A Method for Determining the Cost of Highly Available Electricity Considering Grid Unavailability: A case study and applied analysis in Uganda

By Patrick Mark Murphy

B.S. in Electrical Engineering, May 1992, University of Notre Dame
B.A. in Government, May 1997, University of Notre Dame
M.A. in Science and Technology Policy, August 2000, George Washington University

A Dissertation Submitted to

The Faculty of
The School of Engineering and Applied Science
of the George Washington University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

August 31, 2015

Thesis directed by

Johan Rene van Dorp
Professor of Engineering Management and Systems Engineering

The School of Engineering and Applied Science of The George Washington University certifies that Patrick Mark Murphy has passed the Final Examination for the Degree of Doctor of Science as of April 8, 2015. This is the final approved form of the dissertation.

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Patrick Mark Murphy

Dissertation Research Committee:

Johan R. van Dorp
Professor of Engineering Management and Systems Engineering
Dissertation Director

Ekundayo Shittu
Assistant Professor of Engineering Management and Systems Engineering
Committee Chair

Jonathan Pierce Deason
Professor of Engineering and Applied Science
Committee Member

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Acknowledgements

When I began my doctoral studies, I intended to build on my work at the Department of Homeland Security and continue to study problems of electricity resilience in the face of natural disasters and deliberate attacks. Then I was introduced to **Bishop Nicholas Djomo**, Bishop of Tshumbe, Sankuru, Democratic Republic of the Congo, **Sister Rebecca Walo Omana**, President of the Université de Notre Dame de Tshumbe, Sankuru, Democratic Republic of the Congo, and **Father. Joseph Okumu**, Executive Director of BOSCO-Uganda, and Director of the Catechists Training Center in Gulu, Uganda. Their passion, vision and drive to provide for their people's spiritual and economic growth inspired me to change my focus to help improve electricity availability for the more than 1 billion people without access to reliable power. I thank them both for their guidance and assistance. Losaka Fula, Monsignor. Losaka Fula, ma Soeur. Apwoyo Matek, Fr. Joe.

I would also like to thank my advisor, **Professor Rene van Dorp** his patient guidance, and for his flexibility in helping me continue my studies after moving away from DC. Thank you to my doctoral committee, **Professor Ekundayo Shittu, Professor Jonathan Deason, Professor Thomas Mazzuchi,** and **Dr. Ariel Castillo** for their diligent reviews, recommendations and assistance.

My colleague **Ssennoga Twaha**, upon whose foundations I have built this research, is an inspiration. He manages to conduct world class research while working in the challenging conditions outlined in this paper. I thank **Lindsey Forsberg** for her help gathering data and testing models. I thank **Jordan Engel** for his editing assistance, which overcame my inability to write in a consistent tense.

Finally, I thank my children, Emilia, Owen and Charlotte, for their patience while I locked myself in my office to write, for their love and support while I travelled overseas for months on end, and most especially, for bringing me joy.

Abstract

A Method for Determining the Cost of Highly Available Electricity Considering Grid Unavailability: A case study and applied analysis in Uganda

People in developing countries have limited access to electricity, especially in rural and remote areas. As electricity consumption is correlated with economic development, the lack of access to electricity is a key obstacle to achieving economic growth. Techniques for improving access to electricity include grid extension and distributed energy resources (DER), but analyzing the tradeoff between grid extension and distributed generation requires a better understanding of the impacts of grid unreliability. In this dissertation, a new method for simulating unreliable electric grids is presented. The method is then used to determine the cost of reliable electricity in areas where the grid is unreliable. The method is extended in order to calculate the distance at which grid extension of an unreliable grid and DER have the same cost, a point known as the economic distance limit (EDL). Finally, the method is applied to analyze the impact of grid sell-back prices on electricity cost and EDL. The methods are demonstrated for a village in Uganda, but hold universally.

Results indicate that demand for increased availability increases cost, but now the cost per unit of availability can be calculated and used in decision making. Similarly, with fixed demand availability, we see increasing costs as grid availability decreases. This also results in EDL decreasing as grid availability decreases, as there is little value in extending a grid that functions poorly. From the simulation results, linear approximations of some of the key outputs are developed and are demonstrated to be consistent with results. These provide a method for rapidly calculating electricity costs and EDL without the need to perform numerous simulations. Simple calculations for cost of highly available electricity will enable more informed choices for grid-tied and stand-alone electricity generation for system operators and for policy makers.

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Glossary

AC	Alternating Current
ALS	Additional Load Served
CDF	Cumulative Distribution Function
DC	Direct Current
DER	Distributed Energy Resources, electricity generating systems installed near point of use, usually on the customer side of the electric meter.
EDL	Economic Distance Limit, the distance at which electricity from distributed generation and grid extension have the same cost.
FiT	Feed in tariff, the policy mechanism for establishing sellback prices
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GIS	Geographic information system
HDI	Human Development Index, a composite statistic consisting of GDP, life expectancy and years of schooling
HOMER	Hybrid Optimization Model for Electric Renewables, simulation tool developed by the National Renewable Energy Lab
kW	Kilowatt, a measure of power
kWh	Kilowatt-hour, a measure of energy
LCOE	Levelized cost of electricity, the cost per unit of electricity including capital, operations and maintenance, amortized across the life of the system
MLE	Maximum likelihood estimator
MTBF	Mean time between failure, the average time until a system or component fails

MTTR	Mean time to repair, the average amount of time until a failed system is fixed
Net metering	A billing mechanism that credits distributed energy system owners for the electricity they provide to the electric grid; often allowed up to but not exceeding the amount of electricity purchased from the grid, and credited against consumption
PV	Photo-voltaic
Sellback	Selling electricity to the grid from a DER

List of Notations

A	Availability, the fraction of time a system is operational
T_{up}	Up time
T_{down}	Down-time
$I_{j,k,l}$	Indicator variable for simulating grid up time
L_{fail}	Maximum likelihood estimator for grid failure events
L_{repair}	Maximum likelihood estimator for grid repair events
t_i	Time fail event i occurs
t_{il}	Lower interval time for event i, for events occurring outside of observation
t_{iu}	Upper interval time for event i, for events occurring outside of observation
λ	Estimated failure rate
φ	Estimated repair rate
$F_n(t)$	Random variable cumulative distribution function (CDF)
$S_n(t_i)$	Rank ordered cumulative distribution function from observed failure and repair data
E[A]	Expected value of Availability
avg.MTTR/MTBF	Average MTTR/MTBF achieved in simulation
se. MTTR/MTBF	Standard error MTTR/MTBF achieved in simulation
ub.MTTR/MTBF	Upper bound of the 95% confidence interval for *avg.MTTR/MTBF*
lb.MTTR/MTBF	Lower bound of the 95% confidence interval for *avg.MTTR/MTBF*
in.MTTR/MTBF	Input MTTR/MTBF
$\hat{A}$	Availability achieved in simulation

