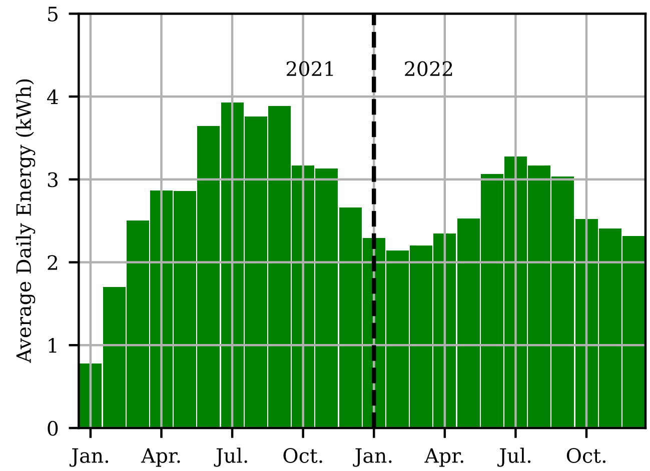

Fig. 4. Average of average daily consumption by month.

Fig. 4 shows the averaged average daily consumption of all homes by month for the period under study. The consumption shows a distinct seasonal trend, which peaks in late summer (August/September) and reaches its nadir in late winter (February/March).

This seasonal trend has several possible explanations. One reason is that the Navajo Nation's climate features summertime highs of 30° C. At least some homes use small air conditioning units or evaporative coolers. Although the winters are cold, with lows below -5° C, it is expected that few homes rely on electric heat. Rather, biomass (fire wood) and propane are much more common. The summertime peak may also be attributed to school and seasonal work patterns. During the summer, more people may occupy a home and for longer periods of the day, leading to increased consumption. Another contributing factor could be that the homes had to consume less energy in the winter due to the lower PV energy production potential, but then increased consumption during the sunny summer months.

Annual energy

Off-grid homes being provided with incipient electricity access, at least in Sub-Saharan Africa, tend to increase consumption over time (Blodgett et al., 2017). However, for the homes on Navajo Nation, the average daily consumption in 2021 and 2022 were 2.90 kWh/day and 2.61 kWh/day, respectively. This corresponds to a 10.3 percent decline in consumption. Ten months exhibited a year-over-year decline in consumption. There can be several explanations for the observed decline. In 2021, COVID-19 precautions were enforced on the Navajo Nation, with residents encouraged to stay home. This would naturally increase consumption. In 2022, the restrictions were relaxed with presumably less work-from-home or online school occurring. This would decrease consumption in 2022. It remains to be seen if the consumption continues to decline, stabilizes, or even increases. There could also be technical reasons that contributed to the decline, for example accelerated aging of the lead-acid battery bank or the PV array may constrain consumption in some homes.

Daily energy use statistics

With the insight gained from the time-series exploration of the data, we next consider the statistical characteristics of the daily energy use.

Table 1
Statistical characteristics of daily energy consumption.

Statistic	Avg.
Mean (kWh/d)	2.78
Std. deviation (kWh/d)	1.82
Skewness	1.59
Kurtosis (Excess)	3.90
Daily variation (%)	66.2

Table 2
Quantiles of daily energy data.

Statistic	Avg. (kWh/day)	Median (kWh/day)	Max. (kWh/day)
Maximum	10.49	10.31	46.47
Q(0.975)	7.90	6.55	34.42
Q(0.95)	5.76	4.99	28.16
Q(0.90)	4.89	4.38	22.43
Q(0.50)	2.44	2.09	11.41
Q(0.10)	0.84	0.77	3.72
Q(0.05)	0.65	0.47	2.83
Minimum	0.35	0.00	1.58

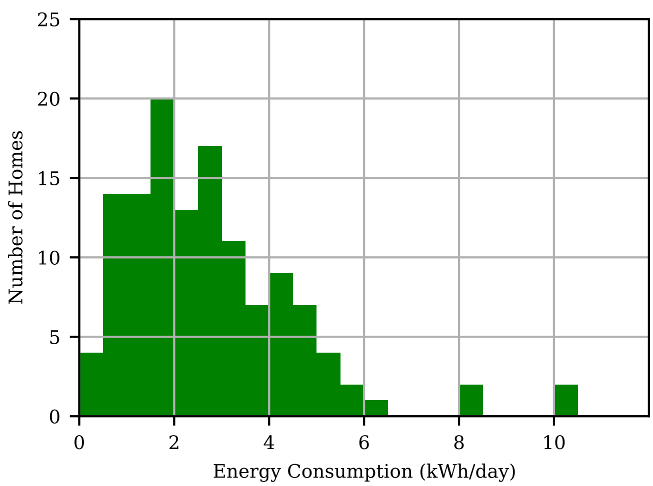

Fig. 5. Distribution of average daily energy consumption. (N=127).

