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Cost versus reliability sizing strategy for isolated photovoltaic micro-grids in the developing world

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ABSTRACT

For many isolated regions in the developing world micro-grids which combine photovoltaic electricity generation and battery storage may represent the most reliable and least expensive form of energy service. Due to climate induced solar resource variations, achieving high reliability levels necessitates excess generation and storage capacity which can significantly increase the end consumer cost of energy. Due to severe financial limitations, many consumers in the developing world may prefer cost versus reliability trade-offs, as long as their basic energy needs are met. Defining reliability as the percent of electricity demand a grid can deliver, we utilize a time series energy balance algorithm at hourly resolution to create cost versus reliability curves of micro-grid performance. We then propose a micro-grid sizing strategy which enables designers with knowledge of local energy needs to determine the acceptability of potential micro-grids. Our strategy relies on visualizing simulation data at increasing levels of temporal resolution to determine where energy shortfalls occur and if they interfere with high priority energy demand. A case study is presented which utilizes the proposed methods. Results suggest that the methodology has the potential to reduce the cost of service while maintaining acceptable consumer reliability.

1. Introduction

As the size of electricity distribution networks is decreased, so is the diversity of demand sources and the diversity of generation. Thus, the smaller an electricity distribution grid, the more vulnerable it becomes to fluctuations in demand and electricity generation. As a result, small standalone micro-grids must rely more heavily on energy storage in order to buffer variability and meet demand. The inclusion of storage capacity greatly increases the capital cost of micro-grids. Thus, it is vital to appropriately size electricity storage capacity.

The issue of appropriately sizing small-scale micro-grid installations is highly pertinent to the electrification of rural locations within the developing world. This article is focused specifically on the sizing of micro-grids with solar photovoltaic, PV, electricity generation and battery storage. Within the developing world, proper maintenance and repair of fossil fuel engine generators can be difficult. Likewise, gasoline and diesel supply chains can be expensive and unreliable. As a result, depending on the availability of other renewable resources, PV micro-grids may offer the least expensive and most reliable form of energy service [1,2]. PV infrastructure needs only minimal maintenance. Maintenance consists primarily of valve-regulated lead-acid battery replacement which must be completed every two to five years. Another advantage of small-scale photovoltaic technology is its modularity. As long as additional hardware constraints are satisfied, PV generation and battery storage capacity can be increased to meet the growing needs of first time electricity customers [3].

Recognizing the importance of proper micro-grid sizing, numerous studies have been conducted with the goal of designing stand-alone systems for a specified reliability, which is usually near 100%. These studies often rely upon a single or multi-year time series of solar data in order to simulate micro-grid performance. Researchers [4–6] used time series simulations to develop curves of PV electricity generation versus battery storage for a desired reliability. As illustrated by Hadj Arab et al. [5], once the per unit cost of PV and battery installation are known, it is then possible to determine the lowest cost generation and storage combination for

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a fixed reliability. They stress the importance of their work by illustrating that the shape of an iso-reliability curve is dependent upon a location's weather profile, the relative cost of PV and battery installations, and the desired micro-grid reliability. Moreover, they stress that these influences may be lost while using simpler methods.

Within the developed world, micro-grid consumers can afford and expect 100% system reliability. Thus, the role of micro-grid designers is to choose the lowest cost PV and battery combination on an iso-reliability curve for 100% up-time. Given stringent financial limitations, consumers in rural regions in the developing world are unwilling and unable to pay for unnecessary surplus capacity. Moreover, cost versus reliability trade-offs can be made, as long as, the micro-grid satisfies consumers' basic energy requirements [7]. In such a case, micro-grid designers should determine the minimum cost solution for a series of reliabilities. The designers should then choose a design from the locus of minimum cost solutions which meets the consumers' basic reliability requirements and fits within the consumers' budget constraints. Although not exhaustive, some research has been conducted into populating a list of micro-grids which provide a range of reliabilities, and observing how system reliability affects the cost of delivered electricity. Researchers [5,8,9] touched upon the issue of cost versus reliability trade-offs for stand-alone micro-grid designs. The work of Kanase-Patil et al. [9] observes how the cost of delivered energy and the composition of hybrid renewable energy systems changes as a function of reliability. Similarly, Wissem et al. [8] observe how the reliability of autonomous PV systems influences the cost per kWh of electricity. Hadj Arab et al. [5] determine the least expensive PV to battery ratio for several system reliabilities.

Existing research illustrates the feasibility of calculating cost versus reliability relationships for potential micro-grid designs. However, this research does not provide a systematic approach for understanding how increasing or decreasing micro-grid reliability affects the consumer experience of delivered electricity. To address the shortfall in existing literature, we propose a methodology which aids a system planner in selecting a grid reliability that is well aligned with the energy usage patterns and budget constraints of consumers. Our methodology requires the production of a locus of PV generation and battery storage combinations, each of which is optimized for a particular reliability. It then follows a step-by-step decision-making process which enables the system planner to select the PV and battery combination that best fits the needs of consumers.

The goal of our step-by-step procedure is to determine when energy shortfalls are concentrated, and then to observe how these shortfalls affect local energy consumption patterns. When analyzing a potential micro-grid design, we begin our temporal analysis by quantifying its reliability for each month of the year. This allows us to observe seasonal trends in micro-grid performance. After identifying the month or months of principal importance, or lowest reliability, we isolate those periods and analyze their performance using sub-daily resolution. Depending on the accuracy of the input parameters, the results should be quantitatively and qualitatively representative of trends in micro-grid performance.