E_d	Desired total energy load
E_u	Unmet energy load
E_s	Actual energy load served
r_u	Unmet load ratio
$\bar{P}_d$	Average power demand
$\bar{P}_u$	Average unmet power
$\bar{P}_s$	Average power of load served
$\bar{P}_d$	Average power demand
$C_a{}^{j,i}$	Average cost of each additional kWh provided by Option j vs Option i
C_t^i	Total cost per year for Option i
L_s^i	Annual load served for Option i
LCOE(A)	Cost of electricity as a function of grid availability (A)
LCOE(A,D)	Cost of electricity as a function of grid availability (A) and grid extension distance (D)
$\partial LCOE/\partial D$	Slope (derivative) of LCOE in terms of grid extension distance
k_{GE}	Electricity cost for extending the grid, per km per year
K_{GE}	Capital cost per kilometer of grid extension
e	Annual electricity demand
EDL(A)	EDL as a function of grid availability (A)
$EDL_{A=1}$	EDL assuming a perfectly reliable grid
$R(A)$	Ratio of electricity cost with and without net metering
LCOE(A,D,S)	LCOE as a function of Availability (A), Distance from the grid (D), and Sellback price (S)

1. Introduction

Electricity is a fundamental driver of economic development. Developing countries are characterized by limited access to electricity, especially in rural and remote areas. More than 1.5 billion people lack access to grid electricity, and 80% of them are in developing countries. Uganda is one such under-electrified country, where less than 15% of the general population has access to grid electricity [1]. To address the lack of electricity access, the research on this topic has been largely devoted to grid extension, grid-connected Distributed Energy Resources (DER) and stand-alone DER. Although researchers and practitioners explore numerous potential solutions, the body of research on the impact of under-electrification in developing countries conducted to date assumes that, where there is access to the electrical grid, there is *continuous* access to the grid. This assumption fails to account for a key variable – the fact that even in places where electrical grids reach people, the grids are unreliable. In developing countries like Uganda, most of the population lives beyond the reach of the electrical grid. Those who live within reach of the grid still experience *hundreds* of outage hours per month.

1.1 Problem Statement and Purpose

Analyses on the trade-off between DER and grid extension performed to date fail to address a fundamental issue – that even where the electric grid reaches people in the developing world, the grids are often not reliable and so fail to address the high outage rates and long outage durations experienced in the developing world, as illustrated in Fig. 1.1. The failure to address reliability and availability along with access may be resulting in a bias toward grid extension and grid-connected systems as the solution to Africa's

electricity shortfalls, when in fact, grid extension should only be a part of the access and availability solution.

The lack of electricity access for 1.5 billion people worldwide and the lack of electricity available electricity for those who have access are the over-arching problems that drive the need for this research, but a complete solution to these problems will take years and billions of dollars. To support this effort, this dissertation focuses on the lack of useful analysis and decision tools for selecting alternatives and determining the cost of delivering reliable electricity.

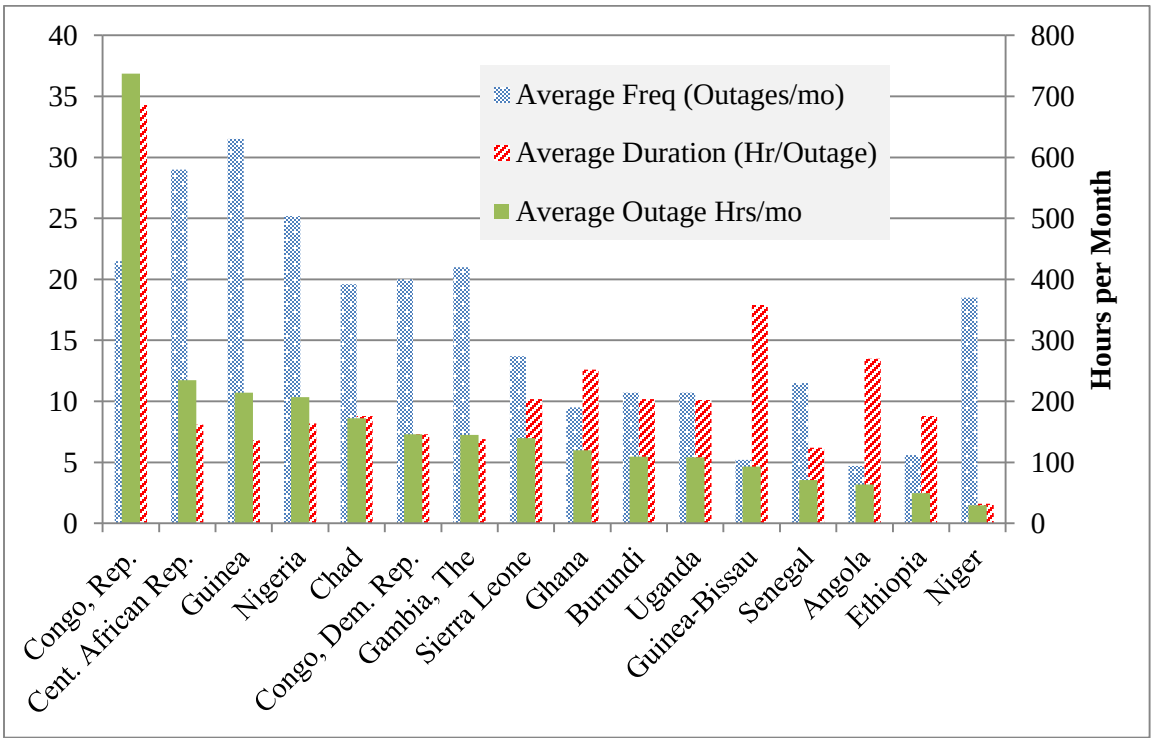

Fig. 1.1 Outage frequency (events/month) and duration (hours/outage) (left axis) and total average outage hours per month (right axis); data from World Bank [2].

1.2 Contribution of the Research

To address this key problem, we generate new simulation techniques and use them to develop simple, closed form methods for estimating electricity costs and economic trade-offs for self-generation vs. grid extension that will better inform the decision between these

options. The purpose of this research is to develop and implement new methods to simulate an unavailable grid in order to analyze the impact of electricity availability from a demand perspective and determine the cost for achieving improved electricity availability. This research addresses the analytical deficit that ignores electrical outages by (1) providing new methods to analyze the impact of grid availability to identify lowest cost DER system configurations to improve electricity availability; (2) applying these methods to calculate the distance at which the economic cost of electrical grid extension and the economic cost of electricity stand-alone generation are the same, a metric known as the Economic Distance Limit (EDL); (3)extending the analysis to then study the impact of Feed in Tariff and grid sellback prices on electricity cost and EDL; and finally (4) presenting simple linear formulae that overcome the need to perform numerous simulations.