Average daily consumption

The average daily consumption was computed for each of the 127 homes. The average daily consumption of a home is of particular interest because it is often used to size the PV array and battery bank of an off-grid system. A histogram of the average daily consumption is shown in Fig. 5, with the corresponding statistics and quantiles shown in the second columns of Tables 1 and 2. Note that $Q(x)$ refers to the xth quantile, so that, for example $Q(0.50)$ is the median. The skewness is positive and the distribution is leptokurtic, showing the tendency for outliers of high consumption.

We note that the average daily consumption is 2.78 kWh/day. However, Fig. 5 shows that there is large variation in consumption among the homes both above and below the mean. Ten percent of the homes had an average consumption of no more than 0.84 kWh/day, whereas ten percent of the homes averaged no less than 4.89 kWh/day. The home with the greatest average daily consumption averaged 10.49 kWh/day. The variation in consumption is readily seen from the inverse empirical cumulative distribution function (CDF) of average daily consumption in Fig. 6.

The data show that a small number of homes have much greater average consumption than others. The consumption inequality can be expressed in a Lorenz Curve. The Lorenz Curve shows which proportion of a population (homes) consumes which portion of a quantity

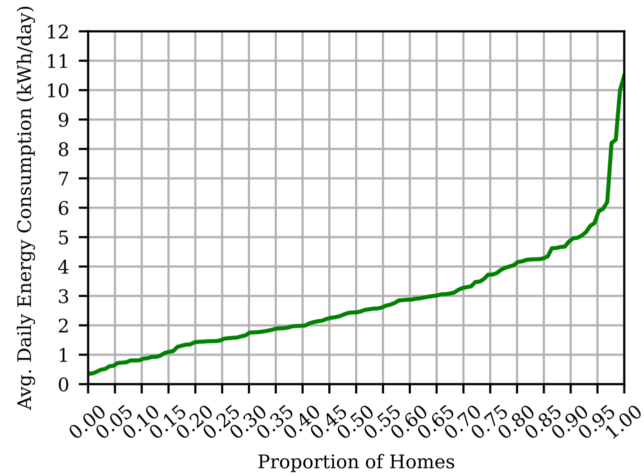

Fig. 6. Inverse empirical cumulative distribution function of average daily energy use. (N = 127).

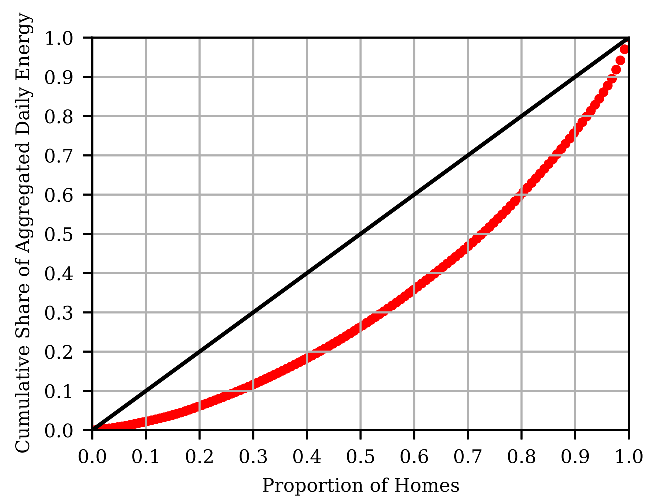

Fig. 7. Lorenz Curve of daily energy consumption. The straight diagonal line is the reference line for entirely equitable consumption.

(energy) (Alem, Caunhye, & Moreno, 2022; Gastwirth, 1971). The Lorenz Curve of the data is shown in Fig. 7. A straight line on a Lorenz Curve shows a scenario of fully equal consumption (each home consumes the same energy). It is important to highlight two points on the Lorenz Curve: the bottom 20 percent of consumers consume just 5 percent of the total energy, whereas the top 20 percent of the homes consume roughly 40 percent of the total. A metric commonly used to measure inequality is the Gini coefficient (Alem et al., 2022). A Gini coefficient of 0 corresponds to perfectly equitable distribution, whereas a coefficient of 1.0 is maximum inequality (a single home consuming all the energy). The Gini coefficient of the daily consumption is 0.34.

