2012 IEEE Global Humanitarian Technology Conference

Simulations of Efficiency Improvements using Measured Microgrid Data

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***Abstract*—Reaching unelectrified populations in the developing world with distributed solar requires agressive 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 systems must be optimized to sustainably provide electricity to the customers beyond the reach of the grid. Private energy service companies (ESCOs) may be able to supply power where utilities have failed to reach. However, as private companies, ESCOs will be especially sensitive to the price of generation and the ability to collect tariffs. This constraint makes it necessary to optimize energy systems for cost. Since these systems are often paid for by the revenue collected from electricity sales, these optimizations 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. Our data show that villages whose primary electricity use is lighting, television, and cell phone charging have wide variation in power. This work presents opportunities for efficiency and therefore cost reduction in the areas of power conversion and storage. These recommendations are based on data 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. There are many optimizations of system size in the literature [1]. This work adds to the literature by considering the effects of the time of day of usage and the efficiencies of commonly used inverters and batteries. Conventional inverters cannot service this variation in power at a consistent efficiency. This decrease in efficiency leads to an increase in both generation and storage costs.

Two approaches to mitigation of this load variation exist, the first is scheduling or addition of loads that smooth consumption. The second approach is developing a power converter architecture that is less sensitive to the variation in loads. We present data addressing the first approach, where two of our sites have added freezers. Our microgrid data and simulations show that these daytime loads can increase the cost-effectiveness of a microgrid. For the second approach we model the cost reductions possible for a hypothetical inverter that has a more constant efficiency across all loads in its operating range. This could be achieved through multiple inverters with different operating regimes or future improvements in inverter technology. Although modest gains are available through load management or inverter efficiency, larger efficiency gains are possible as battery technologies improve. In addition to modeling effects of inverter efficiency and load variation, we model the system cost using existing sealed lead acid battery technology and promising Lithium and Lead Carbon technologies. The improved efficiency and lifetimes of these emerging technologies can significantly reduce the cost of off-grid electricity where per kWh costs are currently dominated by the need for storage.

II. Microgrid and Data Description

The simulations in this paper will use data collected from 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

978-0-7695-4849-4/12 $26.00 © 2012 IEEE
DOI 10.1109/GHTC.2012.84

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 1. Customers in these microgrids were provided with two light bulbs as part of the installation. In Figure 1, 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.

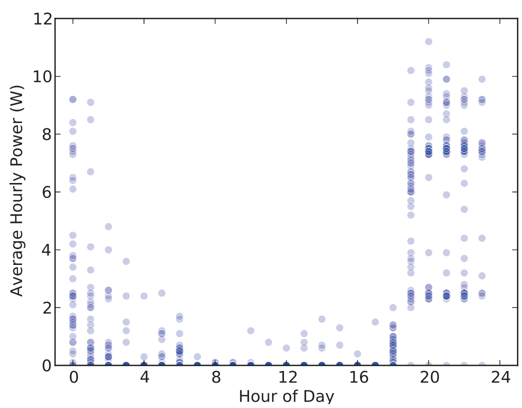

Fig. 1. Customer exhibiting two bulb lighting load. Each data point is the hourly load for a single day. Multiple days are superimposed. Points are transparent so that frequent measurements appear darker. This customer displays two common evening power levels corresponding to the use of one or two lightbulbs. 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 2. 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.

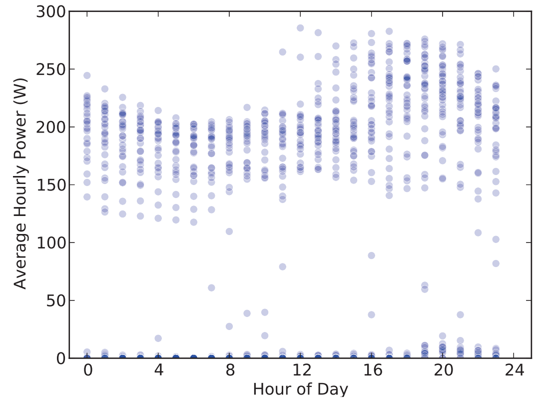

Fig. 2. Circuit with freezer. Each data point is the hourly load for a single day. The absolute variation in power is still significant but the ratio between high and low use is lower.