To perform this analysis, we use the Hybrid Optimization Model for Electric Renewables (HOMER). As the grid simulated in HOMER is assumed to be reliable, a method to simulate an unavailable grid and integrate it with HOMER is required. This method developed allows us to account for the impact of unavailable grid electricity and determine optimal DER system configurations, predict electricity costs for delivery of reliable power in regions with unreliable grid electricity, and study the impact of the cost of reliable electricity on EDL We demonstrate the methods for a village in Uganda, but the methods hold universally.

Our results indicate that to achieve reliable end user electricity, costs of delivery of electricity increase as grid availability decreases. The methods developed to determine this allows for rationalized investment in DER where the cost increase is justified by a need for improved electricity availability. Options to improve energy access and availability include

grid extension, decentralized microgrids with diesel and renewable based distributed energy resources (DER), and hybrid systems consisting of both grid extension and DER. From the simulation results, we develop and demonstrate simple, closed form estimates of electricity costs to better inform decisions between self-generation vs. grid extension.

1.3 Organization of the Document

Chapter 1 is an introduction to electricity, development, and the challenges faced in the developing world due to a lack of electricity access and availability. Chapter 2 provides a deeper review of the problems and how they are and are not being addressed in the literature. The review is organized in the same manner as the problem statement: electricity access; electricity availability and cost of improved availability; grid extension and EDL; and an additional section detailing the issues faced in Uganda.

Chapter 3 outlines the goals of the research, the hypothesis and the data required to test the hypothesis. Chapter 4 describes the method for testing the hypothesis, beginning with developing grid failure models and incorporating them into economic analysis. This includes some analysis and justification for the use of the exponential random variable based on data from outages in Uganda. The method and the results follow the same pattern of model development, examination of demand availability, extension to grid extension distance, and finally analysis of grid sellback prices. Chapter 5 describes the statistics that drive the analysis, and previews the expected conclusions.

Chapter 6 describes the results, and provides detailed observations on the results. In addition, future work building on this effort is described. The appendix details the HOMER modeling inputs required to replicate the research.

2. Literature Review

The problems to be addressed by this research are summarized as (1) a lack of electricity access for 1.5 billion people worldwide; (2) a lack of electricity availability for those who have access; and (3) a lack of useful analysis and decision tools for selecting alternatives and determining the cost of delivering reliable electricity to those who lack access and availability. The review of literature follows this problem framework, with a final excursion to discuss particular challenges in Uganda.

2.1 Access challenges are well documented

Lack of access to electricity is well documented by the World Bank and the International Energy Association. The World Bank data set "World Development Indicators: Electricity production, sources, and access" provides electricity access data on 88 countries; the numbers have been summarized in Fig. 1.2 [3]. Fifty of these countries leave more than 10% of their populations disconnected; thirty countries have more than 50% disconnected; and a dozen countries leave more than 75% of their population disconnected from modern energy services.

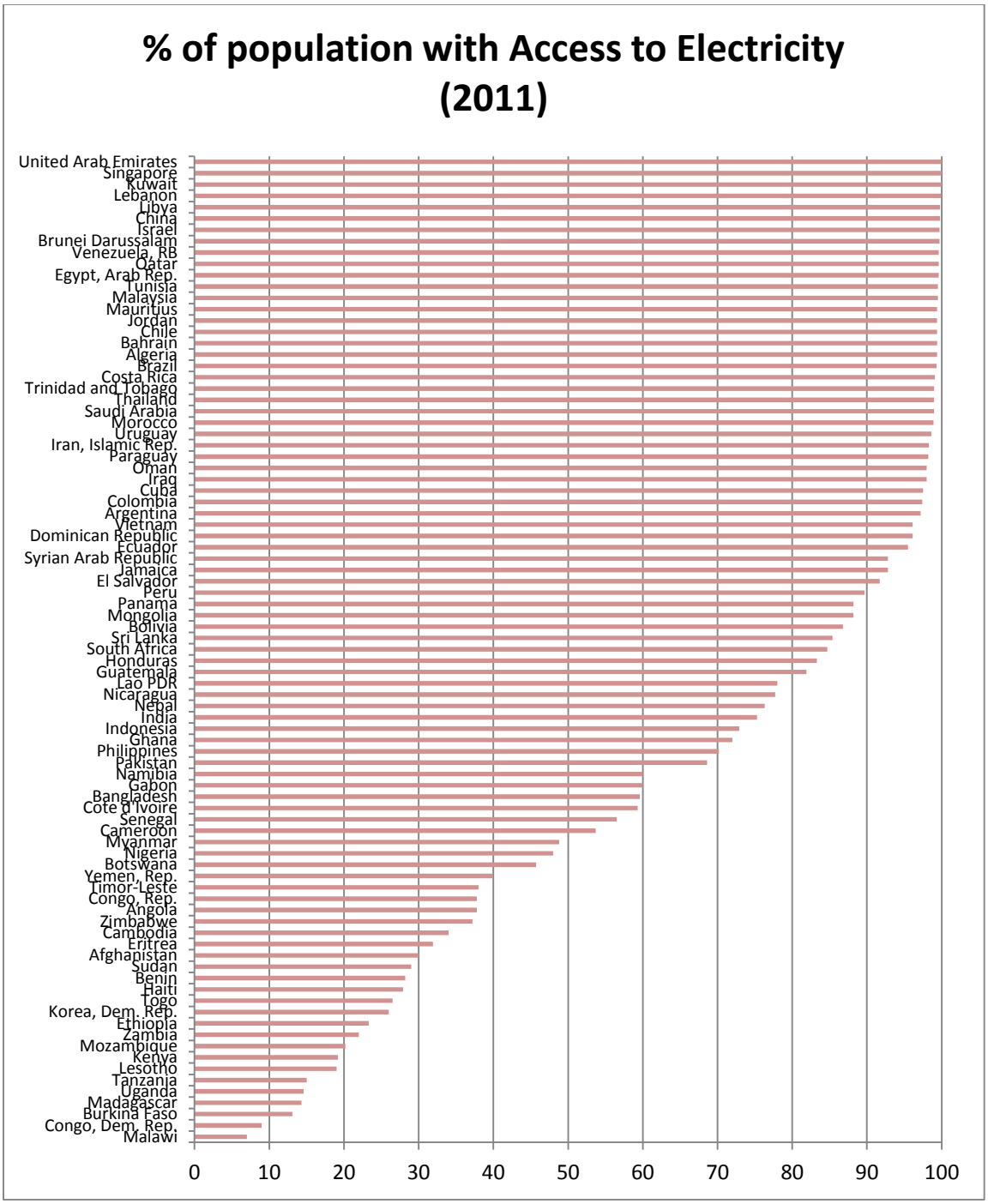

Fig. 1.2 Access to electricity comparison showing that fifty countries leave more than 10% of their populations' disconnected; thirty countries leave more than 50% disconnected; and a dozen countries leave more than 75% of their populations' disconnected from modern energy services. [3]