Variation in daily consumption

While the average daily consumption is an important characteristic of energy use, it is also worthwhile to consider how the daily consumption of a home may vary from its average. As an example, consider the histograms of daily consumption for two homes shown in Fig. 8. The distribution in Fig. 8A exhibits a relatively narrow range of daily consumption, with approximately symmetric consumption around the mode. This is an example of a home that exhibits consistent energy consumption. Contrast this with the distribution in Fig. 8B, which exhibits a flatter, broader distribution. There are many days in which the

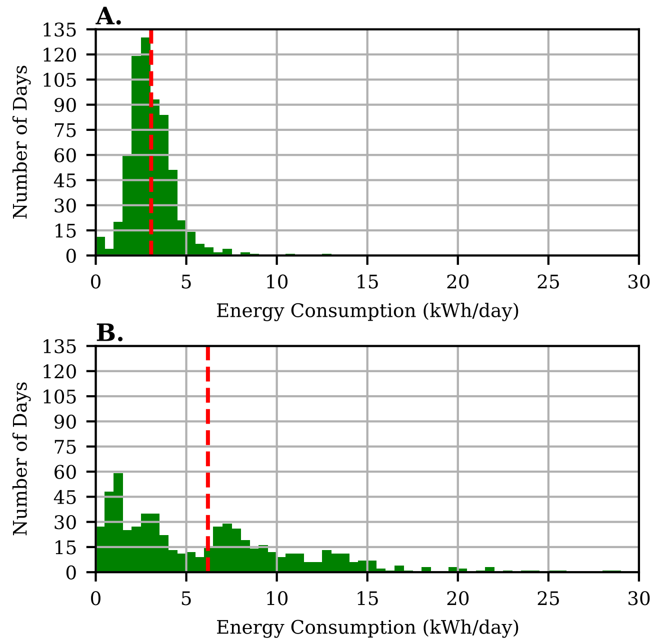

Fig. 8. Example distributions of A. a home with relatively consistent consumption, B. a home with widely variable consumption. The dashed vertical lines correspond to the average daily consumption for each home. The bin width of the histograms is 0.5 kWh/day.

consumption is several times above and below the average. This is an example of a home whose daily consumption has varied considerably during the period considered.

The variation of daily consumption as expressed in the form of box plots for 25 randomly-selected homes is shown in Fig. 9. The boxplot shows that the homes exhibit a variety of daily consumption characteristics. The quantiles for the median consumption of all the homes is provided in the third column of Table 2. Ninety percent of the medians lie within the range 0.47 to 4.99 kWh/day.

The daily variation is often used as a parameter in computer-aided off-grid system design methodologies. In programs such as HOMER Pro (UL, 2020), the daily variation is expressed as the standard deviation divided by the mean (Williams et al., 2017). The average of this value for all homes is provided in the last row of Table 1. It is worth noting, however, that some simulation-based design programs assume the daily energy consumption in a home follows a Gaussian distribution. However, from inspection of Fig. 9, the distributions tend to be non-Gaussian, with a pronounced positive skewness.

Maximum daily consumption

The maximum single-day energy consumption of a home can provide insight into a home's potential to consume energy. The maximum daily consumption of each home was computed, with quantiles shown in the fourth column of Table 2. The maximum single-day consumption recorded was 46.5 kWh, but in most homes the maximum consumption was far lower. The daily consumption never exceeded 22.43 kWh in 90 percent of homes, and the median maximum consumption was 11.4 kWh.

Daily consumption

We next consider the statistical characteristics of all the daily energy consumption data together, rather than grouped by home as was done in the previous analyses. The inverse empirical CDF of all 74,610 data points is provided in Fig. 10. The figure shows that the median consumption of all the days in the data set is approximately 2.25 kWh/day.

Table 3
Statistics of estimated daily DC energy data.

Statistic	DC avg. (kWh/day)
Maximum	11.93
Q(0.975)	9.34
Q(0.95)	7.20
Q(0.90)	6.33
Mean	4.22
Q(0.50)	3.88
Q(0.10)	2.28
Q(0.05)	2.09
Minimum	1.79

The hockey stick-like bend shows just how infrequent days of high consumption are. In 95 percent of the days, the consumption is less than approximately 8 kWh/day.

DC energy consumption

The energy consumption characteristics described thus far have been computed from measurements from the AC-side of the inverter. The consumption at the DC-side of the inverter is of interest when considering the design of the PV array and battery bank. The DC-side consumption can be estimated from the AC-side consumption data. To do so, constant (no load) and variable losses of the inverter are normally considered. The no-load consumption for the inverter is reported as 60 W, or 1.44 kWh/day. For perspective, 1.44 kWh/day is greater than the average AC-side consumption of approximately 20 percent of the homes.

