Cost Versus Reliability Sizing Strategy for Isolated Photovoltaic Micro-grids in the Developing World

Mitchell Lee [a], Daniel Soto [b], Vijay Modi [a, b]

[a] Department of Mechanical Engineering, Columbia University, New York, USA
[b] The Earth Institute, Columbia University, New York, USA

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.

Research Highlights

- Procedure for developing cost versus reliability curves for isolated micro-grids
- Propose cost/reliability trade-offs to increase energy accessibility
- Case study: sizing micro-grid for village outside of Segou, Mali

Keywords

Isolated micro-grids; cost versus reliability; micro-grid system sizing

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 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 percent. 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 a fixed reliability. They stress the importance of their work by illustrating that the shape of an isoreliability 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 percent system reliability. Thus, the role of micro-grid designers is to choose the lowest cost PV and battery combination on an isoreliability curve for 100 percent 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 kWhr 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 by which a system planner may subjectively determine on a case by case basis an optimum point where both cost and customer satisfaction are met. The guiding principle behind our methodology is to determine where energy shortfalls occur using simulations with sub-daily resolution and then to observe how these shortfalls affect local energy consumption patterns. We create a locus of cost optimized PV and battery combinations for a range of system reliabilities. Embedded in each point on the cost reliability curve is a one year temporal simulation of micro-grid performance with hourly resolution. We then iteratively analyze points on the curve while observing when energy shortfalls occur and how they correlate to consumer demand 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: methodology, we present a detailed description of our procedure for designing standalone PV micro-grids. This section introduces several figures which are used to facilitate our micro-grid sizing strategy. Section 3 is an illustrative example of how we used our proposed micro-grid design strategy to develop a micro-grid design for consumers in Segou, Mali. Within section 3, the figures from section 2 are reintroduced in order to illustrate how they informed design decisions for our particular micro-grid. In the discussion section of this article, we summarize the lessons learned from our work. We also elucidate on how similar methodologies may be employed to design other micro-grids for the developing world.

2 Methodology

Within this section, we describe our methodology of identifying the lowest cost system which subjectively satisfies consumer energy needs. Our methodology may use real or forecast 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 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 Figure 1.

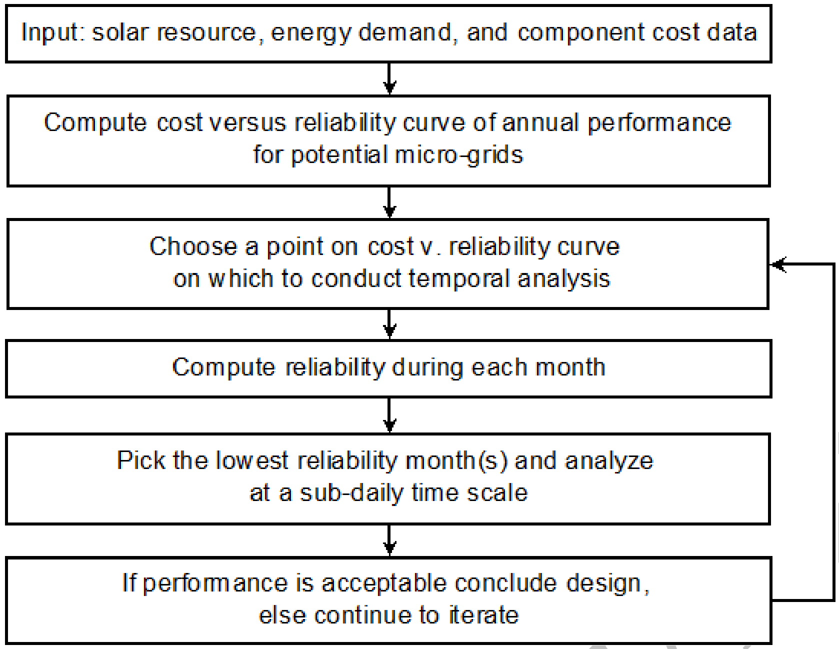

Figure 1: Overview of design procedure for stand-alone micro-grid systems.

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 spacial resolution finer than 10 km and a temporal solution finer than one hour [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 spacial 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 Figure 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. Within

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

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 the cost versus reliability curves, like that illustrated in Figure 2, the cost of reliability is that of the cost optimized PV generation and battery storage combination to achieve that reliability. The algorithm we used to determine the PV and battery combinations is further discussed in appendix A.2.