2.2 Availability documentation is not as extensive, but is indicative

Fig. 1.1 illustrates the frequency and duration of outages in Uganda and 15 other sub-Saharan African countries. On average, Uganda experiences an average of 10.7 outages per month, with a mean duration of 10.1 hours – more than 100 hours of outage per month [2]. As unreliable as the Ugandan grid is, Fig. 1.1 shows that it is far from the least reliable grid in the region. Detailed statistics on outage duration and frequency are available only on a subset of the World Bank surveyed countries, with the best data available on those with recent small and microbusiness surveys. An additional dataset with more countries is the "number of days with outages" survey compiled by Nationmaster.com [4]. This set is lacking detail necessary for estimating duration of outages, but can be used for comparison against more detailed data for consistency. For example, Uganda experiences 70.8 days with outages per year, while DR Congo experiencers 184.0 days with outages per year. This is consistent with the frequency and duration data shown in Fig. 1.1, where DR Congo experiences both more and longer outages than Uganda. Conversely, Nationmaster data on Guinea-Bissau is less consistent with the World Bank Data. Nationmaster shows Guinea-Bissau has 110.5 outage days per year, although Guinea-Bissau's outage frequency is lower than Uganda's at 5.2 outages/month. Average outage durations in Guinea Bissau are longer than Uganda's at 17.9 hours [4]. In sum, the days with outage metric is not terribly useful as an input to stochastic outage modeling; but because the data exists for many more countries than the World Bank data set, it proves useful for some economic comparisons. For modeling, though, we focus on frequency and duration data, where it is available.

It is well understood that a lack of access to affordable energy stunts economic growth and human development, and that increased energy consumption correlates with increased gross domestic product (GDP) and increased human development index (HDI) scores [5] [6] [7] [8]. In addition, a regression of GDP per capita versus the average number of days per year with outages from 91 countries is shown in Fig. 1.3, where the negative correlation between outage days and incomes is observed. Reducing outage days from 100/yr to 10/yr correlates to an increase in GDP per person from $1,900 to more than double that at $5,500. Note that no country with an average of less than one outage day per year has a GDP per capita of less than $10,000. This indicates that reduced power outages are associated with increased GDP, improved economic growth, and development. If constructive efforts are made to reduce or mitigate grid outages, increased GDP can be achieved in Uganda and the dozens of countries that yearly experience an average of more than ten days with outages.

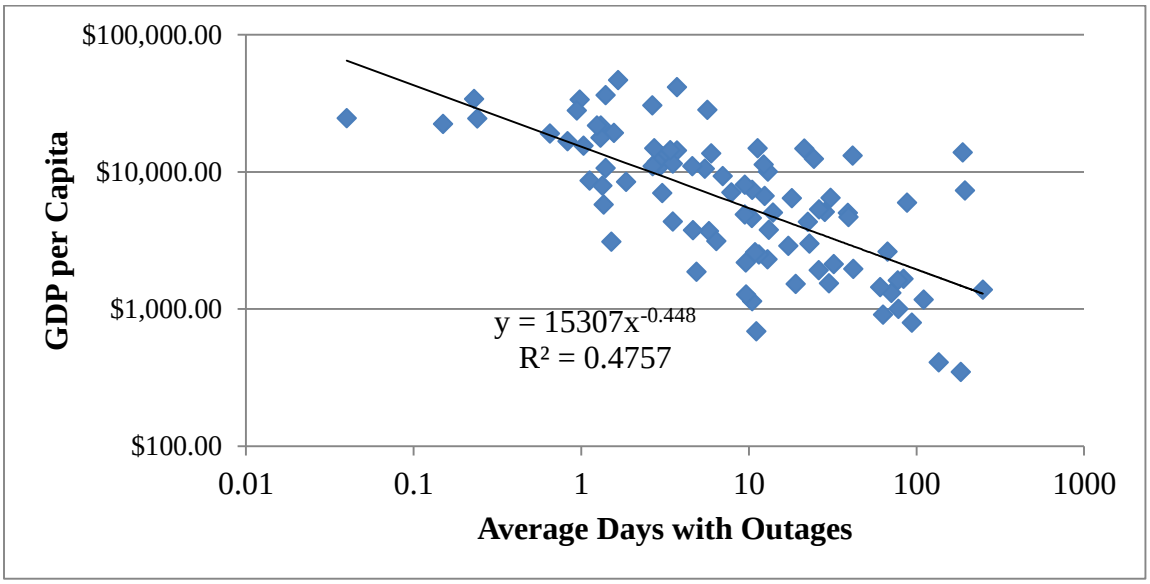

Fig. 1.3. GDP per capita is negatively correlated with the average number of days per year with outages, as shown in the (log-log) plot, data from the World Bank [2]

2.3 Methods and tools for analyzing impact of availability are lacking

One of the reasons grid availability and reliability and random outages are not taken into account in the analysis is that a leading tool for economic analysis of microgrids, Hybrid Optimization Model for Electric Renewables (HOMER), does not include simple methods for incorporating grid availability and reliability. HOMER was developed by the U.S. Department of Energy's National Renewable Energy Lab, and is a powerful tool for analyzing renewable and fuel based DER, especially because it has built-in algorithms to simulate thousands of different systems for every hour of the year, over multiple systems and lifecycles [9]. HOMER then ranks the considered systems by financial performance according to Net Present Value after demonstrating technical feasibility. As such, HOMER has been used extensively for stand-alone and off-grid DER in practical application and in the literature. It remains a preferred tool, because other tools lack HOMER's simple integration into weather, economic and system component and system configuration data.

A number of studies analyze DER comprised of diesel, wind, biomass, and photovoltaic (PV), with comparisons between standalone and grid tied, or grid only systems. Many researchers observe that at short distances and with large loads (driven by large singular loads or by dense populations of smaller loads), grid extension is economically preferable. Das and Balakrishnan [24] add that grid extension is an economical option *if the grid is reliable* [emphasis added]. But grid availability is not considered in most trade-off studies between grid extension and self-generation.

The key metric for such studies is the distance at which grid extension and DER become economically equivalent, named the EDL (economic distance limit). Some EDL results are presented in the literature cited below, but note that EDL is a function of local variables,

and does not apply to different locations, nor even in the same location as key variables change.

Harish et al. [25] suggest that even when grid disruption costs are included in the analysis, standalone DER remains uncompetitive to grid extension at distances of less than 17 km. Methods to address the unreliable grid were not considered, but an interruption cost penalty was calculated and incorporated in the analysis. Mahapatra and Dasappa [26] factor grid availability, but only an average outage-time-per-day is considered, with no analysis of actual duration or frequency of outages; they contend EDL is linearly related to grid availability.

Chueco-Fernández and Bayod-Rújula [27] contend that grid extension projects are preferred at distance of at most 9 km while at higher distances from load location to the existing grid, off-grid PV solutions were found to be more cost-effective than grid extension; grid availability was not considered. For hybrid DER systems in Bangladesh, sensitivity analysis revealed that grid extension is well-suited at a distance of 8 km to 12 km, dependent on wind speed and solar radiation variations; again, grid outages were not considered [28]. Similar studies are also available with varying grid extension distance limits dependent on numerous factors, but not grid availability [29] [30] [31] [32]. [33] [34] [35] [36] [37] [38] [39] [40] [41].