Within Section 2, we present a detailed description of our procedure for designing standalone PV micro-grids. This section introduces several figures. When discussed within Section 2, the specific data within the figures and the implications on the design of a particular micro-grid are of secondary importance. Instead, Section 2 discusses how these types of figures can be used in general terms to facilitate our micro-grid sizing strategy. Section 3: case study is included as an illustrative example of how to use our proposed methodology to develop a micro-grid design. Within our illustrative example, we size the battery bank and PV module for a micro-grid in a village in Segou, Mali. However, balance of system components, BOS, is not included because their size and cost are not strongly correlated to reliability. Within Section 3, the figures from Section 2 are reintroduced. Instead of being discussed in general terms as in Section 2, Section 3 highlights the specific data contained within the figures in order to illustrate how they informed design decisions for a particular micro-grid. In the discussion section of this article, we summarize the lessons learned from our work. We also explain how similar methodologies may be employed to design other micro-grids for the developing world. In Section 5, we summarize our findings and the applicability of our research. We also remind the reader of important considerations that must be made when using the proposed methodology. In Appendix A.1, we describe the algorithm used in order to simulate micro-grid behavior over a year at hourly resolution. Appendix A.1 also describes the metric we use to quantify grid reliability. Appendix A.2 describes an optimization tool we developed in order to select the lowest cost PV generation and battery storage combination needed to achieve a desired reliability. In Appendix B.1, we describe the origins of the weather and electricity demand data that was used in order to conduct our analysis, and in Appendix B.2 we describe how we arrived at the cost estimates used in the paper.

2. Methodology

Within this section, we describe our methodology of identifying the lowest cost system which satisfies consumer energy needs. Our methodology may use real or forecasted customer demand and weather data and price estimates for photovoltaic panels and storage. Unlike previous research, our micro-grid sizing strategy is concentrated on understanding the consumer experience of future micro-grid installations. In this methodology, we adjust the system reliability to minimize cost while simultaneously observing the times when the system is unable to meet demand. We begin our temporal analysis by quantifying the micro-grid reliability for each month of the year. This allows us to observe seasonal trends in reliability. After identifying the month or months of principal importance, or lowest reliability, we isolate those periods and analyze their performance using sub-daily resolution. Although subjective, this iterative procedure allows a

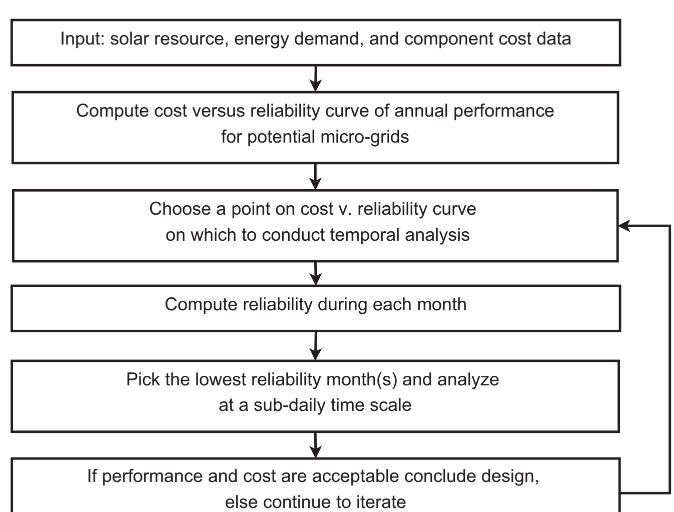

Fig. 1. Overview of design procedure for stand-alone micro-grid systems.

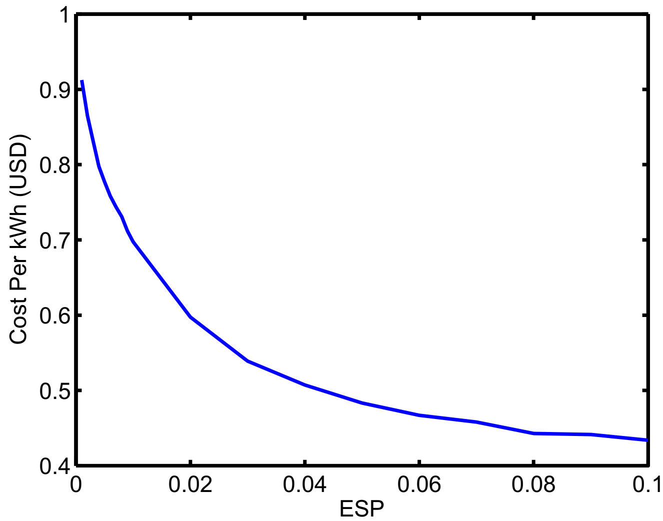

Fig. 2. Cost in USD/kWh versus ESP of micro-grid with freezer base load. In the underlying model, the costs of PV and battery capacity were 0.1762 USD/W and 0.0804 USD/Wh, respectively. The simulation uses the insolation profile from Segou, Mali. ESPs range from 0.001 to 0.10. The cost for each reliability is the optimal combination of PV generation and battery storage which achieves that reliability. Thus, PV generation and battery storage capacity do not have a fixed ratio. For more information on our optimization strategy refer to Appendix A.2.

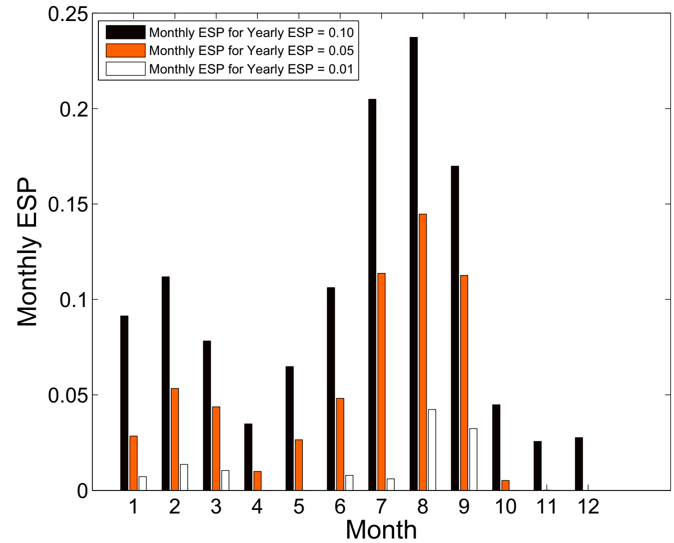

Fig. 3. A bar plot of monthly ESP given annual ESPs of 0.10, 0.05, and 0.01. The underlying model relies on the weather profile of Segou, Mali. The demand data is for the micro-grid with a freezer base load. The PV and battery composition of each micro-grid design is listed in Table 1.

system designer with knowledge of local demands to design a lower cost system without the complexity of backup fossil fuel based generation. A process diagram summarizing our iterative procedure is illustrated as Fig. 1.