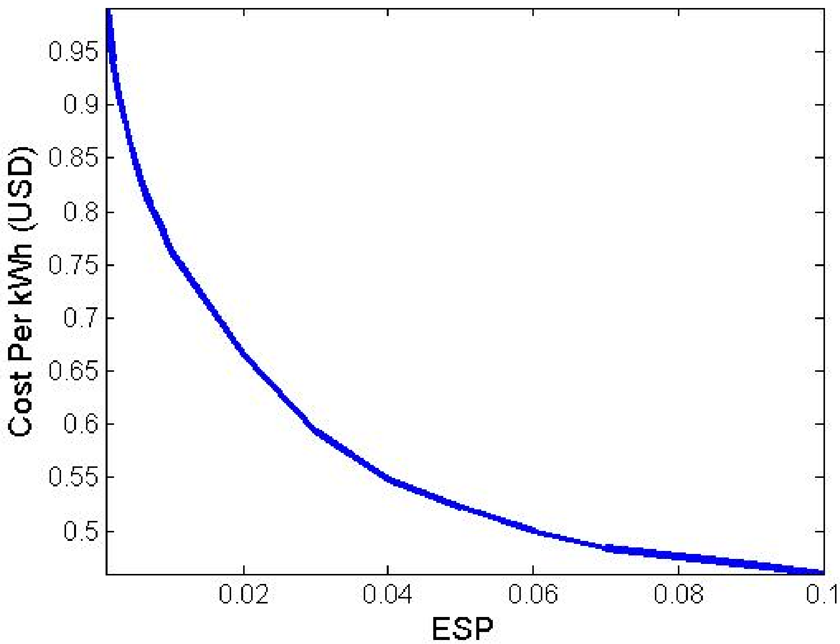

Figure 2: Cost in USD/kWhr versus *ESP* of micro-grid with freezer base load. In the underlying model, the costs of PV and battery capacity were 0.1762 USD/W and 0.0804 USD/Whr, respectively. The simulation uses the insolation profile from Segou, Mali. *ESPs* range from 0.001 to 0.10. The cost for each 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.

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 Figure 3. This figure includes the monthly *ESPs* of three different micro-grid alternatives for a single location.

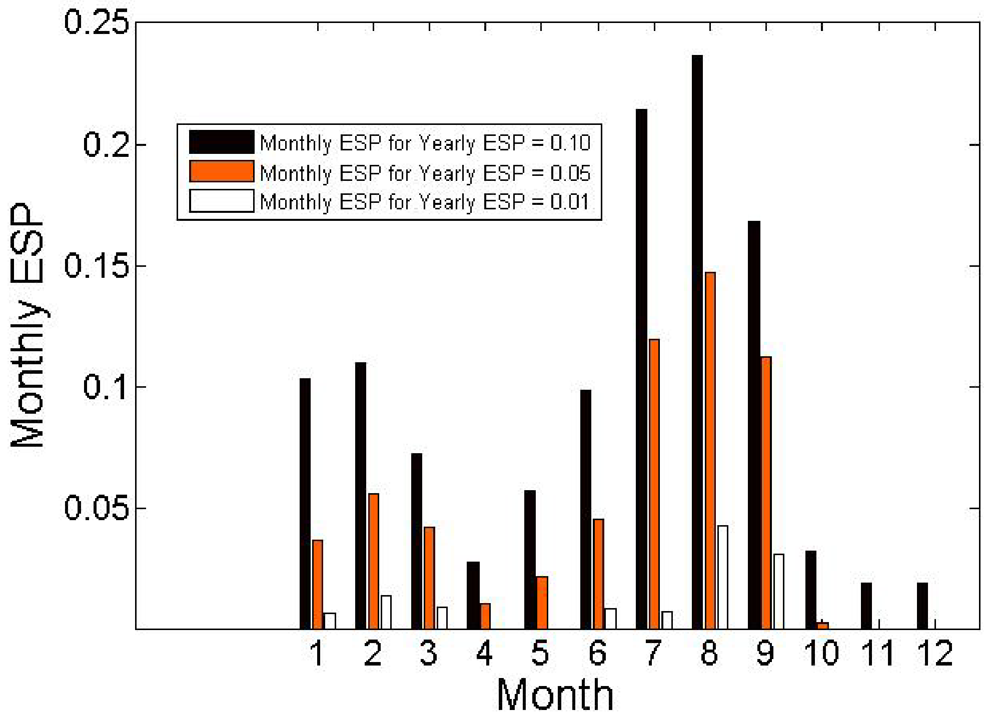

Figure 3: A bar plot of monthly *ESP* given annual *ESPs* of 0.10, 0.05, and 0.01. The underlying model relies on the weather profile of Segou, Mali. The demand data is for the micro-grid with a freezer base load. The PV and battery composition of each micro-grid design is listed in Table 1.

