Simulations of Efficiency Improvements using Measured Microgrid Data

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***Abstract*—Reaching unelectrified populations in the developing world with distributed solar requires aggressive cost optimization of generation and storage. Conventional solar generation architectures using photovoltaic panels, sealed lead acid batteries, and inverters show room for cost improvement. Using data collected from photovoltaic microgrid users and simulations we demonstrate potential cost reductions using alternate technologies and architectures. Reducing losses from power conversion could lower wholesale energy costs by 20% while improved battery chemistries could lower costs by up to 50%.**

I. Introduction

The cost of renewable and distributed energy must be lowered to be competitive with fossil energy systems. In the developing world, solar photovoltaic systems are extremely attractive because of the low operating cost. However, the high initial costs, especially of energy storage, threaten the viability of this as an option for the people of the world lacking electricity. Private energy service companies (ESCOs) have started supplying power where utilities have failed to reach. However, when operating as unsubsidized private companies, ESCOs will be especially sensitive to the initial cost of generation and the ability to collect tariffs. Since these systems are often paid for by the revenue collected from electricity sales, lowering initial cost and effectively collecting tariffs are important. [4] Our previous work has focused on the improved collection of tariffs through mobile commerce and prepayment [2]. This work will focus on potential cost reductions which allow the same level of energy to be delivered for a lower total investment and cost per kWh.

Our observations of electricity use in newly electrified villages show usage patterns that are difficult to serve efficiently with existing technology. Villages whose primary electricity use is lighting, television, and cell phone charging have wide variation in power from day to night. This wide variation in power requires that inverters often operate below their optimal operating point, where they are less efficient. These villages also consume most of their energy at night. Storage costs are then a large part of the system cost making it a target for cost reduction. This work quantifies the impact of these load features on the cost of electricity as well the benefit of two possible solutions: increases in inverter efficiency, and increases in battery efficiency. The simulations use both measured demand data from rural villages and synthetic data to test different loads. The measured data is collected from customers who have recently been provided with a near-grid-quality electrical connection and are paying for that power on a per kilowatt-hour basis. Most discussion of cost reduction focuses on the photovoltaic panel cost but this work shows that work on power conversion and storage could yield significant cost reductions as well.

II. Simulation Description

The simulation takes as input the location of the system and the simulated or measured energy demand of the customers and provides as an output the minimum panel size and battery capacity that will meet the energy demand. This model is intended to allow comparisons between systems and load profiles rather than provide accurate guidance for system sizes over a typical meteorological year. The simulation takes as input the hourly load profile from a set of either real or hypothetical customers. The model then uses a series of assumptions on battery and solar panel parameters to calculate the power and storage at each hour. The battery is considered to be a simple energy storage device with perfect efficiency during charging and an efficiency of η_B on discharge. We can calculate the energy in the battery in discrete time steps according to the following equation.

$$E_B(t+\Delta t) = E_B(t) + P_{charge} \cdot \Delta t - \frac{P_{discharge} \cdot \Delta t}{\eta_B}$$

Where P_{charge} is the power flow when the photovoltaic production is greater than the inverter demand and $P_{discharge}$ is the power flow when the inverter demand is greater than the photovoltaic power available. They are given by the following equations.

$$P_{charge} = \begin{cases} 0 & P_{inv} > P_{pv} \\ P_{pv} - P_{inv} & P_{inv} < P_{pv} \end{cases}$$

$$P_{discharge} = \begin{cases} P_{inv} - P_{pv} & P_{inv} > P_{pv} \\ 0 & P_{inv} < P_{pv} \end{cases}$$

Where P_{inv} is the DC power demanded by the inverter and P_{pv} is the power being delivered by the charge controller. P_{inv} is calculated using the efficiency of the inverter as a function of AC load according to

$$P_{inv} = \frac{P_{AC}}{\eta_{inv}(P_{AC})}$$

Rated Power	750 W
Peak Efficiency	94%
No-load Power Consumption	13 W

TABLE II
INVERTER ASSUMPTIONS FOR MODELING.

Panel Efficiency	13.5%
Panel Latitude	14 N
Panel Cost	$1/W
Panel Lifetime	20 years

TABLE III
SOLAR PANEL ASSUMPTIONS FOR MODELING.

Where P_{AC} is the hourly power demanded by the consumers of the microgrid.