The first step in our design procedure is to input insolation and demand data. Several strategies have been employed to estimate the electricity demand of new micro-grid installations for the developing world. Camblong et al. [10] and Alzola et al. [11] used extensive surveying to estimate the magnitude of electricity demand on a per load consuming device basis. The surveys also included time of day information about electricity usage which the authors employed to create a daily power profile with hourly resolution. Nfah et al. [12] estimated the electricity demand of future installations by using historical data of grid connected households with similar electricity consumption behavior. Tools are also available which assist in estimating solar resource data. Given the scarcity of ground-based solar resource data, these tools have been developed to convert geostationary imagery into site-time specific solar data. For instance, Mines ParisTech and the Center for Energy and Processes utilized Meteosat geostationary satellite imaging to create insolation data sets for all of Africa and Western Europe. For most locations, from 2005 to the present, these data sets have a spatial resolution finer than 10 km and a temporal solution finer than 1 h [13]. Similarly, the NASA Langley Research Center has completed a worldwide solar energy data set using satellite imagery. The data set embodies 20 years of data with a 100-km spatial resolution and a daily temporal resolution [14]. NASA has also used this data to compute the average daily insolation for each month at each location. As a result, this data may easily be imported into a tool such as HOMER in order to create synthetic data sets at sub-daily resolution [15].

After energy demand and insolation data inputs have been specified, the next step in our design procedure is to create a cost versus reliability curve. Such a curve allows the designer to understand the marginal cost of added micro-grid reliability. An example of one such curve is illustrated as Fig. 2. The metric we use in order to express system reliability is called energy shortfall probability, ESP. First introduced by Wissem et al. [8], ESP is equal to the annual consumer energy demand a micro-grid could not supply divided by the annual consumer energy demand.[1] We compute ESP using an energy balance model with an hourly time step. Although a pre-existing and more robust algorithm could have been employed, we decided to develop our own micro-grid modeling tool so that we would have complete access and understanding of the source code. Within Appendix A.1, we provide further explanation of our energy balance algorithm. Within Appendix A.1, we also provide our motivation for using ESP. For curves like that illustrated in Fig. 2, the cost at each reliability is that of the cost optimized PV generation and battery storage combination need to achieve that reliability. The algorithm we used to determine the PV and battery combinations is further discussed in Appendix A.2.

As the next step of our micro-grid selection strategy, we plot the ESP for each month. This allows micro-grid designers to observe seasonal variations in reliability and identify portions of the year that may be of concern. They are then able to strategically target these areas with a finer level temporal resolution. Seasonal variations in reliability may be the result of variations in demand or solar resource. Concern over a temporal region may result from a peak in ESP, or it may also result from seasons which have high consumer demand priority. If it is found that seasonal reliability and demand priority are relatively constant, it is up to the discretion of the micro-grid designers to conduct fine resolution temporal analysis on the entire year or to sample certain months. An example of one such monthly ESP plot is illustrated as Fig. 3. This figure includes the monthly ESPs of three different micro-grid alternatives for a single location.

Once we have identified the seasonal areas of concern, we are then able to observe them on a sub-daily time frame. This allows us to qualitatively and quantitatively understand micro-grid performance from a consumer perspective. For our sub-daily analysis we used hourly increments; however, larger, or smaller, increments

[1] Wissem et al. referred to this variable as lack of energy to generate probability (LEGP).

can be used depending on data availability. We are able to observe trends in time of day reliability by plotting it for a month or season of interest. An example of one such time of day reliability plot, for three different micro-grid designs, is illustrated as Fig. 4. Each bar in Fig. 4 represents the combined reliability for the specified micro-grid at a time of day over the course of the month. Plots like Fig. 4, allow micro-grid designers to observe how the probability of energy shortfall changes throughout an average day. From these trends in time of day reliability, micro-grid designers observe how varying reliability may impact sub-daily patterns in peak, or high priority, electricity demand.

We are able to further assess with sub-daily resolution the consumer acceptability of potential micro-grid designs by creating energy shortfall, ES, maps. These maps allow us to qualitatively analyze how energy shortfalls are distributed across days and weeks. ES is the amount of demand, in Wh, that the micro-grid was unable to supply. Examples of ES maps for one month are illustrated within Fig. 5. Each cell within the ES maps corresponds to 1 h of micro-grid performance, and the color of the cell corresponds to the magnitude of energy shortfall. Using ES maps to understand inter-day reliability can answer questions such as, “is a low time of day reliability the result of several small energy shortfalls, or a handful of complete blackouts?” In addition, these figures, combined with an understanding of relevant weather and demand data, allow micro-grid designers to assess whether energy shortfalls are supply or demand driven. For example, energy shortfalls randomly spaced across days would suggest weather driven outages; whereas, energy shortfalls spaced at seven-day intervals would suggest demand driven outages.

The primary purpose of our micro-grid design strategy is to isolate periods when a micro-grid is under the most stress and determine if its performance is acceptable. One way to determine the acceptability of a micro-grid design is through the use of clearly defined thresholds. For example, depending on the devices connected to a grid, such a telecom service, water pump, or refrigerator, there may be a certain number of hours per day or per week that a grid must be operational. If micro-grid performance meets acceptability requirements while under the most stress, it will be acceptable during the rest of year; an exception being that seasonal