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 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 Figure 4. Each bar in Figure 4 represents the combined reliability for the specified micro-grid at a time of day over the course of the month. Plots like Figure 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 trends in peak, or high priority, electricity demand.

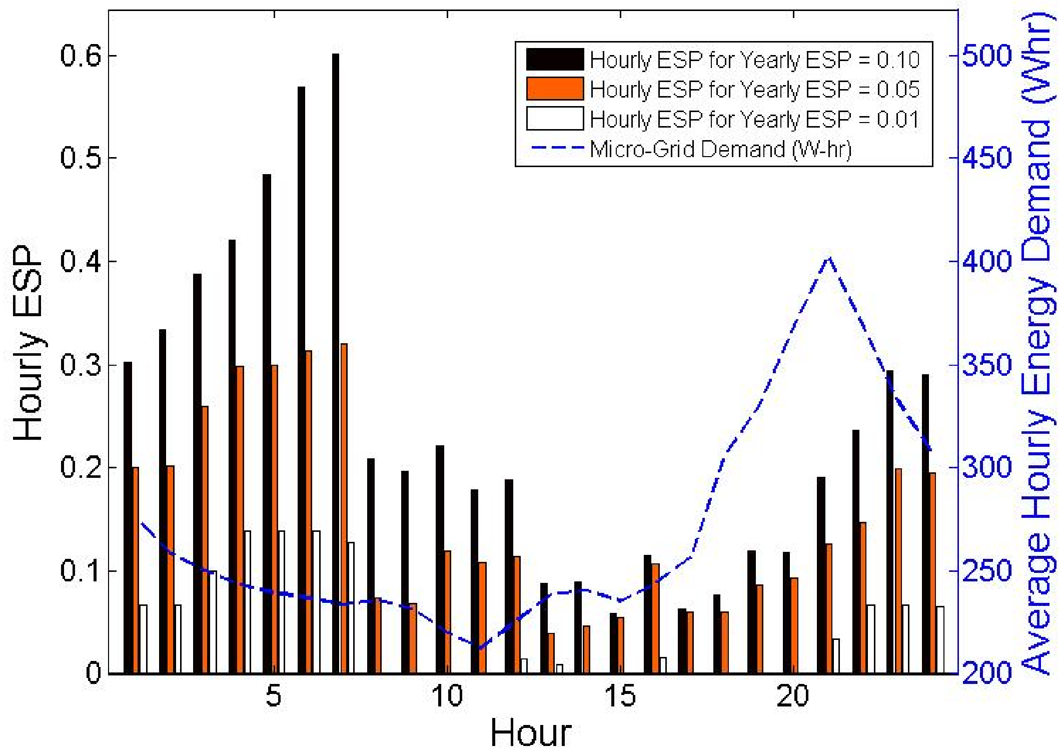

Figure 4: Bar plot of hourly *ESP* during the month of August. As indicated in the legend, the different bar column types are for micro-grids with Annual *ESPs* of 0.10, 0.05, and 0.01. Superimposed on the bar plot is the average hourly demand in Whr. The underlying model relies on the weather profile of Segou, Mali. The PV and battery composition of each micro-grid design is listed in Table 1.

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 Whr, that the micro-grid was unable to supply. Examples of *ES* maps for one month are illustrated within Figure 5. Each cell within the *ES* maps corresponds to one hour 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.