The difference equation is run in a loop where the panel size in the model is adjusted until the energy remaining in the battery at the end of the simulation is equal to the energy at the start of the simulation. The minimum battery size is then the peak-to-peak variation of the battery energy time series. A time series trace is shown in Figure 1. Once the simulation finds a solution where the starting and final storage are equal, the model outputs the minimum battery size to meet the storage need at 100% depth of discharge and the minimum solar panel size to meet the demand. Based on panel size and battery size output along with the assumptions on panel cost and battery cost and life, the model predicts the net present value (NPV) of the system over the life of the system. In this model we use a 7% discount factor and a 20-year time horizon. The battery, inverter, and panel assumptions for these simulations are listed in Table I, Table II, and Table III.

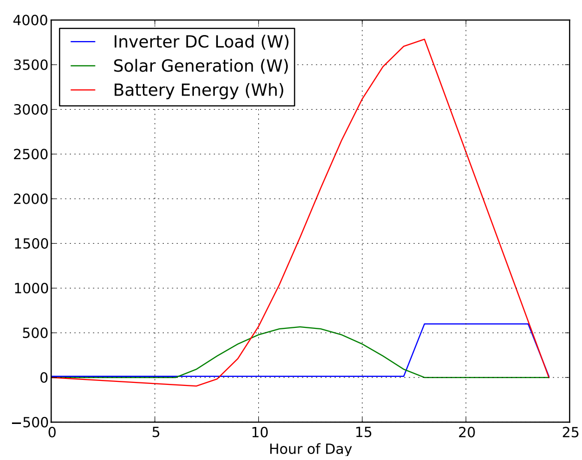

Fig. 1. Time series of simulation. The DC load of the inverter is plotted along with the solar generation as a function of hour. The solar panel size is adjusted until the battery energy at the end of the simulation is the same as the start value.

III. SIMULATION RESULTS AND DISCUSSION

A. Types of Loads Simulated

The simulation results compare the performance of hypothetical systems to the baseline system and report potential

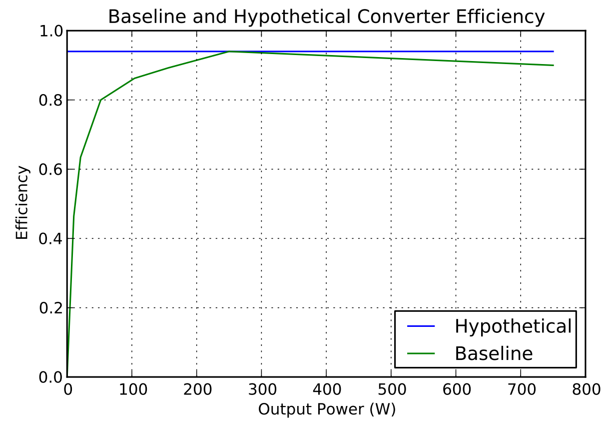

Fig. 2. Efficiency curves for baseline and proposed system. The proposed is a hypothetical system that has uniform efficiency at all power output levels.

improvements. These simulations use 5 different load data sets, 3 are simulated and 2 are measured data from our existing microgrids. Each of these loads has been normalized so that the total daily energy for each of the loads is equal. This normalization allows the comparison of efficiencies based on the load shape rather than overall level of consumption. We define a "Night" load that has the entire day's load occurring between 6pm and midnight. We also define a "Day" load that occurs between 9am and 3pm and a "Constant" load that is evenly spread across the entire day. In addition to these three hypothetical loads, we also use loads representative of the measured customer loads at our microgrids. The "Lighting" village load uses a representative day from one of the village microgrids and has a small constant load and a large nighttime load. The "Freezer" village load is from one of our microgrids using a freezer to provide ice for sale and is very close to the "Constant" load in shape.

B. Baseline System

The simulated baseline system is based on the system we have installed in the field. The inverter efficiency for this baseline system is shown in Figure 2 as the "Baseline" curve. The battery used in the baseline system is the Sealed Lead Acid battery in Table I. The solar panel assumptions used in the baseline and all other simulations are listed in Table III. This baseline system is used for comparison against the improvements discussed below.

C. Impact of load shape on storage and generation

To demonstrate the effect of the load profile on the generation and storage capacity of the system, we calculate the panel and battery size for the five loads described above. The storage and generation necessary to service a given daily amount of energy can vary depending on what time of day that energy is delivered. We calculate the minimum generation and storage for each of these five loads. We do not include balance of system costs or distribution costs since these will be much

Battery Chemistry	Initial Cost (USD/kWh)	Lifetime (yr)	Optimal DOD	Storage Efficiency
Sealed Lead Acid (SLA)	$140	2	50%	75%
Lithium Iron Phosphate (LFP)	$1000	6	100%	95%
Lead Carbon (PbC)	$140	6	50%	75%

TABLE I
BATTERY ASSUMPTIONS FOR MODELING.