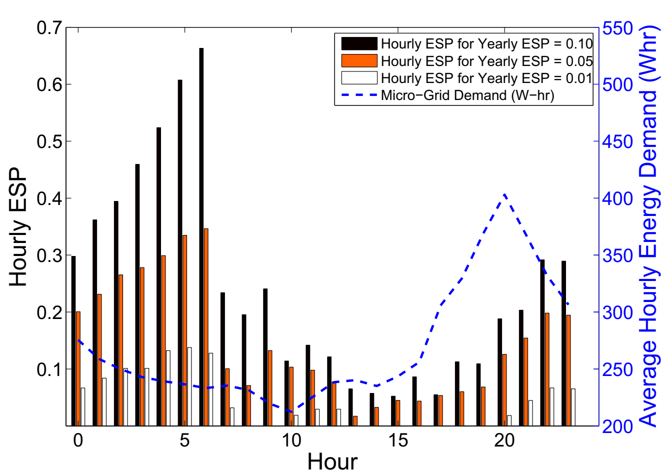

Fig. 4. Bar plot of hourly ESP during the month of August. As indicated in the legend, the different bar column types are for micro-grids with annual ESPs of 0.10, 0.05, and 0.01. Superimposed on the bar plot is the average hourly demand in Wh. Data are plotted on the hour beginning a 1-h period. For example, the energy ESP for the period between 12:00 and 13:00 is marked at 12:00. The underlying model relies on the weather profile of Segou, Mali. The PV and battery composition of each micro-grid design is listed in Table 1.

variations in micro-grid usage can necessitate time of year variations in acceptable system reliability. Regardless, our procedure allows micro-grid designers to also analyze the performance of months with the highest priority demand.

3. Case study: Segou, Mali

This section is intended as an illustrative example. The methodology introduced in the previous section is utilized in order to size a micro-grid for a village outside of Segou, Mali. There is currently a micro-grid on the site. From consumer feedback, the micro-grid is deemed to have an unacceptable reliability. According to our model, the micro-grid has an ESP of 0.125. In order to facilitate the design process, and motivate specific micro-grid design decisions, the figures from Section 2 are reintroduced.

3.1. Input parameters

The following subsection describes the input parameters of our model. The primary input types are as follows:

- an 8760 element vector of hourly available insolation for one year,
- an 8760 element vector of hourly net consumer demand for one year,
- the geographic location and the orientation of the collector, and
- cost parameters which determine the relative and total cost of PV generation and battery storage.

Insolation data illustrates significant seasonal variations in solar resource availability. These variations are primarily driven by weather patterns and not by changes in clear sky solar resource. Segou, Mali is located at 13°27′ 0″N, 6.13°16′ 0″W. Being between the Tropic of Capricorn and the Tropic of Cancer, this location has little variation in seasonal clear sky solar resource availability; the hours of daylight for the summer and winter solstices are 12 h, 55 min and 11 h, 20 min, respectively. Although the clear sky irradiance is relatively constant throughout the year, irradiance at ground level is not. Segou's weather is characterized by a rainy season which lasts from June until September, and a dry season throughout the rest of the year.

From historical demand data, and knowledge of the villagers' energy usages, we are aware that a majority of electricity demand is used to operate a 250 L freezer. Due to the warm climate, and being frequently loaded beyond capacity, the freezer operates nearly 24 h a day with minimal on/off cycling. Ice bricks and frozen drinks produced by the freezer are sold to neighboring villages. From the one week of available data, the circuit with the freezer drew on average 153 Wh/h. For this same circuit, during a typical day, energy consumption peaked in the early evening at approximately 210 Wh/h. In addition to powering the freezer, the micro-grid serves approximately 20 households. Each household is equipped with two 5 W LED light bulbs and a two plug 230 VAC outlet. The outlets are used primarily for cell phone charging. A few households may also have larger electronics, such as a television or radio. All households are individually metered, and are charged on a per watt hour basis. The combined energy demand of the non-refrigeration consumer usage, refrigeration, and metering loads averages 270 Wh/h with peaks in the early evening around 400 Wh/h. The average diurnal day of the combined energy consumption data used in our analysis is illustrated in Fig. 4. The energy consumption includes non-refrigeration consumer usage, refrigeration, and metering loads. Fig. A1 part A illustrates a one week time series of the net energy demand of the micro-grid.

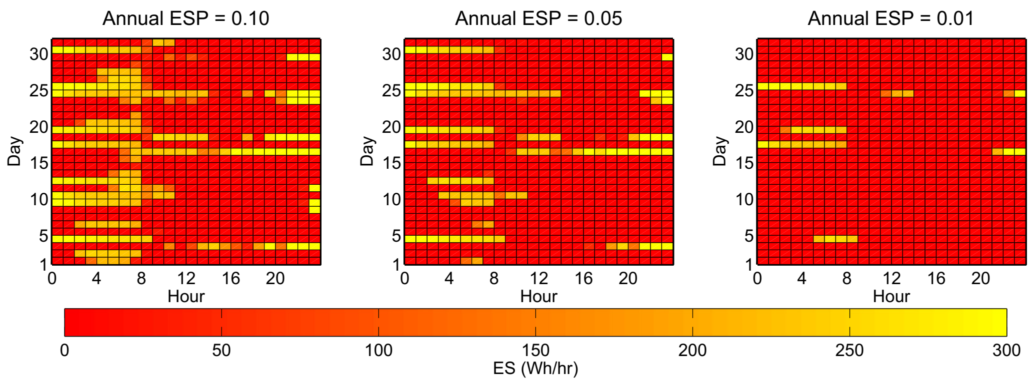

Fig. 5. Maps of energy shortfall, *ES*, at an hourly resolution for the month of August. From left to right, subplots are for Annual ESPs of 0.10, 0.05, and 0.01. The underlying model relies on the weather profile of Segou, Mali. The PV and battery composition of each micro-grid design is listed in Table 1.

When conducting our financial analysis, we estimated the annual cost of PV capacity to be 0.1762 USD/W. We also estimated the annual cost of battery capacity to be 0.0804 USD/Wh. For a more detailed explanation of how the weather, demand, and economic parameters were generated, please refer to Appendix B.

3.2. Case study procedure and results

Sizing the micro-grid for Segou, Mali, required several iterations of steps three through six of the design procedure illustrated in Fig. 1. Each iterations generated a unique micro-grid configuration. The ESP, PV capacity, battery capacity, and cost per kWh of select iterations are printed in Table 1.