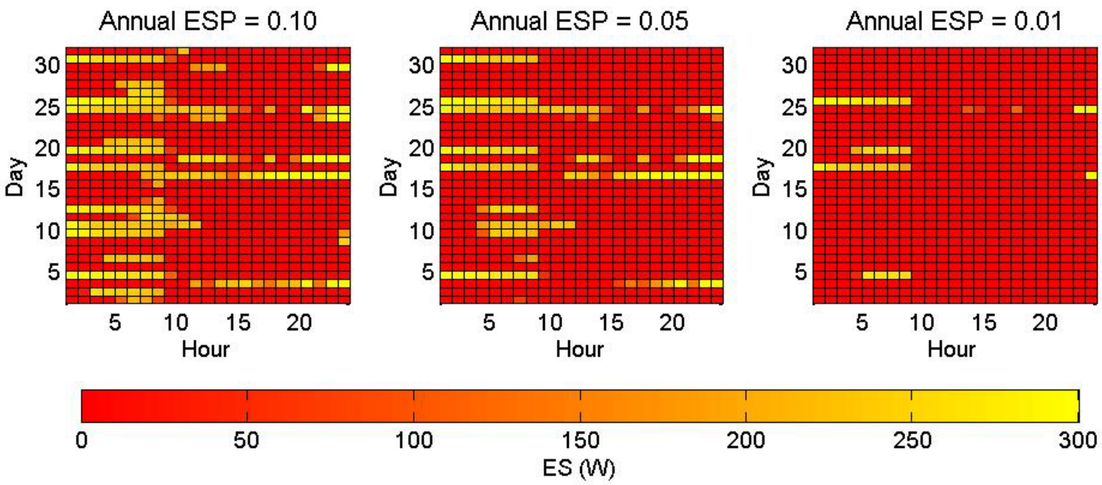

Figure 5: Maps of energy shortfall, *ES*, at an hourly resolution for the month of August. From left to right, subplots are for Annual *ESPs* of 0.10, 0.05, and 0.01. The underlying model relies on the weather profile of Segou, Mali. The PV and battery composition of each micro-grid design is listed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

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 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 a *ESP* of 0.146. 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:

- 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 hours, 55 minutes and 11 hours, 20 minutes, 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 villager's energy usages, we are aware that a majority of electricity demand is used to operate a 250 liter freezer. Due to the warm climate, and being frequently loaded beyond capacity, the freezer operates nearly 24 hours a day without on/off cycling. On average the freezer draws 160 W. Ice bricks and frozen drinks produced by the freezer are sold to neighboring villages. 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. On average, residential electricity demand peaks during the early evening at 150 W. Hourly averages of the demand data used in our analysis are illustrated as the dashed line in Figure 4.

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/ Whr. 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 Figure 1. Each iteration generated a unique micro-grid configuration. The *ESP*, PV capacity, battery capacity, and cost per kWhr of select iterations are printed in Table 1.

ESP	PV Capcity W	Bat Capacity Wh	Combine Cost of PV and Bat Bank USD/kWh
Current Grid 0.146	1400	17280	0.810
0.10	1800	8400	0.460
0.05	2500	9200	0.522
0.03	3300	9800	0.593
0.01	3200	15200	0.761
0.001	3900	20600	0.991

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/Whr, respectively. Note that the *ESP* and the cost per kWhr 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*.

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 0.146 *ESP* of the current system. After specifying an annual *ESP* of 0.10, we plotted the *ESP* for each operational month. Figure 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 qualitatively understand the temporal spacing of energy shortages, and how they affect electricity demand, we created Figure 4 and Figure 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 resident demand. We found that micro-grid performance was insufficient for the residential consumers because a significant number of energy shortages occur during times of significant residential demand. As illustrated by Figure 4, we can see that there is a significant level of residential electricity demand between 6:00 PM and 1:00 AM, with peak demand occurring between 8:00 PM and 9:00 PM. Between 6:00 PM and 1:00 AM reliability steadily decreases, with *ESP* rising from 0.0763 to 0.302. During the peak demand window, which occurs between 8:00 PM and 9:00 PM, the *ESP* of the micro-grid was 0.191. The 0.10 *ES* map within Figure 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. Figure 5 indicates that there were nine energy shortfall events which curtailed demand during the 6:00 PM to 1:00 AM period. Four 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 five hours or longer would significantly impact the production of ice and frozen drinks. As Figure 5 illustrates, energy shortfalls lasting five or more hours occurred prior to, or during, sixteen separate work days.