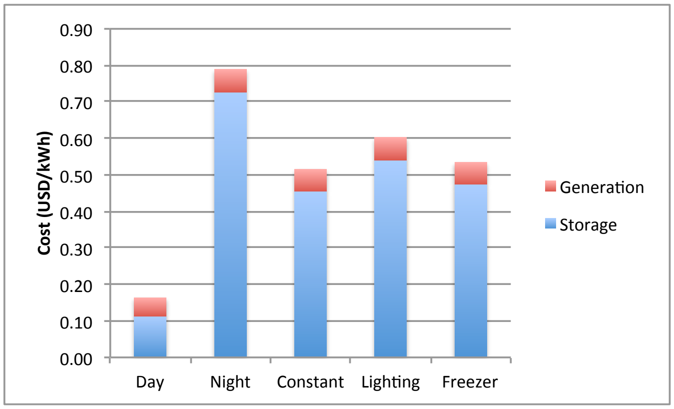

Fig. 3. Cost of electricity for different load profiles using Baseline inverter and battery system and hypothetical and measured loads. Storage costs are the dominant cost in each of these systems.

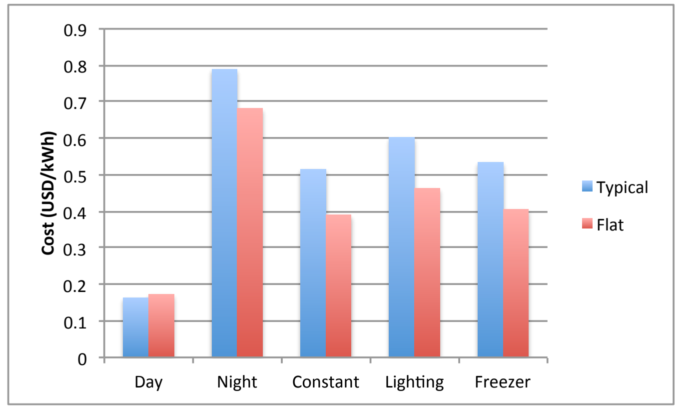

Fig. 4. The hypothetical "Flat" inverter efficiency curve results in a modest reduction of electricity cost.

less sensitive to these load types. Table IV shows a detailed output of the panel and battery sizes in kWp and kWh. It also shows the NPV costs for storage and generation over an assumed 20 year lifetime with a 7% discount factor. The NPV is necessary to account for the multiple battery replacements over the life of the solar system. Figure 3 shows these results in terms of an estimated cost of delivered electricity. The table and figure show that storage cost is much larger than the generation cost for all of the loads. There are variations in the size and price of the panel necessary to meet the load, but the cost impact is small compared to the storage costs. The lowest total cost is delivered for the "Day" load since there is very little storage necessary. The highest total cost is incurred for the "Night" load since the storage demand is the greatest. The large fraction of initial and operating cost needed for storage led us to investigate ways of reducing the storage capacity and cost through more efficient power conversion and battery chemistries.

D. *Inverter Efficiency*

We simulate the cost savings of an inverter system that is less sensitive to load variations in this section. In a system with a wide variation in power levels the inverter can be a significant loss of power. A typical inverter is inefficient at loads below its preferred operating point. If the load is usually close to this high efficiency point, the lower efficiencies at low power are not important. If however, as we observe, there is a high variability in the power output where daytime loads are very small but evening loads are greater, this inefficiency can have a significant impact. If the system is run inefficiently during the daytime, the inefficiency burden only impacts the amount of generation capacity needed. If the system is run inefficiently during the evening, both the generation and the storage costs are affected, multiplying the penalty. Late-night and early morning cellphone charging and vampire loads can cause this inefficiency. To address this issue, inverter manufacturers have created inverters with a master-slave feature that allows a chain of inverters to turn on and off based on total load. To demonstrate this effect, we run our simulation with a hypothetical power conversion device that has an efficiency equal to the peak efficiency of the baseline inverter at any power level. Table V shows the detailed simulation results. The increase in inverter efficiency reduces the generation and storage needed for four of the five load types in comparison with the values in Table IV. The reductions in battery NPV and solar NPV could offset the additional cost of a dedicated low-power inverter with a cross-over circuit for when the load requires the high-power inverter. Figure 4 shows the impact on the delivered price for the five loads we consider in this work. These cost and capacity savings are on the order of 20%.