Levin and Thomas's [42] analysis and results on Uganda indicate that grid extension is likely the best option in this densely populated country, but they do not consider the availability of the grid, and in application grid extension has not provided reliable electricity across Uganda. Similarly, Szabo et al. analyze grid extension vs. DER in Africa, providing Geographic Information System (GIS) images and analysis to compare grid

extension to renewable and fuel based DER [43] [44]. Again, much of Uganda is shown to have high potential for grid extension to be the least cost alternative for electricity, but grid availability is not considered.

Letendre and Perez [45] contend that "outage mitigation should be kept in mind to promote deployment of solar PV in such a way that it would have the greatest impact on system reliability". But the reliability impact can only be assessed if grid unavailability is considered. Castillo [46] argues that the lack of consideration may come from the difficulty in calculating the value of improved availability and resiliency. But even where the value cannot be intrinsically calculated, the relative cost of alternatives can be compared to find the optimal architecture for grid-tied and stand-alone DER.

Consideration of grid availability changes the demand for self-generation, alter the optimal DER system configuration, and weaken the case for grid extension as the primary method for increasing access to electricity in the developing world. As grid extension and investment in bulk generation and transmission infrastructure has been the method of choice for expanding access to electricity, this could have important impacts on energy policy in the developing countries.

To address the failure to consider grid availability, here we expand on the method to determine optimal microgrid architectures considering an unavailable grid with randomized outages from Murphy et al [47]. Murphy et al.[47] re-examined the grid-connected PV system presented in Twaha et al. [48]. Twaha et al. [48] did not consider grid availability; Murphy et al. [47] use the village loads, microgrid architecture and economics from Twaha et al. [48] to incorporate grid unavailability impact and determine how grid outage duration and frequency affect the resulting optimal configurations,

components and the Levelized Cost of Electricity (LCOE) at various thresholds for demand availability. The research presented includes an improved method for simulating an unreliable grid and use of that method to perform a detailed analysis of stand-alone generation vs. grid extension with simulation and calculation of EDL.

Table 2.1 Summary of EDL calculations from Literature Survey

EDL (km)	Country / Region	Citation	Note
17	India	Harish et al, 2014	• GM Morgan; • Interruption cost penalty; • Accepts unreliability • EDL < 0 for some A (disconnect and DER)
8-12	Bangladesh	Nandi and Ghosh, 2010	• Dependent on wind speed and solar availability
9	Chile	Chueco-Fernandez and Bayod-Rujula, 2010	• Focus on pumping; ~large singular load
NA	Uganda, SSA	Levin and Thomas,	• GIS sensitivity analysis
NA	Africa	Szabo et al, 2011 Szabo et al, 2013	• GIS for grid vs various DER; not hybrid grid connected
NA	multiple	Mahapatra and Dasappa, 2012	• EDL linear w/ availability; support for SA vs. GE

2.4 Illustration in Uganda

Decades of international development efforts have failed to deliver reliable electricity to the developing world. Eighty percent of people in the developing world lack access to grid electricity, leaving 25% of the world's population unable to connect to modern energy services [10] [11] [12]. Across the developing world, even where energy is available, grid

systems are unreliable. Many African countries experience hours of electrical outages each day [13]. For example in Uganda the fewer than 15% of individuals who do have access to the grid experience 70 to 125 days per year with electrical outages [4]. From World Bank statistics we can also see that Ugandans experience an average of 10.7 outages a month, each approximately 10.1h in length [2].

This level of unreliability stifles economic activity and generates indirect costs that are much higher than the cost of lost electricity. As a point of comparison, in Germany, cost of unmet demand has been estimated at $11.60/kWh – more than 30 times the market cost per kWh of electricity [14]. In the Netherlands, the average of one outage of 2 hours every 4 years incurs costs of $68 million per year, at a cost per year per household of $3.81, and per year per small and medium-sized enterprise of $45.07. Considering that Uganda averages more than 2 hours of outages *every 12 hours* (1500 times more grid down time than the Netherlands) we can expect a much higher impact on the Ugandan population and economy, if only as un-met growth potential [15].

The grid in Uganda fails to provide reliable electricity where it currently reaches, which does not instill confidence in grid extension as a method for delivery of reliable electricity to the disconnected. In other words, extension of the grid alone will at most provide unreliable electricity to more people. Especially considering that increased connections will also increase the demand that already exceeds production capacity, grid extension alone will likely *decrease* grid reliability and availability.

Despite investment in generation capacity like the Bujagali Dam, alleviation of generation shortfalls has only been temporary and rolling blackouts are expected to be reinstated within the next 6 months [16] [17] [18]. The trend is consistent across Africa,

where new electrical connections are not keeping up with population growth and even when new capacity is installed and a quarter of installed capacity is idle due to aging plants and poor maintenance [19]. Lack of electricity access and availability in the developing world must be addressed, but various solutions continue to face economic and policy barriers [6] [19] [20]. For example, in both Mozambique and Tanzania, barriers to renewable energy exploitation for on and off grid installations were summarized as: (1) a lack of trained personnel, (2) ineffective planning and (3) other technical issues [21]. For Brazil, Gomez and Silveira [22] conclude that the institutional and financial support to rural electrification makes off-grid renewable energy technically and economically suitable solutions for the Amazon region. They cite regulatory framework as one of the major barriers that may affect these initiatives. Blum et al. [23] noted that limited private-sector investment accounts for the low distribution of renewable-energy based village grids and therefore delays rural electrification. In effect, the lack of access and lack of availability means that in Uganda and much of Africa, it is not a choice between grid extension and distributed energy resources (DER); it is a choice between DER and building a new bulk grid from the bottom up.

3. Research Goals and Hypotheses

3.1 Research Goals

The goal of this research is to generate new simulation techniques and use them to develop simple, closed form methods for estimating electricity costs and economic trade-offs for self-generation vs. grid extension that will better inform the decision between these options. We incorporate consideration of grid availability into calculations for LCOE for grid connected DER when the availability of the grid does not meet energy quality demands of the customers served. The resulting simulations, calculations and analysis improve the economic justification for self-generation, increase the scale of local generation in grid tied hybrid DER, and weaken the case for grid extension in many circumstances. As grid extension and investment in bulk generation and transmission infrastructure has been the method of choice for expanding access to electricity, this could have important impacts on energy policy, especially in developing countries.

3.2 Hypotheses

Electricity availability demand can be considered a demanded quantity, as per traditional economic supply and demand theory. The relationship between electricity availability demanded and electricity price will thus follow classic supply and demand curves. Given a fixed level of availability, this is effectively equivalent to a fixed supply of (unreliable grid) electricity. Increased electricity availability demanded translates literally to additional units of electricity demanded, shifting the demand curve to the right. Similarly, for a fixed level of electricity demand (e.g. 100% end user availability), decreasing grid availability effectively shifts the supply curve to the left.