When sizing the micro-grid for the village outside of Segou, we started by specifying an annual ESP of 0.10. Recognizing the severe financial limitations on micro-grid design, we wanted to start with a reliability that was marginally better than the 0.125 ESP of the current system. After specifying an annual ESP of 0.10, we plotted the ESP for each operational month. Fig. 3 illustrates that, as expected from the weather patterns of Segou, the months of July through September had the lowest reliability. Because it had the lowest reliability, with an ESP of 0.237, we chose to analyze the month of August with an hourly resolution.

In order to understand the temporal spacing of energy shortages, and how they affect electricity demand, we created Figs. 4 and 5. After analyzing the figures, we concluded that the 0.10 ESP micro-grid did not offer adequate reliability for either the freezer base load or the residential demand. We found that micro-grid performance was insufficient for the residential consumers because many energy shortages occur during times of significant residential demand. Given that the freezer base load remains relatively constant, from Fig. 4, we can see that there is a significant level of residential electricity demand between 5:00 PM and 12:00 AM, with peak demand occurring between 8:00 PM and 9:00 PM. Between 5:00 PM and 12:00 AM reliability steadily decreases, with ESP rising from 0.0549 to 0.290. During the peak demand window, which occurs between 8:00 PM and 9:00 PM, the ESP of the micro-grid was 0.1883. The 0.10 ES map within Fig. 5 also illustrates that the system provides insufficient electricity service to the residential customers. In particular, we can see that the high ESPs were the result of regularly occurring energy shortages and not isolated outages. Fig. 5 indicates that there were nine energy shortfall events which curtailed demand during the 5:00 PM to 12:00 AM period. Five of these inhibited electricity consumption during the hour of peak demand, 8:00 PM to 9:00 PM. We also found that the micro-grid failed to provide sufficient service for the freezer system because there were several outages of long duration. We estimate that any energy shortfalls lasting 5 h or longer would significantly impact the production of ice and frozen drinks. As Fig. 5 illustrates, energy shortfalls lasting five or more consecutive hours occurred on sixteen separate days.

Table 1
Performance, size, and costs characteristics of current and potential micro-grids for Segou, Mali. The costs of PV and battery capacity were 0.1762 USD/W and 0.0804 USD/Wh, respectively. Note that the ESP and the cost per kWh were estimated by our model and do not constitute measured reliability or cost data. All PV/battery combinations, except for that of the current grid, represent the optimal ratio for the desired ESP.

ESP	PV Capacity W	Bat capacity Wh	Combine cost of PV and Bat bank USD/kWh
Current grid 0.125	1400	17,820	0.790
0.1	1800	7600	0.434
0.05	2400	8400	0.483
0.03	3200	8400	0.539
0.01	3000	13,800	0.697
0	3300	19,600	0.913

Recognizing that an ESP of 0.10 was insufficient to meet our consumers' demand, we iteratively increased system reliability and observed the temporal characteristics using the Section 2 methodology. An intermediate design was a micro-grid with an annual ESP of 0.05. Although the performance of the 0.05 ESP micro-grid was significantly better than that of the 0.10 ESP micro-grid, we found that its performance was nonetheless unacceptable. Like the 0.10 ESP micro-grid, this design would have a significant negative impact on residential electricity usage during August. Recognizing that most residential demand occurs between 5:00 PM and 12:00 AM, Fig. 5 illustrates that there were six instances in which power outages would inhibit residential electricity supply during that timeframe. With respect to the freezer operators, we found that there would be ten days with outages of five consecutive hours or longer. Subjectively, we determined that ten days of lost revenue concentrated within a one-month period would be unacceptable to the freezer operators.

As a result of our iterative design process, we decided upon a micro-grid with an annual ESP of 0.01. After isolating the lowest reliability month, and analyzing it with an hourly resolution, we decided that the micro-grid was acceptable to residential consumers. Fig. 5 indicates that there were only two energy shortages between 5:00 PM and 12:00 AM, representing two events in which residential consumption was significantly impacted. We also found that the 0.01 ESP micro-grid significantly improved freezer operation, especially when compared to the aforementioned alternatives. There were only three energy shortfall occurrences which were 5 h or longer. Furthermore, as indicated in Table 1 we can see that for ESPs below 0.01, the cost of electricity continues to increase significantly.

4. Discussion

The results of the case study illustrate that a combination of optimization tools and designer discretion can produce a micro-grid design that is more reliable, and less expensive, than a micro-grid designed using "rule of thumb" techniques. Moreover, we were able to come about a design which made an acceptable and significant cost versus reliability trade off. As indicated in Table 1, we arrived at a design with an ESP of 0.01 and a break even cost of electricity of 0.697 USD/kWh. For a reliability which would be demanded by an off-grid customer in the developed world, the cost of generation would be significantly higher. To achieve an ESP of 0.001, the break even cost of electricity would have been 0.913 USD/kWh. In essence, in order to reduce the micro-grid's ESP by 0.009, the consumer cost of electricity would have to be increased by at least 31%.

As previously stated, within the illustrative case study, the cost of balance of system, BOS, components, such a charge controller, or an inverter, is not included. Because BOS costs are not a function of reliability, the primary result of their inclusion would be the upward translation of the cost versus reliability curve in Fig. 2 without changing its shape. Thus, in absolute terms the cost of adding reliability will be the same, regardless of whether or not BOS costs are included.

In our analysis we assumed that the batteries would have a fixed life of 3 years. This lifespan is a conservative estimate based on our acquired experience with heavily utilized isolated micro-grids. We believe that a more advanced model of battery performance would not significantly impact our findings. Within of the micro-grid simulations presented, we used the same depth of discharge, 50%, as well as, the same energy demand and solar radiation time series. As a result, an improved battery performance model would influence all micro-grid simulations similarly. Our findings would not significantly change because our analysis is concerned with relative differences in the cost of energy for various micro-grid options.