E. *Battery Chemistry*

The largest potential for cost reduction can come from improved battery technologies. New battery chemistries could reduce the fraction of investment that goes toward storage of electricity. In terms of initial cost, batteries are comparable to the photovoltaic panel cost but their frequent replacement makes the storage cost dominant over the lifetime of the system. The incumbent battery technology is lead acid with both flooded lead acid (FLA) and sealed lead acid (SLA) being used widely. Emerging technologies of interest are Lithium

Load Type	Panel Capacity (kWp)	Minimum Battery Size (kWh)	Battery NPV (USD)	Solar NPV (USD)
Day	0.59	0.76	1306	595
Night	0.74	4.92	8421	738
Constant	0.70	3.08	5281	704
Lighting	0.73	3.66	6270	727
Freezer	0.70	3.21	5500	703

TABLE IV

IMPACT OF LOAD TYPE ON SYSTEM SIZE AND COST. LOADS ARE NORMALIZED TO 3.0 KWH PER DAY.

Load Type	Panel Capacity (kWp)	Minimum Battery Size (kWh)	Battery NPV (USD)	Solar NPV (USD)
Day	0.50	0.88	1509	498
Night	0.62	4.26	7289	621
Constant	0.53	2.33	3993	532
Lighting	0.55	2.81	4819	553
Freezer	0.53	2.44	4176	532

TABLE V

IMPACT OF INVERTER NON-IDEALITY ON SYSTEM SIZE. SIMULATIONS USE SINGLE-POINT EFFICIENCY INVERTER AND SLA BATTERY. LOADS ARE NORMALIZED TO 3.0 KWH DAILY.

Iron Phosphate (LFP) and Lead Carbon (PbC). Several factors impact the life-cycle cost of storage in a battery: round trip power efficiency, cost per kWh stored, optimal depth of discharge, and cycle life. The values used in the simulation for each battery type are found in Table I. Relative to SLA batteries, LFP batteries have better cycle life, higher specific cost, and better turnaround efficiency. PbC batteries are not yet mature but promise improved cycle life and likely similar specific cost and turnaround efficiency.

The initial battery cost is given by

$$C_B = E_{storage} \frac{1}{\eta_B} \frac{1}{DOD_{optimal}} c_B$$

Where $E_{storage}$ is the storage necessary, η_B is the round trip energy efficiency, $DOD_{optimal}$ is the desired operating point of the battery for long life, and c_B is the initial cost of the battery per kWh. The total cost over the life of the system depends on the cycle life of the battery.

We simulate the impact of these on system size and total cost in Table VI. Figure 5 shows the impact of battery type on the per kWh cost of electricity. For the case of typical village data, the lifetime cost of lead acid and LFP are similar. If LFP costs reach the $500/kWh cost targets mentioned in the context of electric vehicles, these batteries will be a clear choice. If PbC batteries are able to maintain their cost while improving cycle life, they will provide a clear improvement in the life-cycle cost. Both of these battery simulations are speculative but given the dominance of storage costs in these systems, attention to emerging battery technologies is worthwhile.

IV. DISCUSSION / FUTURE WORK

While the simulation results discussed are based on technology speculation, we want to encourage cost reductions through newer technologies. We have emphasized supply and generation optimizations in this work but would like to point out the importance of efficient appliances. Efficient appliances allow services to be delivered at the lowest possible price.

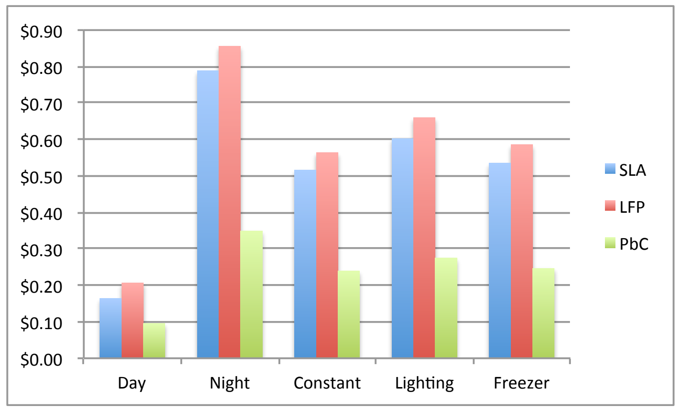

Fig. 5. Cost of electricity for different battery chemistries.