The variable losses increase with the loading of the inverter. A survey of the minutely inverter power output data shows that peak power in excess of 2 kW occurs in fewer than one percent of the days, and that ten-minute consumption usually ranges between 100 and 300 W. At such low loading given the inverter rating of 8 kW, the constant losses dominate and the variable losses can be reasonably ignored.

The energy consumption on the DC-side of the inverter is estimated by adding the inverter's constant losses to the average daily AC-side consumption as:

$$\bar{E}_{DC} = \left(\bar{E}_{AC} + 1.44\right) \tag{1}$$

where $\bar{E}_{DC}$ is the average daily energy consumption on the DC-side of the inverter and $\bar{E}_{AC}$ is the AC-side consumption, both expressed in kilowatthours. The average and quantiles of the estimated DC-side consumption are then simply the corresponding AC-side values increased by 1.44 kWh/day. By the same reasoning, the estimated average DC-side consumption of the homes is 4.22 kWh/day, compared to 2.78 kWh/day for the AC-side. The quantiles and mean of the estimated DC-side consumption are shown in Table 3. The DC-side consumption will be used in the next section to evaluate the performance of differently-sized PV and battery banks.

Discussion

The analyses presented in this paper provide important, actionable information about residential off-grid solar system design and use on the Navajo Nation. Furthermore, the results provide some insight into the importance of setting and context – namely the Navajo Nation context vis-à-vis the Sub-Saharan African context – in how electricity is used when a home gains first access to electricity. Before doing so, it is important to discuss the limitations of this research.

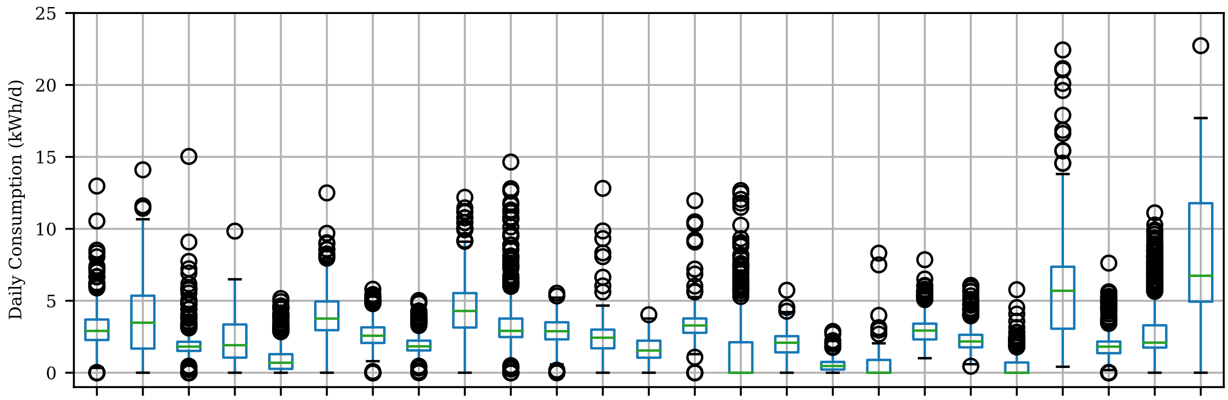

Fig. 9. Box plots of daily energy consumption for 25 homes in the data set. The box plots show the Q(0.25), Q(0.50) and Q(0.75) quantiles; the whiskers extend to 1.5 times the interquartile range, and the outliers are shown as circles.

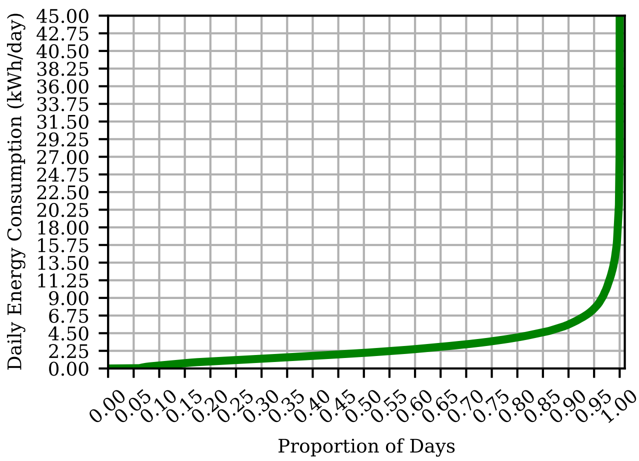

Fig. 10. Inverse empirical cumulative distribution function of daily energy consumption considering all days in the data set. ($N = 74{,}610$).