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 3) 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

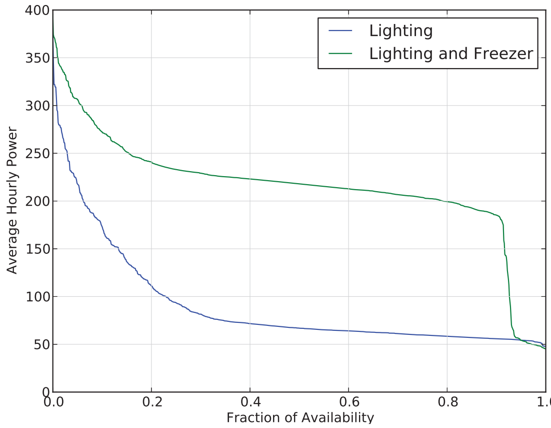

Fig. 3. Load duration curve for two typical microgrid systems, including metering, computing, and computation. Inverter and charge controller consumption is not included. One system includes a significant daytime refrigeration load, while the other does not.

are causing.

III. Simulation Description

We examine the effect of load variation and alternate technologies on the size and cost of the system by creating an energy simulation of the system. The simulation finds the minimum panel size and battery capacity that will meet the demand assuming clear-sky radiation. 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}

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

TABLE II
Inverter Assumptions for Modeling.

is calculated using the efficiency of the inverter as a function of AC load according to

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

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 4. 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.

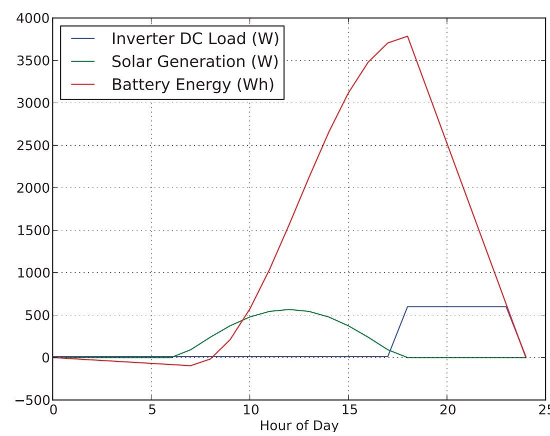

Fig. 4. Time series of simulation. The DC load of the inverter is plotted along with the solar generation as a function of hour. The solar panel size is adjusted until the battery energy at the end of the simulation is the same as the start value.

IV. Calculation Results and Discussion

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

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.

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

TABLE III
SOLAR PANEL ASSUMPTIONS FOR MODELING.

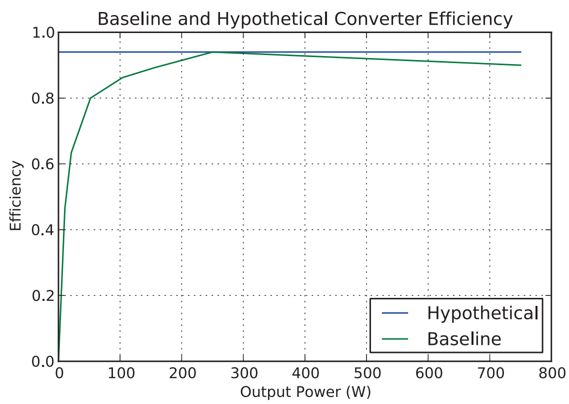

Fig. 5. Efficiency curves for baseline and proposed system.

A. 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 5 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.

B. Impact of load shape

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. To demonstrate the effect of the time of day that power is consumed on the generation and storage capacity of the system, we calculate the panel and battery size for five loads with the same total daily energy but occurring at different times of day. 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.

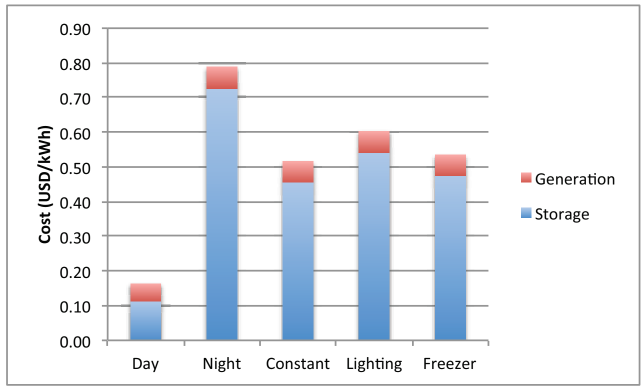

Fig. 6. Cost of electricity for different load profiles using Baseline inverter and battery system and hypothetical and measured loads.