Nonetheless, operational characteristics of a micro-grid can influence battery life, and, in turn, affect the net present cost and the leveled cost of energy of a potential solar micro-grid project. As a result, designers may wish to incorporate modeling of battery degradation into their analysis when using our micro-grid sizing strategy to size future systems. Dufo-Lopez et al. describe and evaluate three types of existing battery lifetime models. These models are the fixed energy throughput model used in HOMER, the "rain flow" cycles counting model, and the Schiffer weighted Ah-throughput model [16]. Additional information on battery lifetime modeling is present in Refs. [17–19].

In writing this article, we narrowed our scope to stand-alone PV and battery micro-grids, and we chose to demonstrate our methodology using one specific example. Nevertheless, we believe that the combination of optimization tools and pseudo-subjective cost versus reliability trade-offs can be utilized to design a wide array of isolated micro-grids for the developing world. These techniques can be implemented using well-established tools, such as HOMER, which accommodate several generation and storage types. Moreover, our methodology allows micro-grids to be designed with respect to their unique load requirements. For example, if the base load in our case study were a freezer used to store vaccines, instead of frozen drinks, we would have specified different reliability requirements. Similarly, if a community has seasonally elevated energy consumption as a result of important economic activity, the proposed methodology allows such information to be incorporated into design decisions.

5. Conclusion

We believe that the proposed methodology can be used in unison with existing sizing tools, such as HOMER, to size many future isolated micro-grids within the developing world. As illustrated by the case study in Section 3, our research suggests that cost versus reliability trade-offs have the potential to significantly reduce the cost of energy while maintaining an acceptable level of service. In order to produce an acceptable design, two factors must be considered. The first is determining high priority electricity applications or devices. Identifying the uses of electricity will help specify reliability requirements. The second important factor is determining when high priority electricity demand occurs. Answering this question will help to ensure energy shortfalls do not happen when energy is most needed.

Appendix A

A.1. Energy balance algorithm and ESP

As previously stated, the efficacy of a micro-grid is assessed through the use of an energy balance algorithm with an hourly time scale. In order to conduct a one-year simulation, the maximum allowable battery charge level in Wh, E_{Bmax}, and the maximum percent depth of discharge, $\mathrm{DOD}_{\mathrm{max}}$, must be specified. As illustrated by Eq. (A.1), E_{Bmax} together with $\mathrm{DOD}_{\mathrm{max}}$, define the minimum level of battery charge in Wh, E_{Bmin}.

$$E_{\mathrm{Bmin}} = E_{\mathrm{Bmax}}(1 - \mathrm{DOD}) \tag{A.1}$$

In order to conduct the simulation, it is also necessary to compute $E_{\mathrm{PV}}(t)$, the energy generated by the photovoltaic module for all hours. We calculated $E_{\mathrm{PV}}(t)$ using Eq. (A.2), where P_{nom} is the nominal power capacity of the PV module in watts, and $I_{\mathrm{C}}(t)$ is the insolation on the collector. We then compute the charge level of the battery bank, $E_{\mathrm{B}}(t)$, for all hours using Eq. (A.3).

$$E_{\mathrm{PV}}(t) = I_{\mathrm{C}}(t)P_{\mathrm{nom}} \Big/ 1000\ \mathrm{W/m^2} \tag{A.2}$$

$$E_{\mathrm{B}}(t+1) = \begin{cases} E_{\mathrm{Bmax}}, & E_{\mathrm{B}}(t) + E_{\mathrm{PV}}(t) - E_{\mathrm{dem}}(t), \geq E_{\mathrm{Bmax}} \\ E_{\mathrm{B}}(t) + E_{\mathrm{PV}}(t) - E_{\mathrm{dem}}(t), & E_{\mathrm{Bmin}} \leq E_{\mathrm{B}}(t) + E_{\mathrm{PV}}(t) - E_{\mathrm{dem}}(t), \leq E_{\mathrm{Bmax}} \\ E_{\mathrm{Bmin}}, & E_{\mathrm{B}}(t) + E_{\mathrm{PV}}(t) - E_{\mathrm{dem}}(t), \leq E_{\mathrm{Bmin}} \end{cases} \tag{A.3}$$

Within the equation, $E_{\mathrm{dem}}(t)$ is the energy demanded by the micro-grid consumers. Represented as Fig. A1 is the output of the energy balance algorithm for one week of data. When the battery capacity has been depleted, we quantify the demand that cannot be met using a variable called energy shortfall, ES, which was proposed by Wissem et al. [8]. We define ES using Eq. (A.4).

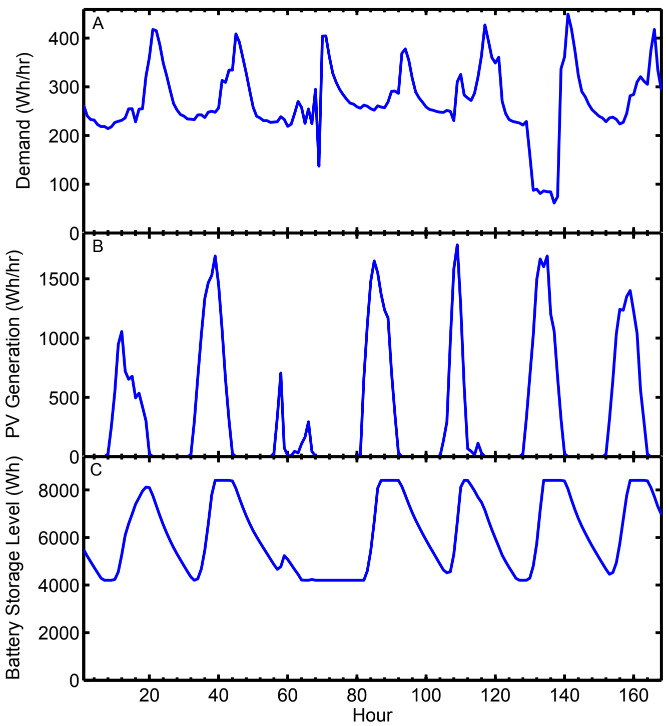

Fig. A1. Energy balance algorithm calculations using weather from August 1, 2005 until August 7, 2005. Simulation uses micro-grid demand with refrigerator base load and insolation profile from Segou, Mali. Micro-grid contains 2400 W of nominal PV capacity, and 8400 Wh of nominal battery capacity. Battery low-charge disconnect is 4200 Wh. Sub-figure A.1.A plots hourly energy demand in Wh/h. Sub-figure A.1.B plots hourly energy generated in Wh/h. Sub-figure A.1.C plots the energy contained within the battery bank in Wh.