Study limitations

Although the analyses presented in this paper are the most comprehensive of its kind, relying on 74,610 data points from 127 homes on a Tribal Land, some limitations must be acknowledged. First is that the energy consumption is naturally constrained by the actual or perceived capabilities of the off-grid system. The results do not represent the unconstrained energy appetite of the homes. If the homes were connected to the grid, one could reasonably assume that consumption would increase.

Second, and importantly, the influence of missing data likely results in the energy consumption being somewhat understated. To understand why, consider that there are two reasons why raw data would be missing from the data set: a data system outage or an energy system outage. In a data system outage, an error or failure in the data acquisition, communication, or data storage system occurred, but the energy system was not affected. In an energy system outage, however, power to the AC-side of the inverter is interrupted, which causes the data acquisition system to lose power and cease to function. Although there are several possible reasons for an energy system outage, experience with off-grid systems suggests that a low voltage disconnect by the inverter due to a depleted battery bank is the most likely culprit. A depleted battery bank is associated with high energy consumption, suggesting a positive correlation between days that were filtered out of the data set due to missing raw data and days of high consumption. This would then put a downward bias on daily consumption reported in this paper.

Despite this, the effect of the bias on average daily consumption is likely limited to a few percent because relatively few days overall suffered energy system outages. Of the 127 homes included in the analysis, a total of 18,100 (19.5 percent) out of 92,710 total days were filtered from the data set because they were missing more than 48 ten-minute (8 h) data points. Eighty four percent (15,199) of those days filtered from the data set were days in which raw data for the entire day was missing. These missing days almost surely correspond to data system outages, since energy system outages tend to end shortly after sunrise. The omission of these days likely does not bias the results. The number of days with partial outages – which could be attributed to energy system or data system outages – that were filtered from the data set is 2901, which is three percent of the total days. Note that 94 percent of the days included in the final data set that the analyses were based on are not missing a single ten-minute data point. The other six percent were missing between ten minutes and eight hours of data.

The filtering process likely introduced a bias in the analysis that underestimates the consumption. On the other hand, the consumption of the data acquisition system itself somewhat inflates the consumption, by perhaps 100–200 Wh/day. A final limitation of this study is that the systems were installed during the COVID-19 pandemic, which may have applied upward or downward pressure on consumption.

Design implications

The preceding analyses of energy consumption provides several insights into the design of off-grid solar installations in similar contexts. In the following, we use the measured average daily consumption to estimate how different inverter, PV array, and battery bank sizes would perform. To do so, we estimate the required PV array and battery bank capacities needed to serve different levels of DC-side energy consumption. There are several ways of doing so, but all rely on estimates and assumptions for various parameters that can never be exactly known, so the results should be interpreted accordingly. The approach taken here is to generally, but not exactly, follow a standards-based calculation based on IEEE 1013 (IEEE Std 1013–2007, 2007). For the purposes of clarity and concision some simplifications and omissions from IEEE 1013 are made, but these would not detract from the overall conclusions made.

Inverter design

Inverters for off-grid applications are typically sized to exceed the peak AC power demand, inclusive of a design margin. A rigorous study of the peak power demand is beyond the scope of this present study. However, two observations are important. First, the inverters are robustly sized given their 8 kW rating and the generally low power demand. Second, a consequence of this robustness is the greater constant losses that accompany higher inverter ratings. For perspective, the 1.44 kWh/day of constant inverter loss from the Sol-Ark 8-kW inverter is greater than the average AC-side consumption of approximately 20 percent of the homes. Smaller-sized inverters in the range of 3–5 kW with their attendant lower constant losses could then significantly reduce the portion of energy produced that is lost to inverter inefficiency.

PV array design

We next consider the sizing of the PV array and how differently-sized arrays may have performed. The average daily energy production potential of a PV array can be estimated from the PV array's capacity, the average insolation, and the effects of losses such as those from wiring, temperature, aging, dust coverage, module mismatch, and other non-idealities as:

$$\tilde{E}_{PV} = P_{rated} \times \bar{I} \times (1 - L) \tag{2}$$

where $\tilde{E}_{PV}$ is the estimated average daily energy production potential, P_{rated} is the rated power capacity of the array, $\bar{I}$ is the average daily insolation, and L is the losses. The average insolation is conservatively set to 4.5 kWh/m^2/day. This value corresponds to the average of the lowest-month (January) average plane-of-array insolation for all locations. For comparison purposes, the average highest-month insolation is 7.2 kWh/m^2/day. The losses are set to 25 percent, which is in-line with typical loss estimations for off-grid systems (IEEE Std 1013–2007, 2007). The estimated average daily PV production potential should be greater than the average DC consumption to account for consumption variation, battery charging losses and other factors. The required average daily PV energy production to serve a certain DC consumption is then:

$$\tilde{E}_{PV} = A \times \bar{E}_{DC} \tag{3}$$

where A is the array-to-load ratio, which is typically 1.1 to 1.3. A conservative value of 1.3 is used in this analysis. Combining equations (2) and (3) show that the required PV capacity rating to serve any average daily DC energy consumption can be computed as:

$$P_{rated} = A \times \frac{\bar{E}_{DC}}{\bar{I} \times (1 - L)} \tag{4}$$

Note that the loss and array-to-load parameter values assumed are conceptually equivalent to a Performance Ratio of 0.58, which is appropriately lower than for grid-connected PV systems, whose Performance Ratios typically range from 0.70 to 0.85 (Martín-Martínez, Cañas-Carretón, Honrubia-Escribano, & Gómez-Lázaro, 2019; Srivastava, Tiwari, & Giri, 2020).

Table 4 shows the estimated portion of homes that can be supported by various PV capacities as estimated by (4). A PV array rated at just 1.50 kW would be sufficient to serve half of the homes. However, incrementally increasingly greater capacity is needed to serve a larger portion of homes. For example, increasing the portion of homes served from the 90th quantile to the 95th requires just 0.33 kW of additional capacity, but increasing the portion of homes served from the 90th quantile to the 97.5th requires 1.16 kW of additional capacity.

Eq. (4) can be algebraically manipulated to determine the DC energy consumption that can be served by any array size. Using the present size of the PV array, 3.8 kW with a 5 percent bi-facial boost, the off-grid systems can support an average daily DC consumption of 10.38 kWh/day which places it between the 97.5 and 100 quantiles of consumption. That it does not serve all 100 percent is an artifact of the conservative assumptions made for losses, insolation, and array-to-load ratio. It does suggest, however, that for a very small portion of homes, a larger-sized array may be justified. The existing array can serve an AC consumption of 8.94 kWh/day. This is well above the actual average AC consumption of 2.78 kWh/day, suggesting that for most homes, the consumption can be considerably increased.

The results reveal that based on these estimates, a PV array of 2.44 kW would still adequately supply 90 percent of homes. A strategy that could be used is to segment the market, offering larger capacity arrays to some and smaller capacity arrays to others. The challenge here, however, would be in identifying which system suits which user beforehand.

Table 4
PV array size requirements.

Statistic	DC load (kWh/day)	PV capacity (kW)
Maximum	11.93	4.60
Q(0.975)	9.34	3.60
Q(0.95)	7.20	2.77
Q(0.90)	6.33	2.44
Mean	4.22	1.63
Q(0.50)	3.88	1.50
Q(0.10)	2.28	0.88
Q(0.05)	2.09	0.81
Minimum	1.79	0.69

Battery bank design

We next consider the sizing of the battery bank. In an off-grid system, the size of the battery bank primarily affects the reliability of the system. The battery bank is usually sized to achieve a certain number of "Days of Autonomy". Days of Autonomy (DoA) is customarily defined as the number of days an off-grid system can serve the *average* daily DC consumption without additional input from an energy source, while not following below a certain maximum depth-of-discharge (DoD). Note that DoD in the context of Days of Autonomy should not be confused with the daily depth-of-discharge, but rather it is the maximum allowable DoD during a prolonged interruption in PV power, which should rarely occur. A deeper discharge usually up to 80 percent is typically considered in these scenarios (IEEE Std 1013–2007, 2007). The usable capacity of the battery is often somewhat adjusted downward to account for the effects of temperature and other losses. The DoA is also typically calculated based on the diminished battery capacity at the end of the battery's life, typically assumed to be 80 percent (IEEE Std 1013–2007, 2007).

There is an inherent trade-off when selecting the targeted days of autonomy for an off-grid system: increased autonomy is achieved with a larger capacity battery bank. The DoA and battery bank cost scale proportionally, so that increasing the days of autonomy from one day to two days approximately doubles the cost of the battery bank. NTUA targeted three DoA for these systems.

The DoA is calculated as:

$$DoA = \frac{E_B \times EoL \times DoD \times C}{\bar{E}_{DC}} \tag{5}$$

where E_B is the nominal battery bank energy capacity in kilowatthours, EoL is the portion of the battery's rated capacity available at the end of life, DoD is the maximum allowable depth of discharge, and C is the battery capacity adjustment to account for temperature effects and other losses. Here, E_B is calculated as the 20-h charge capacity of the battery bank (183 Ah × 4 strings) multiplied by the nominal voltage (48 VDC). The following analyses assumes maximum DoD of 70 percent, EoL of 80 percent, and capacity adjustment of 87 percent unless otherwise specified.