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 6:00 PM and 1:00 AM, Figure 5 illustrates that there were six instances in which power outages would inhibit residential electricity supply. With respect to the freezer operators, we found that there would be nine outages which occur for five hours or longer. Subjectively, we determined that nine 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. Figure 5 indicates that there were only two energy shortages between 6:00 PM and 1:00 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 five hours or longer. Furthermore, as indicated in Table 1 we can see that for *ESPs* below 0.01, the cost of electricity dramatically increases.

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 0.761 USD/kWhr. 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 0.991 USD/kWhr. 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 30 percent.

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 was 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.

A Appendix

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 and minimum allowable battery charge levels E_{Bmin} and E_{Bmax} must be specified in Whr. We then compute the charge level of the battery bank for all hours using equation A.1.

$$E_B(t+1) = \begin{cases} E_{Bmax}, & E_B(t+1) \geq E_{Bmax} \\ E_B(t) + E_{PV}(t) - E_{dem}(t), & E_{Bmin} \leq E_B(t+1) \leq E_{Bmax} \\ E_{Bmin}, & E_B(t+1) \leq E_{Bmin} \end{cases} \quad \text{(A.1)}$$

Within equation 1, E_B(t) is the energy contained within the battery bank, E_{PV}(t) is the energy generated by the PV array, and E_{dem}(t) is the energy demanded by the micro-grid consumers. Represented as Figure A.1 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 equation A.2.

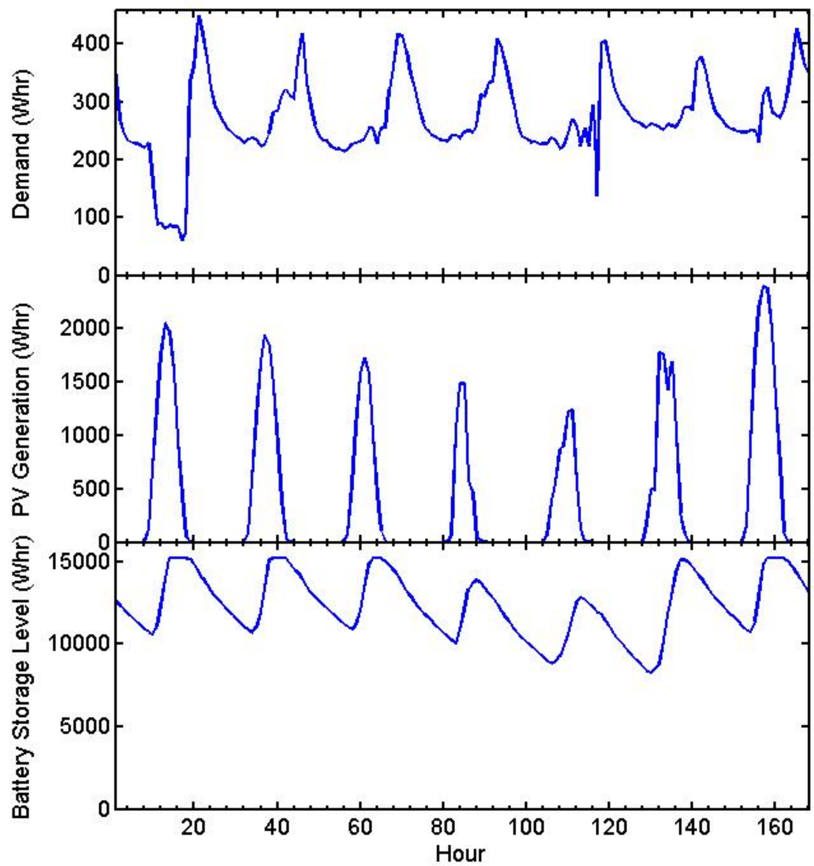

Figure A.1: Energy balance algorithm calculations using weather from January 9, 2005 until Jan 16, 2005. Simulation uses micro-grid demand with refrigerator base load and insolation profile from Segou, Mali. Micro-grid contains 2500 W of nominal PV capacity, and 13000 Whr of nominal battery capacity. Battery low charge disconnect is 6500 Whr. Vertical axis scale for electricity supply and demand in W is on the left side of the figure. Vertical axis scale for battery storage in Whr is on the right of figure.

$$ES(t+1) = E_{dem}(t+1) - (E_{PV}(t+1) + E_B(t) - E_{Bmin}) \quad \text{(A.2)}$$

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 equation A.3.

$$ESP = \frac{\sum_{t=1}^{T} ES(t)}{\sum_{t=1}^{T} E_{dem}(t)} \tag{A.3}$$

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 Appendix Optimization Algorithm

The optimization algorithm calls upon the energy balance algorithm to find all of the PV generation and battery storage combinations which satisfy a particular *ESP*. It then determines which PV and battery combination has the lowest cost. This algorithm can be applied 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 by which the battery bank and the PV array are allowed to change,
- the weather 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 Whr of installed battery capacity.