$$\mathrm{ES}(t+1) = E_{\mathrm{dem}}(t+1) - (E_{\mathrm{PV}}(t+1) + E_{\mathrm{B}}(t) - E_{\mathrm{Bmin}}) \qquad \text{(A.4)}$$

We are then able to assess the micro-grid's performance using a metric called energy shortfall probability, ESP, which was also proposed by Wissem et al. [8]. ESP is equal to the electricity demand that a micro-grid was unable to meet divided by the total demand over a specified time frame. It is calculated using Eq. (A.5).

$$\mathrm{ESP} = \frac{\sum_{t=1}^{T} \mathrm{ES}(t)}{\sum_{t=1}^{T} E_{\mathrm{dem}}(t)} \qquad \text{(A.5)}$$

Although time based metrics such as loss of load probability (LOLP) may be used to evaluate system performance, these tend to inflate the perceived performance of micro-grids in the developing world. Many of the micro-grids we have observed are only used for a small fraction of the day. We are more concerned about a micro-grid's ability to supply the energy demanded, and thus chose ESP as our primary performance metric.

A.2. Optimization algorithm

The optimization algorithm calls upon the energy balance algorithm to populate an iso-reliability curve, which defines all PV generation and battery storage combinations which satisfy a particular ESP. It then determines which PV and battery combination has the lowest cost. We can then apply this algorithm to a range of ESPs to understand how system reliability influences the consumer cost of electricity. We must specify several inputs in order to utilize the optimization algorithm. The inputs are:

- the range of ESPs on which to perform system optimization,
- the incremental step sizes $E_{\text{B-step}}$ and $\mathrm{PV}_{\text{nom-step}}$ by which the battery bank and the PV array, respectively, are allowed to change,
- the insolation and electricity demand data which are called upon by the energy balance algorithm, and
- the cost per watt of installed PV capacity and the cost per Wh of installed battery capacity.

Establishing an end point on the iso-reliability battery versus PV capacity curve

For a specified ESP, $\mathrm{ESP}_{\mathrm{target}}$, the algorithm first uses Eq. (A.4) to model the performance of the micro-grid system with a greatly oversized PV module and battery bank. P_{nom} and E_{Bmax} are set to 50 times and 100 times, respectively, the maximum value of $E_{\mathrm{dem}}(t)$. Then, while keeping E_{Bmax} constant, P_{nom} is reduced by a fixed step size, $P_{\text{nom-step}}$, and ESP is recalculated. The process of reducing P_{nom} is iterated until we find from Eq. (A.5) that ESP is less than $\mathrm{ESP}_{\mathrm{target}}$. We then set the last P_{nom} before the ESP fell below $\mathrm{ESP}_{\mathrm{target}}$ as $\mathrm{PV}_{\mathrm{nom},1}$. We notate the maximum battery and nominal PV capacity of this combination as $E_{\mathrm{Bmax},1}$ and $P_{\mathrm{nom},1}$, respectively. This point constitutes the far right end of the iso-reliability curve illustrated as Fig. A2.

Populating the other points on the iso-reliability battery versus PV capacity curve

In order to populate the next point on the iso-reliability curve, P_{nom} is increased from $P_{\mathrm{nom},1}$ to $P_{\mathrm{nom},2}$ by $P_{\text{nom-step}}$, and E_{Bmax} is set to zero. Then while keeping P_{nom} equal to $P_{\mathrm{nom},2}$, E_{Bmax} is iteratively increased by a fixed step size, E_{Bstep}, until the ESP is greater than $\mathrm{ESP}_{\mathrm{target}}$. We call the maximum battery capacity $E_{\mathrm{Bmax},2}$ at the point when ESP exceeds $\mathrm{ESP}_{\mathrm{target}}$. Together $E_{\mathrm{Bmax},2}$ and $P_{\mathrm{nom},2}$ constitute the second point on the iso-reliability curve. The process of increasing $\mathrm{PV}_{\mathrm{nom}}$ and finding the corresponding E_{Bnom} to achieve $\mathrm{ESP}_{\mathrm{target}}$ is continued until $\mathrm{PV}_{\mathrm{nom}}$ has reached 50 times $E_{\mathrm{dem}}(t)$.

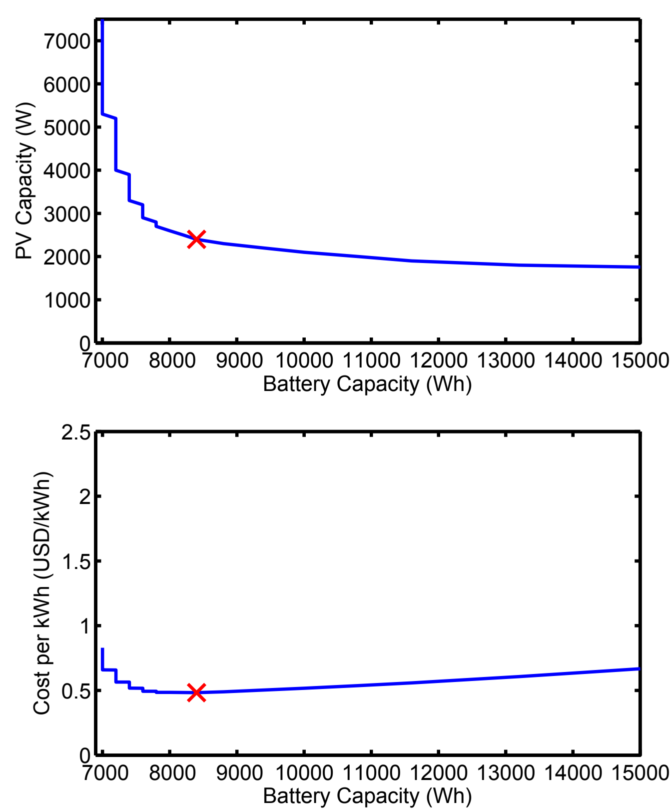

Fig. A2. Plotted using a line in the upper subplot is a curve illustrating the multiple combinations of PV and battery capacity which achieve an ESP of 0.05. Plotted using a line in the lower subplot is the cost associated with each PV and battery combination. Marked with an x in each subplot is the optimal cost solution for an ESP of 0.05.