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.

We calculate the minimum generation and storage for each of these five loads. Table IV shows a detailed output of the panel and battery sizes and NPV costs over an assumed 20 year lifetime which demonstrate the variability of panel size and battery size with the type of load. Figure 6 shows these results in terms of an estimated cost of delivered electricity. Only in the "Day" load is the generation cost a significant fraction of the total cost. 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. For the other loads, the storage cost is dominant. Note that we do not include balance of system costs or distribution costs since these will be much less sensitive to these load types. 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.

C. Inverter Efficiency

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

Configuration	Panel Capacity (kWp)	Minimum Battery Size (kWh)	Battery NPV (USD)	Solar NPV (USD)
typical day lead acid	0.59	0.76	1306	595
typical night lead acid	0.74	4.92	8421	738
typical continuous lead acid	0.70	3.08	5281	704
typical village lead acid	0.73	3.66	6270	727

TABLE IV

IMPACT OF LOAD TIME-OF-DAY ON SYSTEM SIZE. LOADS ARE NORMALIZED TO 3.0 KWH PER DAY.

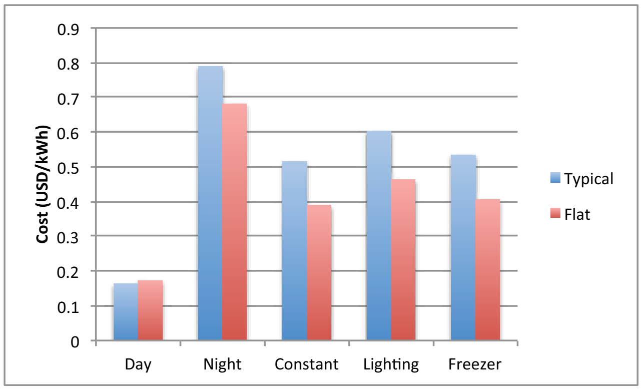

Fig. 7. Cost of electricity for different load profiles using Baseline inverter and battery system and hypothetical and measured loads.

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 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. 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 7 shows the impact on delivered price for the five loads we consider in this work.

D. Battery Chemistry

The largest potential for cost reduction can come from improved battery technologies. Current lead acid technologies lasting 500–1000 cycles, must be replaced every 2–3 years depending on the environment. 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. Differences in allowable depth of discharge (DOD) and the round-trip energy efficiency of the battery can also influence the lifetime cost of the storage.

New battery chemistries could reduce the fraction of investment that goes toward storage of electricity. The incumbent battery technology is sealed lead acid (SLA). Emerging technologies of interest are Lithium Iron Phosphate (LFP) and Lead Carbon (PbC).

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 assumptions for the battery types in the simulation are found in Table I.

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. A very important metric however is the life cycle cost of the battery replacement which depends on the cycle life of the battery.

The life cycle cost is the net present value (NPV) of the initial and replacement battery expenditures over the life of the system. In this simulation we use a 7% discount factor and a 20-year system lifetime. The baseline inverter is used in these simulations.

We simulate the impact of these on system size and total cost in Table VI. Figure 8 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.

V. DISCUSSION / FUTURE WORK

While the simulation results discussed are speculative, we believe that experimentation in this regime is important. 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. Our microgrids use LED lighting to achieve the best cost for lighting in terms of price per

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
Continuous	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.

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.

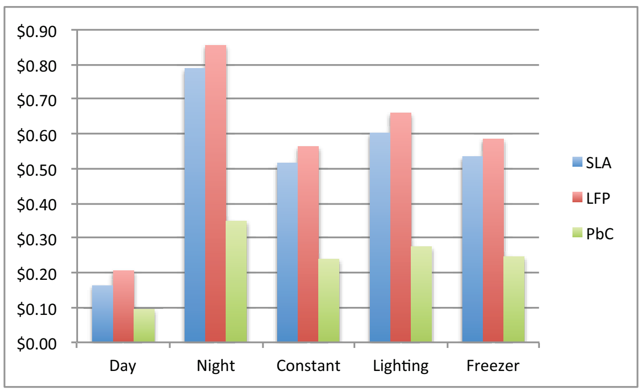

Fig. 8. Cost of electricity for different battery chemistries.

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 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.

VI. SUMMARY

Hourly demand data for newly electrified communities has been gathered. 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.

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