From (5), the existing battery bank capacity of 35.1 kWh is sufficient to provide 4.1 DoA based on the average daily consumption, which is a somewhat high number of DoA for an off-grid residential system. Of course, not all homes will have this number of DoA—some will have more and some will have fewer. Table 5 shows the DoA provided by the existing 35.1 kWh battery bank for different quantiles of average daily DC-side consumption. Values are shown for three different maximum allowable DoD assumptions. For example, at a DoD of 70 percent, half of the homes have at least 4.4 DoA.

Eq. (5) can be algebraically manipulated to determine the required battery bank capacity to supply a specified number of DoA for a given

Table 5
Days of autonomy provided to different quantiles of average dc daily load by the existing battery bank.

DoD	Q(0.5)	Q(10)	Q(50)	Q(90)	Q(95)	Q(97.5)
60%	7.0	6.4	3.7	2.3	2.0	1.6
70%	8.2	7.5	4.4	2.7	2.4	1.8
80%	9.3	8.6	5.0	3.1	2.7	2.1

Table 6
Battery bank size requirements.

Statistic	DC load (kWh/day)	Battery cap. 2 DoA (kWh)	Battery cap. 3 DoA (kWh)
Maximum	11.93	49.0	73.5
Q(0.975)	9.34	38.4	57.5
Q(0.95)	7.20	29.6	44.4
Q(0.90)	6.33	26.0	39.0
Mean	4.22	17.3	26.0
Q(0.50)	3.88	15.9	23.9
Q(0.10)	2.28	9.4	14.1
Q(0.05)	2.09	8.6	12.9
Minimum	1.79	7.4	11.1

average daily DC consumption. Table 6 shows the required battery bank capacity for different levels of average daily DC load. To provide half of the homes with at least two DoA requires a 15.9 kWh battery bank, which increases proportionally to 23.9 kWh if at least three DoA is required.

The battery bank as presently installed is able to provide at least the targeted three DoA for an estimated 85 percent of the homes. In many homes the average daily consumption could significantly increase and still meet the DoA target. Or, alternatively, the battery bank capacity could be somewhat reduced and still achieve the targeted three DoA for many homes. Although the battery banks are not estimated to provide three DoA for all homes, doing so would require more than doubling the battery bank capacity to 73.5 kWh, which is likely not economically justified. Overall, given the complexity of the application, NTUA appropriately sized battery banks to provide the targeted three DoA for nearly all the homes.

Of course, there are many factors that are and should be considered when sizing the inverter, PV array, and battery bank for an off-grid system. For example, in this case, NTUA intentionally sought to oversize system components. The reason for this is that many of the homes are so remote that visiting them to troubleshoot outages is very costly in terms of fuel, vehicle wear-and-tear, and personnel costs. Larger battery banks also should require less frequently replacement. Second, given the nature of the funding, minimizing capital costs was not the main priority, but rather rapidly deploying the systems to serve as many people as possible was the goal, which favors a uniform system design. Third, although IEEE 1013 is generally followed in this analysis, there are some considerations not explicitly accounted for. These include factors like battery capacity adjustments due to deviations in discharge current magnitude, voltage window adjustments, possible accelerated or retarded age- and use-related degradation, or operational restrictions. These factors could somewhat influence the results in either direction. It also must be emphasized that the data analyzed in this paper would not have been available pre-implementation, and so NTUA had could not have known beforehand what consumption to expect when designing the systems.

User behavior implications

The results point to the majority of the homes being able to increase their consumption without degrading reliability or the longevity of the off-grid systems. The data show that over half of the homes could at least double their average daily consumption and be adequately served by the existing PV arrays, assuming the components continue to perform as expected. To stimulate this consumption, which should benefit the users, NTUA could modify their customer education programs and usage guidelines to encourage use of additional appliances, or to use existing appliances more frequently.

Table 7
Data-driven load estimate performance.

	A	B	C	D
Estimate (kWh/d)	2.98	2.76	2.98	2.37
MAE (kWh/d)	1.33	1.62	1.27	1.72
MAPE (%)	120	105	109	54
RMSE (kWh/d)	1.58	2.27	1.47	2.48
Overestimated (%)	70.1	60.8	64.7	43.1
Underestimate (%)	29.0	39.2	35.3	56.9

Use in data-driven load estimation

The data presented in this research has applications in load estimation for off-grid systems. In this data-driven approach to load estimation, daily load from existing systems is used to estimate load for new systems. To test the performance of the collected data for data-driven load estimation, the average daily consumption for a randomly-selected 60% ($N = 76$) of the homes were averaged and used as the load estimate for the remaining 40% ($N = 51$) of the homes. This was done four times, denoted A, B, C, and D. Each time a different random sampling of the homes was used. The results are shown in Table 7. This Table shows the mean absolute error (MAE), mean absolute percent error (MAPE), root mean square error (RMSE), and the bias of the estimate as shown by percentage of the 51 out-of-sample homes whose consumption was overestimated or underestimated.