Our microgrids use LED lighting to achieve the best cost for lighting in terms of price per kilolumen-hour delivered. The televisions that we have observed in these microgrids have been inefficient cathode ray tube (CRT) televisions with power loads of over 50W. The price per hour of entertainment could be lowered by providing more efficient liquid crystal display (LCD) televisions. In addition to increasing the amount of services that the consumer can gain for a given amount, these reductions in demand reduce the amount of generation and storage needed. These demand side improvements can lower the system size and deliver the services people want for less power.

In addition to improving the efficiency of the end-uses of the system, efficiency can be gained by some architectural choices. Casillas and Kammen show that the introduction of meters to a rural microgrid lowered usage [5]. Thomas and coauthors estimate that LED lighting using DC building circuits lower costs relative to AC connected LED circuits [6]. Since all loads in our residential areas are DC loads, AC inverter costs and inefficiencies may be unnecessary. The IEEE/Sirona Haiti

Load Type	Battery Type	Panel Capacity (kWp)	Minimum Battery Size (kWh)	Battery NPV (USD)	Solar NPV (USD)
Lighting	SLA	0.73	3.66	6270	727
Lighting	LFP	0.62	2.93	7043	615
Lighting	PbC	0.73	3.66	2466	727
Freezer	SLA	0.70	3.21	5500	703
Freezer	LFP	0.61	2.57	6186	606
Freezer	PbC	0.70	3.21	2163	703

TABLE VI
SIMULATION RESULTS FOR BATTERY CHEMISTRIES. NET PRESENT VALUE IS CALCULATED AT 7% OVER 20 YEAR TIME HORIZON.

Rural Electric Project uses only DC circuitry and DC-only laptop charging stations are being developed for schools [7]. The addition of meters to a grid installation or the use of a DC only architecture could also lower overall life-cycle cost for new installations.

V. SUMMARY

We find that improving no-load and low-load power consumption of the inverter can reduce storage and generation needs and lower the cost of electricity 20% for many load types. Future battery chemistry types have the potential to deliver 50% reductions in the wholesale cost of electricity to consumers. These results use both simulated data and data gathered from rural villages using solar microgrid systems.

APPENDIX

The simulations in this paper use both simulated energy demand data and data collected from customers in Mali. This section describes the solar photovoltaic microgrid systems that this data is taken from. It will also describe some of the notable features in the data.

A. Data collection

We have installed 17 solar photovoltaic microgrid systems with remote connectivity using Short Message Service (SMS) over the Global System for Mobile Communications (GSM) networks in Mali and Uganda as described in [2]. These systems allow customers to purchase bundles of electricity in advance of use either through a scratch card and cell phone purchase or through a tablet device. Each of these systems consists of a 1.4 kWp array of photovoltaic panels with a 48 V, 360 Ah battery bank. An MPPT charge controller handles battery charging and a 750 W inverter supplies the microgrid with 50 Hz, 220 V power. Up to 20 customers are connected to these systems in a star topology where each customer has a dedicated wire to the central facility. Each customer is metered by a commercially available device that allows for energy measurement and reporting and a switch to automatically connect or disconnect the consumer. In addition to communication regarding the purchase of power, these systems send data on an hourly basis to a central server using SMS messages. Data is collected on the energy consumption of each household as well as the AC energy consumption of the entire system. From the solar controller, we measure and store hourly information on the solar energy delivered to the system and the battery voltage. This data stream allows us to observe consumer usage and payment behavior.

B. Timeseries Description

These messages allow us to create a database of timeseries information from the customers. In this paper we focus on data from a few microgrids in Mali that are representative of the demand from rural residential customers. In these residential settings, the most common appliances are light bulbs, cellphones, and televisions. Consequently, the peak power is consumed in the evening as shown in Figure 6. Customers in these microgrids were provided with two light bulbs as part of the installation. In Figure 6, the two bands in the evening show that usage clusters around these values. Most of the customers have little or no usage during the day time.