3.2.1 LCOE increases with increased demand for available electricity, where grid electricity availability is lower than availability demanded.

As noted, traditional supply and demand theory would indicate that to meet additional demand, DER can be employed, but the unit cost will be higher than the basic grid price (otherwise, DER would be the primary source, and the grid would be unnecessary).

3.2.2 LCOE increases if electric grid availability decreases

For a given level of electricity availability demanded (e.g. customer requires 90%, 95% or 100% of electricity demand met), LCOE increases if electric grid availability decreases (inverse proportionality relationship). This stems again form traditional supply and demand, as the grid supply curve shifts to the left, additional more expensive sources will be sought to meet the demand.

3.2.3 EDL decreases as availability of grid electricity decreases

The price of electricity at a distance from the existing grid is a function of both the distance (capital investment required to extend the grid) and the price of electricity, the cost of electricity (where the grid currently exists). EDL is the distance at which this price is the same as the cost of self-generation. Following from 3.2.3, then EDL should also decease as grid availability decreases.

3.3 Data Requirements for Research

3.3.1 Availability data

Mean Time Between Failure (MTBF) and Mean Time to Repair (MTTR), and/or Availability for the Ugandan grid and various other electric grids for comparison. Data required to calculate both are available from the World Bank [2].

3.3.2 Grid Architecture

To perform this analysis, a microgrid architecture and scenario, including loads and load variation, potential components, component costs, cost of grid extension, cost of electricity from the grid is required. The grid architecture remains consistent with Twaha et al. [48] and Murphy et al. [47] for consistent comparison.

4. Research Method

4.1 Research Plan

The over-arching research plan is to incorporate grid availability as an input into simulations for designing and calculating stand-alone microgrid and grid connected microgrid architectures and economics. To do this, we must first develop methods to simulate grid failures, as detailed below in section 4.1.1. We then incorporate those methods into simulations of microgrids, as shown in section 4.1.2. Outcomes include optimal systems architectures and supporting economics, including impacts on EDL calculation.

4.1.1 Develop methods to simulate grid failures

Including random variation in the number and duration of outages impacts the calculations for cost effectiveness of grid extension and grid tied DER, with additional impacts on the tradeoff and optimal system design that are not straightforward. Consider, for example, the production of an item that requires labor and electricity as inputs. A grid extension with predictable or scheduled outage times of 12 hours per day allows for planning of production schedules to match electricity availability. If the same total duration of outages were achieved with a distribution grid with random outages and a mean time between failures (MTBF) of 12 hours and mean time to repair (MTTR) of 12 hours, it would be much more costly to adapt a workforce to the randomly varying power availability. Also, designing DER optimized for the frequency, duration, and variation in outage times to achieve the desired minimum availability and reliability would be more costly as compared to one that is optimized for a fixed outage schedule. One must conduct

the analysis, either in closed form or in simulation, to determine if grid extension, grid-tied DER or standalone DER are optimal, or whether any such options are even affordable.

One of the reasons grid availability and reliability and random outages are not taken into account in most of the analysis is that one of the leading tools for economic analysis of microgrids, HOMER, does not include simple methods for doing so. HOMER is a useful tool for analyzing renewable and fuel based DER, especially because it has built in algorithms to simulate thousands of different systems for every hour of the year, over multiple year lifecycles [9]. HOMER then ranks the considered systems by financial performance (Net Present Value – NPV) and technical feasibility. HOMER has been used extensively for stand-alone and off-grid DER analysis [28] [38] [29] [39] [48]. But in all of the HOMER-based analyses, if the grid is connected it is assumed available 100% of the time.

In the real world, given the World Bank data shown in Fig. 1.1, we can calculate the actual availability and components of MTTR and MTBF for the grid in Uganda [2]. Availability is the percentage of time that a system is operational, or the time the system is up (T_{up}), divided by the total time at risk ($T_{total} = T_{up} + T_{down}$) [49] [50]. For the average month lasting 730 hours, then Uganda's 10.7 outages per month averaging 10.1 hours long gives a T_{down} = (10.7 x 10.1) or 108 hours of downtime per month.

As shown in the general form in Eqn. (4.1) availability (A) can be calculated for any country or region from only the average downtime experienced per month [49] [51]:

$$A = \frac{T_{up}}{T_{up}+T_{down}} \tag{4.1}$$

$$= \frac{MTBF}{MTBF+MTTR} \tag{4.2}$$

Where

T_{up} = average up-time per month (hours)
T_{down} = average down-time per month (hours)
MTBF=Mean time between failure (hours)
MTTR=Mean time to repair (hours)

As MTTR is defined as the mean time to repair a failed component and bring the system back to a functioning status [49], in this case it is simply the average time the grid is down per outage. Knowing MTTR and A, we can calculate MTBF from Eqn. (4.2). For the Ugandan example, MTTR = 10.1 hours, MTBF is then calculated as 58.1 hours and availability A is 0.85. This signifies that the grid is only available 85%, not 100% as assumed in the previous research, hence the need to incorporate grid availability as a factor into analysis.

Although we can calculate A, MTTR and MTBF for the grid connection in general, HOMER does not include methods to easily enable simulation of an unreliable grid. HOMER does provide a recommendation for a modeling an unreliable grid using a generator module with scheduled downtime to approximate an unreliable grid, and modifying the parameters of the generator and the fuel to match the cost of grid electricity [52]. As advised in the HOMER user group website, Murphy et al. used this method to calculate LCOE for reliable electricity; we created a generator called "Grid Proxy" with 100% efficiency, created a new fuel for the "Grid Proxy Generator" called "Grid Electricity" and defined it to have 1 kWh/kg of fuel, and a price of $0.171/kWh [47]. A full description of the HOMER inputs used is provided in Appendix A.

To approximate random failures, we simulated grid outage times using Excel. The outages were simulated using an exponential pseudo-random variable generator using MTBF and MTTR calculated from the World Bank data for Uganda. See section 4.1.1.1

below for a justification of the use of the exponential random variable to simulate outage durations and frequencies.