The data-driven approach resulted in an average MAE and MAPE of 1.49 kWh/day and 97 percent, respectively. The MAPE is largely driven by homes with consumption less than 1 kWh/day, which results in large errors when expressed as a percentage. The MAPE is considerably lower than the 300 percent reported for mini-grid users based on surveying techniques in Sub-Saharan Africa, and somewhat higher than the 78 percent reported for a data-driven estimation approach applied to aggregate mini-grid user load (Blodgett et al., 2017). The errors could further be reduced if the estimate is based on more than 60 percent of the data. The results show the viability of using the consumption data to estimate load.

Insight into electricity access

As a final point of discussion, the results show the differences between characteristics of energy consumption of off-grid users in the Tribal Land context versus that in the Sub-Saharan African and South Asian contexts. Most notably, the consumption of the off-grid homes on the Navajo Nation is approximately one order of magnitude greater than commonly reported from mini-grid users elsewhere in the world. There are several potential reasons for this, including the considerably higher income and easier access to and familiarity with appliances. The financial terms for the users may also influence the higher consumption, as most mini-grid users pay by the kilowatthour, whereas the users of the NTUA systems pay a flat monthly rate. Still, the energy use of the off-grid homes on the Navajo Nation is modest when compared to the average grid-connected user consumption in nearby New Mexico of 21 kWh/day (Energy Information Administration, 2022). The consumption also showed a stronger seasonal component than found in other parts of the world, which can be partially be attributed to the presence of refrigerators and evaporative coolers. The 5–10 percent per annual growth observed in many off-grid systems in Sub-Saharan Africa was not observed. This is perhaps not surprising, as the electricity growth in Sub-Saharan Africa is often attributed to homes gradually acquiring more energy-intensive appliances.

Conclusions and future work

This research, for the first time, presented and analyzed field-measured energy consumption data from residential off-grid solar systems on the Navajo Nation. After cleaning, the data set consisted of 127 homes, spanning from 1 January 2021 to 31 December 2022—a total of 74,610 daily data points after cleaning.

Through time-series and statistical analyses, several energy consumption characteristics were uncovered. The homes, on average, consumed 2.78 kWh/day, but there was large variation in this consumption. Five percent of the homes consumed an average of over 5.76 kWh/day, and five percent of the homes consumed no more than 0.65 kWh/day. The top 20 percent of homes consumed 40 percent of the total energy. The daily consumption within each home also varied. A general summer-peak pattern emerged, and consumption in the second year was 10.3 percent lower than the first. The use of the average daily load as an estimator in a data driven approach was shown to be promising.

Taken together, the results show that the consumption for many homes is below the estimated energy production capabilities of the PV arrays. A smaller PV array of 2.44 kW could serve 90 percent of the homes. The battery banks offer the targeted three Days of Autonomy reliability for a large majority (85 percent) of the homes.

Somewhat smaller battery banks could be used for many homes, although this may not be economically justified when maintenance costs are considered. To achieve three DoA for all homes is also not likely an economically appealing option, since it would require more than doubling the capacity of the battery bank. Smaller inverters could be considered to reduce the constant inverter losses, which are significant compared to the AC consumption in many homes. When considering the uniform design approach taken, the component sizing appears to have struck a reasonable balance between cost and targeted performance. However, in most homes, the consumption could technically be increased so long as the components perform at their rated capabilities. If consumption levels are static, then a segmented approach may be considered, offering smaller systems to most homes, and reserving the larger capacity systems for those with higher anticipated consumption.

The research will be extended in several ways. While daily energy consumption is perhaps the most significant input information needed to design systems, also of importance is the load profiles of the user. A load profile shows the typical power consumption characteristics over some period of time, usually a day. Improvements in context-based interpretation of the energy consumption will also be done through user surveys. Additional future work includes quantifying the reliability of the systems, and analyzing the performance of the PV arrays through standards such as IEC 61724. There is also opportunity to develop technological solutions that offer feedback to the users, indicating whether or not they can increase their consumption without jeopardizing system reliability.

Declaration of competing interest

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