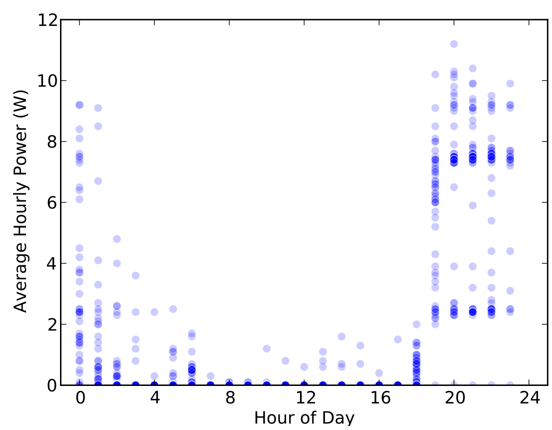

Fig. 6. Customer exhibiting two bulb lighting load. Each data point is the hourly load for a single day. Multiple days are superimposed. Points are transparent so that frequent measurements appear darker. This customer displays two common evening power levels corresponding to the use of one or two lightbulbs. This not that this customer has very small power use during the day.

The addition of daytime loads can reduce the percentage of variation in demand. In two microgrid systems, freezers have been installed that customers are using to sell ice or frozen drinks. These freezers significantly increase the daytime load on the system. The hourly profile for the household using this freezer is shown in Figure 7. These freezers draw a much larger amount of power than the typical lighting load and have a lower variation when measured on an hourly basis.

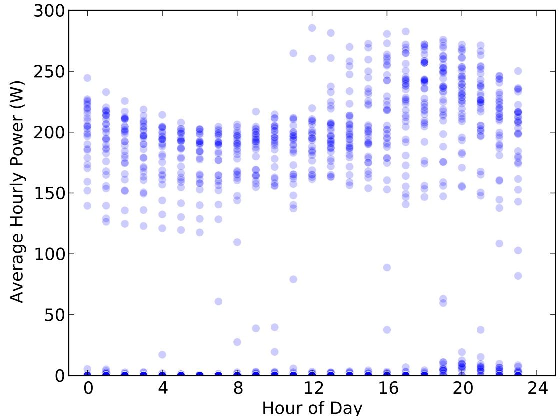

Fig. 7. Circuit with freezer. Each data point is the hourly load for a single day. The absolute variation in power is still significant but the ratio between high and low use is lower.

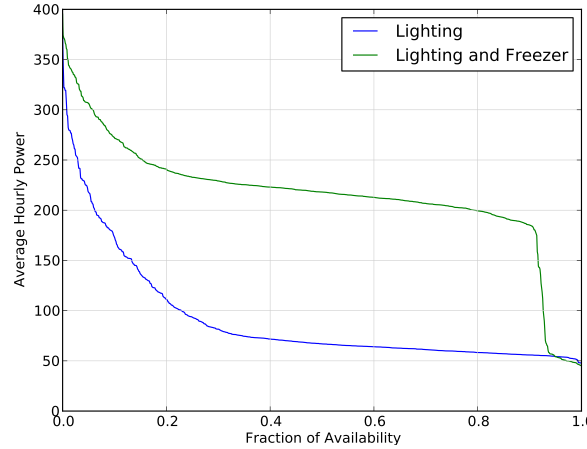

Fig. 8. Load duration curve for two typical microgrid systems, including metering, computing, and computation. Inverter and charge controller consumption is not included. One system includes a significant daytime refrigeration load, while the other does not.

C. Load Duration Curves

To visualize the variation in load, we use a load-duration-curve to summarize the load demanded by the microgrid. If we sort the hourly power demand over a long time period, we construct a load duration curve [3]. A load-duration curve (Figure 8) shows this variation. In the microgrid that does not have a freezer, the most common power level is less than 50W, which is well below the peak efficiency of the inverter. For the system that does have a freezer, the system spends the bulk of its time consuming on the order of 200W, which is much closer to the peak efficiency operating point of the inverter. The inverter is sized so that the maximum customer load is safely accommodated by the inverter. However, there is a substantial efficiency penalty for operating the inverter below the optimal point.

We can express these loads in terms of the capacity factor, where the capacity factor is relative to the rated output of the inverter. Systems with high power variability will lose efficiency since the system will often be operated outside of the range of peak efficiency.

D. Overall System Efficiency

We can estimate an overall system efficiency from the system-wide usage data and information from the solar controller on photovoltaic energy generation. This estimate of the overall efficiency of the system is defined as DC power delivered by solar power controller divided by the AC power delivered to the system to power both the system electronics and the user loads. Our data shows that as the capacity factor of the inverter increases, the overall system efficiency improves. In sites with a freezer and therefore considerable daily load, the inverter capacity factor is approximately 30% and we see an overall efficiency of 0.88–0.90. In a lighting only site, with much less daily load, the capacity factor is less than 15% and the overall efficiency is less than 0.70. The large variations in loads exhibited by these customers prompted us to investigate the impact on system efficiency that these variations in loads are causing.

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