To populate the HOMER generator schedule, the simulator was used to generate 24 up-time and down-time schedules (January weekdays, January weekends, February weekdays, etc.) of 24 hours each. The schedule can be represented as a 24x12x2 matrix of indicators ($\mathbf{I_{jkl}}$) where *j* indicates the hour of the day, *k* indicates the month of the year and *l* indicates weekday (1) or weekend (2). First, a seed value was simulated to indicate whether the grid was up or down in the time preceding the simulation. The seed value $\boldsymbol{I_{0,0,0}}$ was simulated from the Availability in Eqn. (4.1), given that the probability that the system is on at any given time is the availability [49]. The seed value is then modeled in Excel such that:

$$\boldsymbol{I_{0,0,0}} = \begin{cases} 0 \; if \; \boldsymbol{R1} > A \\ 1 \; if \; \boldsymbol{R1} \leq A \end{cases} \tag{4.3}$$

Where

R1 = *Unif* **(**0, 1), generated in Excel

Subsequent $\mathbf{I_{j,k,l}}$ were simulated as exponential arrivals of a failure event if $\mathbf{I_{j-1,k,l}} = 1$ or repair event if $\mathbf{I_{j-1,k,l}} = 0$. For a possible failure event when $\mathbf{I_{j-1,k,l}} = 1$, we simulate another random variable **R2** that is uniform on (0,1), and transform it into an exponential random variable **E1**. This is performed by noting that the failure rate for an exponential random variable, λ_f, is equal to the inverse of the MTBF, that is $\lambda_f = 1/\text{MTBF}$ [53]. The arrival time of the next failure can be generated as: [53] [54]

$$\boldsymbol{E1} = -\frac{1}{\lambda_f}\ln(1 - \boldsymbol{R2}) \tag{4.4}$$

Thus, when $\mathbf{I_{j-1,k,l}} = 1$ (the grid is on), we can simulate whether a failure occurs in the next hour such that if **E1** > 1 hour, no failure occurred and:

$$\boldsymbol{I_{j,k,l}} = \begin{cases} 0 \; if \; \boldsymbol{E1} > 1 \\ 1 \; if \; \boldsymbol{E1} \leq A \end{cases} \tag{4.5}$$

We can continue for each $\boldsymbol{I_{j,k,l}}$ by using the memory-less property of the exponential random variable [54]. The availability realized in simulation, $\hat{A}$, can be calculated using Eqn. (4.1) and the simulation results.

4.1.1.1 Justification for the use of an exponential random variable

Exponential failure rate models are commonly used for analysis and simulation of component and system failures and recoveries [54] [53]. The method is consistent with outage simulations based on a Poisson arrival process, as the exponential arrival times simulated generate Poisson distributions for outages and repairs [55] [56] [53] [54]. To justify the use of exponential models for grid failure and recovery in Uganda, we first confirm that actual failure and repair rates are consistent with exponential failure and repair models. The utility company in Uganda, UMEME, does not publish detailed failure statistics so instead we have collected failure and recovery data from Gulu, Uganda. The data include 21 failure and 18 repair events over 3 months in 2012 and 2013, as shown in Table 2.2.

For both the failure and repair events, we calculate maximum likelihood estimators (MLE) for the rates, perform Kolmogorov-Smirnov (K-S) tests for exponential distribution [57] [58], and compare the sample data to a cumulative distribution function built on the MLE exponential rate. Failure data are extracted from Table 4.1 and shown in Table 4.2 (failures) and Table 4.3 (repairs). For one failure event (number 3), the system was not under observation as the failure occurred at night; it is therefore considered to have failed during the unobserved interval. Similarly, one repair event (number 3) is interval censored.

The first repair event was also unobserved, but occurred after 24 hours of observation' it is therefore right censored.

The MLE for the failure events is thus calculated from [59] as:

$$L_{fail} = \left(e^{-\lambda t_{3l}} - e^{-\lambda t_{3u}}\right) \prod_{i=1,2,4-21} (\lambda e^{-\lambda t_i}) \tag{4.6}$$

where

t_i = time of fail event i,
t_{il} = lower interval time for event i
t_{iu} = upper interval time for event i
λ = the estimated failure rate

Selecting λ that provides the maximum L_{fail} gives λ = 0.0259, with MTBF = 1/ λ = 38.6. This is lower than the MTBF calculated from World Bank data, but that is expected as the World Bank data is largely from Kampala, the capital, and Gulu is a remote location with a more fragile grid.

To confirm that time to fail is exponentially distributed, we perform a Kolmogorov-Smirnov test for exponential distribution [57] [58]. We sort the failure events from shortest to longest duration and calculate $S_n(t_i) = n/m$ where n is the rank order an m is the count of observations. We then use Excel to calculate the cumulative distribution function for the exponential with MLE λ = 0.0259 such that $F_n(t)$ = EXPONDIST(t_i, λ, TRUE). We then calculate the absolute difference between $S_n(t_i)$ and $F_n(t)$. The maximum difference over all *n* becomes the D statistic, which in this case is D = 0.176. We compare the D statistic to the 95% K-S critical value, D_{crit} from Zaiontz [58], D_{crit} = 0.289. As D < D_{crit}, we conclude that there is no significant difference between the data and data coming from an exponential distribution with λ = 0.0259. Fig. 4.1 presents $S_n(t_i)$ and $F_n(t)$ graphically, and further demonstrates that the collected data is consistent with an exponential distribution.

Table 4.1 Failure and recovery events for grid electricity, Gulu, Uganda

Event Time	Event Type	Fail #	Fix #	Hours Lower/ Exact	Hours Upper	Notes
10/31/12 0:00	start					Grid on
11/3/12 9:00	fail	1		81.00		
11/4/12 9:00	fix		1	24.00	inf	
	end					Censored Grid on
1/7/13 0:00	start					Grid on
1/7/13 16:00	fail	2		16.00		
1/9/13 16:00	fix		2	48.00		
1/13/13 21:00	fail	3		101.00	110.00	Failed at night, interval
1/14/13 18:30	fix		3	12.50	21.50	
1/15/13 0:00	fail	4		5.50		
	end					Censored, while failed
1/17/13 6:00	start					Grid on
1/20/13 13:30	fail	5		79.50		
1/20/13 16:19	fix		4	2.82		
1/21/13 7:47	fail	6		15.47		
1/21/13 8:40	fix		5	0.88		
1/22/13 11:41	fail	7		27.02		
1/22/13 14:41	fix		6	3.00		
1/23/13 20:30	fail	8		29.82		
1/24/13 10:00	fix		7	13.50		
1/30/13 13:30	fail	9		147.50		
1/30/13 18:45	fix		8	5.25		
1/30/13 23:59	fail	10		5.23	inf	
	end					Censored, while fail
2/15/13 0:00	start					Grid on
2/15/13 5:00	fail	11		5.00	inf	
2/15/13 6:00	fix		9	1.00		
2/19/13 8:50	fail	12		98.83		
2/19/13 9:45	fix		10	0.92		
2/20/13 12:15	fail	13		26.50		
2/20/13 13:00	fix		11	0.75		
2/21/13 13:05	fail	14		24.08		
2/21/13 19:30	fix		12	6.42		
2/24/13 14:55	fail	15		67.42		
2/24/13 15:55	fix		13	1.00		
2/25/13 12:55	fail	16		21.00		
2/25/13 13:20	fix		14	0.42		
2/26/13 10:40	fail	17		21.33		
2/26/13 11:30	fix		15	0.83		
2/26/13 14:25	fail	18		2.92		
2/26/13 14:45	fix		16	0.33		
2/26/13 16:50	fail	19		2.08		
2/26/13 17:15	fix		17	0.42		
2/27/13 11:50	fail	20		18.58		
2/27/13 12:10	fix		18	0.33		
2/27/13 23:59	fail	21		11.82	inf	
	end					