For a specified *ESP*, the algorithm first finds the smallest PV module which will achieve the *ESP* when given a very large battery bank, with a capacity which is 100 times the peak electricity demand. Then the algorithm increases the PV generation capacity by a fixed step size. With the increased generation capacity, the algorithm recalculates the battery bank capacity, E_{Bmax}, which is necessary to satisfy the desired *ESP*. The algorithm continues to increase PV generation capacity until 10000 Whr have been added. Once we have a comprehensive list of PV and battery options which satisfy a desired *ESP*, the optimization algorithm computes the cost per Whr of electricity for each system combination. Knowing the cost of each PV and battery combination, the algorithm reports the combination with the lowest cost. 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 all reliabilities. From this data, we are able to then construct a cost versus reliability curve for the system. From the cost per kWhr 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 figure A.2

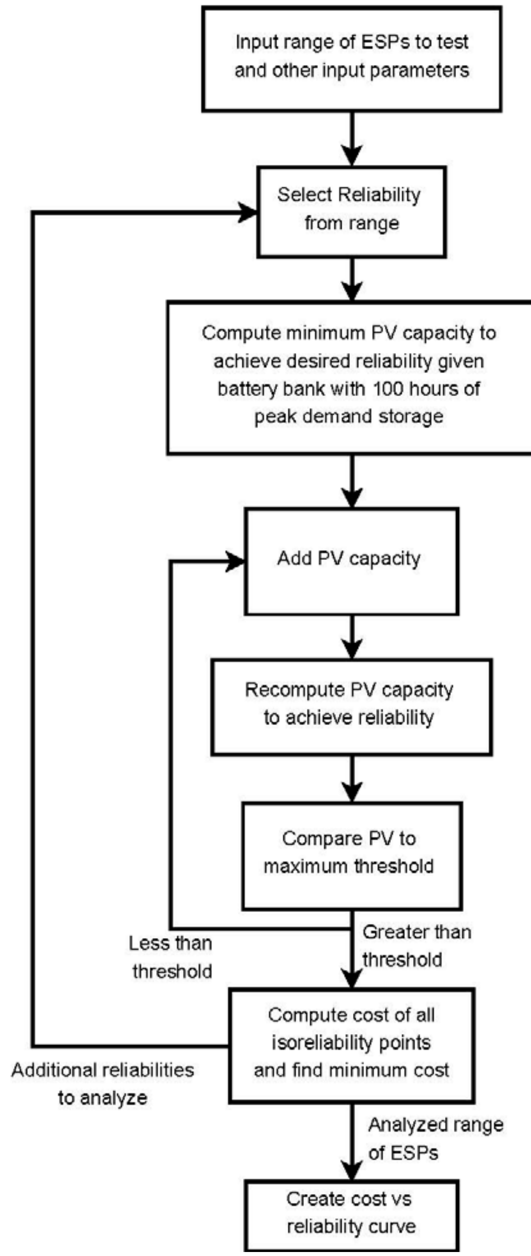

Figure A.2: Summary of Optimization Algorithm

B 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. 133 consecutive data points were missing from the data set. The missing data points were "patched" using the same time of day data from the immediately preceding days. A week of micro-grid generation data is illustrated in Figure A.1

A week of three second resolution demand data was extracted from the main meter on the currently installed micro-grid in the village outside of Segou, Mali. The three second data was 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 generation data is illustrated within Figure A.1

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/Whr. 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 ten percent annual interest rate is added to repayment fees. Table B.1 contains a summary of the input parameters which affected our cost calculations.

	PV	Battery
Cost per Capacity	1.50 USD/W	0.20 USD/Whr
Design Life/Payment Period	20 years	3 years
Interest Rate	10 percent	10 percent
Annual Payment	0.1762 USD/W	0.0804 USD/Whr

Table B.1: Summary of input parameters for micro-grid cost estimation.

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