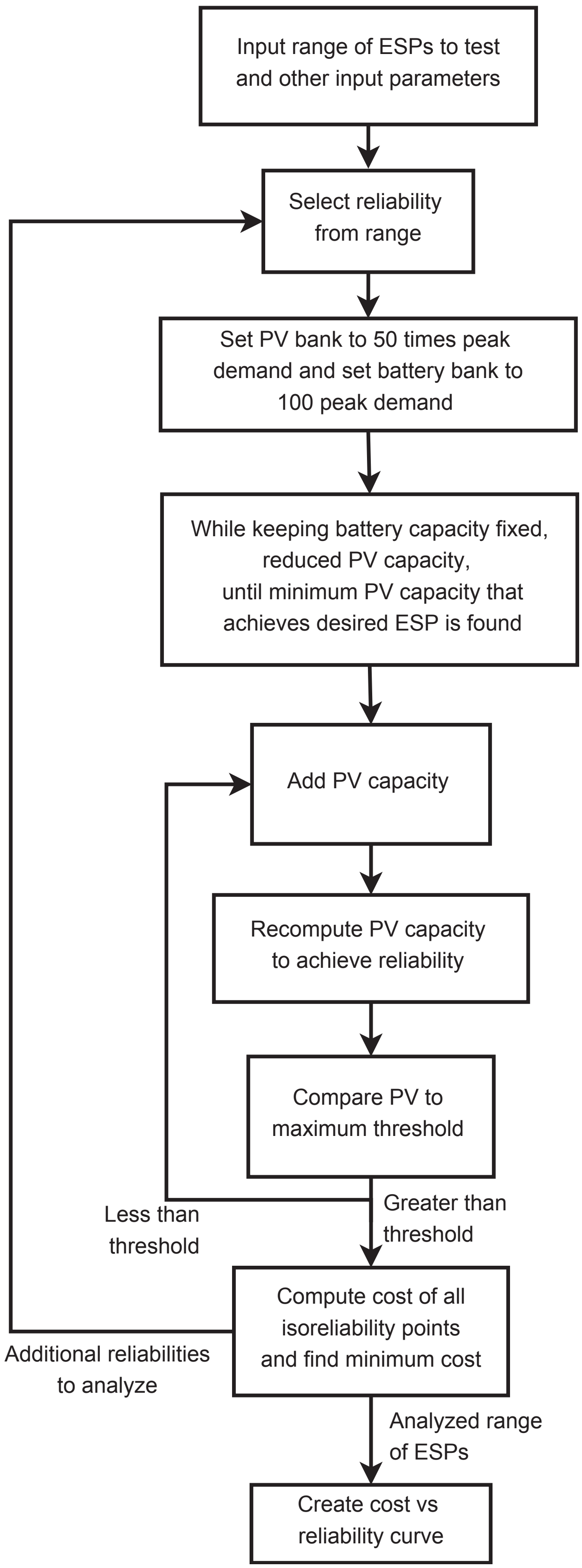

Fig. A3. Summary of optimization algorithm.

If a range of ESPs is input into the optimization algorithm, it will report the lowest cost PV and battery combination and cost associated with each reliability. From these data, we are able to then construct a cost versus reliability curve for the system. From the cost per vs. reliability plot, and the underlying data, we are able to study how reliability drives system costs for any climate and demand profile. It is important to note that due to the incremental step sizes of PV and battery capacity, the achieved reliability of the system will always be marginally higher than the specified value. A diagram summarizing the optimization algorithm is illustrated as Fig. A3.

Appendix B. Explanation of case study input parameters

B.1. Weather and demand data

Weather data was procured from the HelioClim3 database which was produced by Mines ParisTech - Armines. They received Meteosat data from Eumetsat and processed it into time-space insolation data. For our energy simulations, we utilized the hourly normal to sun ground insolation data from 2005. The coordinates 13.45 N, 6.26 W and a ground reflectance of 0.20 were used. One hundred and forty-four consecutive data points, August 24 through August 29, were missing from the data set. The missing data points were "patched" using the same time of day data from the immediately preceding days. Knowing the normal to sun insolation data, ground reflectance, and panel orientation, we calculated the hourly insolation on the collector using Eq. (7.33) of Gilbert Masters [20]. A week of micro-grid generation data is illustrated in Fig. A1 part B.

A week of 3 s resolution demand data was extracted from the main meter on the currently installed micro-grid in the village outside of Segou, Mali. The 3 s data were then aggregated to hourly data. Because the loads in the village do not appear to demonstrate season dependency, this week of demand data was then copied 52.143 times in order to create a full 365-day year. The week of micro-grid demand data is illustrated within Fig. A1 part A.

B.2. Cost parameters

The cost analysis included in this article only considered the cost of the solar and battery equipment. It did not include the cost of installation, maintenance, or additional hardware. We estimated the cost of solar modules to be 1.50 USD/W and the cost of batteries to be 0.20 USD/Wh installed. The max depth of discharge of the battery bank was set to 0.50. It was estimated that the life of the PV modules would be 20 years, and the life of the batteries would be three years. It was also estimated that the cost of PV modules and battery bank would be repaid using annual payments over their respective design lives. A 10% annual interest rate is added to repayment fees. Table B1 contains a summary of the input parameters which affected our cost calculations.

Table B1
Summary of input parameters for micro-grid cost estimation.

	PV	Battery
Cost per capacity	1.50 USD/W	0.20 USD/Wh
Design life/payment period	20 years	3 years
Interest rate	10%	10%
Annual payment	0.1762 USD/W	0.0804 USD/Wh

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