Table 4.2 Failure events

Fail Event #	Censor	Hours
1		81.0
2		16.0
3	Interval	(101.0-110.0)
4		5.5
5		79.5
6		15.5
7		27.0
8		29.8
9		147.5
10		5.2
11		5.0
12		98.8
13		26.5
14		24.1
15		67.4
16		21.0
17		21.3
18		2.9
19		2.1
20		18.6
21		11.8

Table 4.3 Repair Events

Repair Event #	Censor	Hours
1	Right	>24.0
2		48.0
3	Interval	(12.5 - 21.5)
4		2.82
5		0.883
6		3.0
7		13.5
8		5.25
9		1.0
10		0.917
11		0.75
12		6.45
13		1.0
14		0.417
15		0.833
16		0.333
17		0.417
18		0.333

For repair the MLE is calculated from [59] as:

$$L_{repair} = (e^{-\varphi t_1})(e^{-\varphi t_{3l}} - e^{-\varphi t_{3u}}) \prod_{2,4-18} (\varphi e^{-\varphi t_i}) \tag{4.7}$$

where

t_i = time of repair event I,
t_{il} = lower interval time for event i
t_{iu} = upper interval time for event i
φ = the estimated repair rate

Selecting φ that provides the maximum L_{repair} gives φ = 0.135, with MTTR = 1/ φ = 7.41.

To confirm that time to fail is exponentially distributed, we perform a Kolmogorov-Smirnov test for exponential distribution [57] [58]. We sort the repair events from shortest to longest duration and calculate $S_n(t_i) = n/m$ where n is the rank order an m is the count of observations., We then use Excel to calculate the cumulative distribution function for the exponential with MLE φ = 0.135 such that $F_n(t)$ = EXPONDIST(t_i, φ, TRUE). We then calculate the absolute difference between $S_n(t_i)$ and $F_n(t)$. The maximum difference over all *n* becomes the D statistic, which in this case is D = 0.429. We compare the D statistic to the 95% K-S critical value, D_{crit} from Zaiontz [58], D_{crit} = 0.294. As D > D_{crit}, we conclude that there is significant difference between the data and an exponential distribution with φ = 0.135. Fig. 4.2 presents $S_n(t_i)$ and $F_n(t)$ graphically, and further demonstrates that the collected data is inconsistent with an exponential distribution with φ = 0.0259.

To check if an alternate exponential frequency could improve the model fit, we solve for a $\varphi_{bestfit}$ such that it achieves the minimum D statistic, called $D_{bestfit}$. In this case $\varphi_{bestfit}$ = 0.458, MTTR = 2.18, and $D_{bestfit}$ = 0.188. As $D_{bestfit}$ < D_{crit}, we conclude that there is no significant difference between the data and data coming from an exponential distribution with φ = 0.458. Fig. 4.2 shows $S_n(t_i)$ and *[$F_n(t)$ best fit*] along with the previous curves. This demonstrates that the collected data is reasonably consistent with an exponential distribution with φ = 0.458, especially for the repair events with shorter durations.

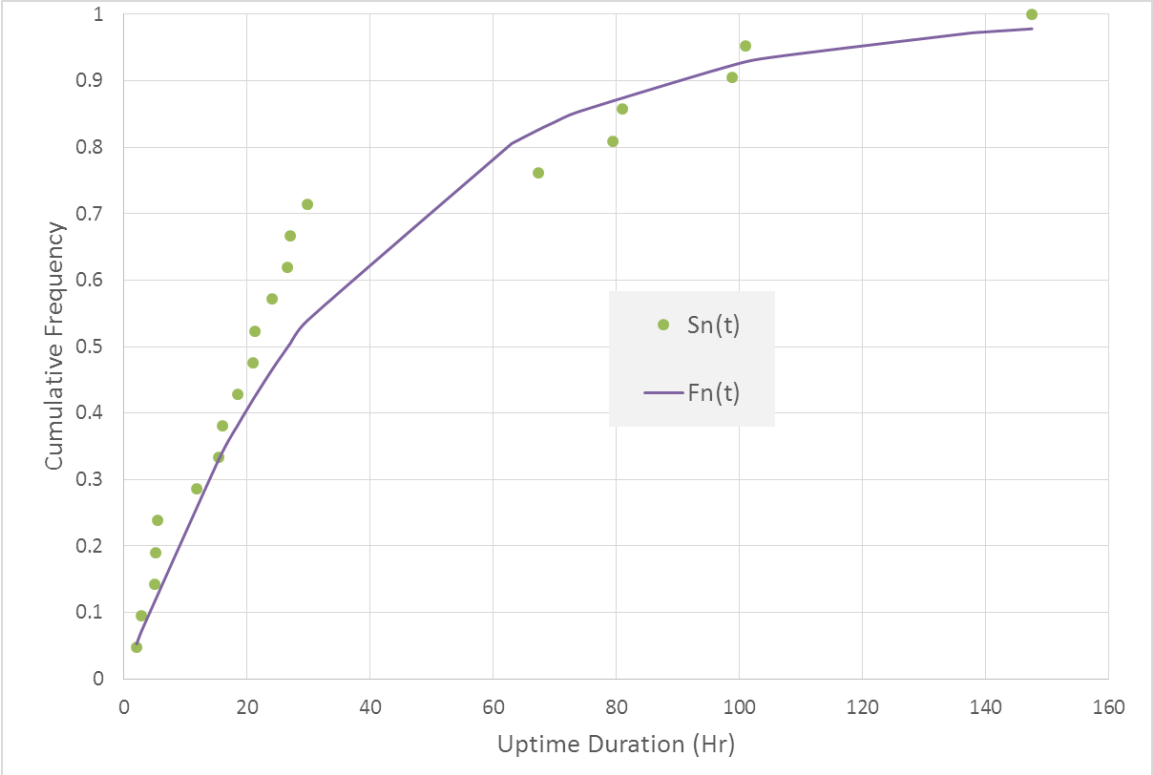

Fig. 4.1. Comparison of sample data and the MLE exponential distribution for grid failure data from Gulu, Uganda.

Although the MLE exponential is not a good fit for the repair events, for several reasons we continue the analysis with the exponential model for both failure and repair. First, we can solve for a higher repair rate exponential that passes the K-S test, so there is an exponential that we fail to reject. Second, the method for inputting MTTR into the HOMER modeling tool does not allow for a completely random schedule and already alters the exponential failure rate, as is shown in section 6.1.1 below. Third, we see in the analysis that the availability rate is the key input variable for explaining electricity cost, regardless of MTTR and MTBF or the random variation in MTTR and MTBF. Fourth and finally, we have only 18 events on which to base the decision. Before an exponential model is incorporated into advanced grid failure analysis tools, more study is required, but for our purposes, generating an appropriate availability rate suffices.

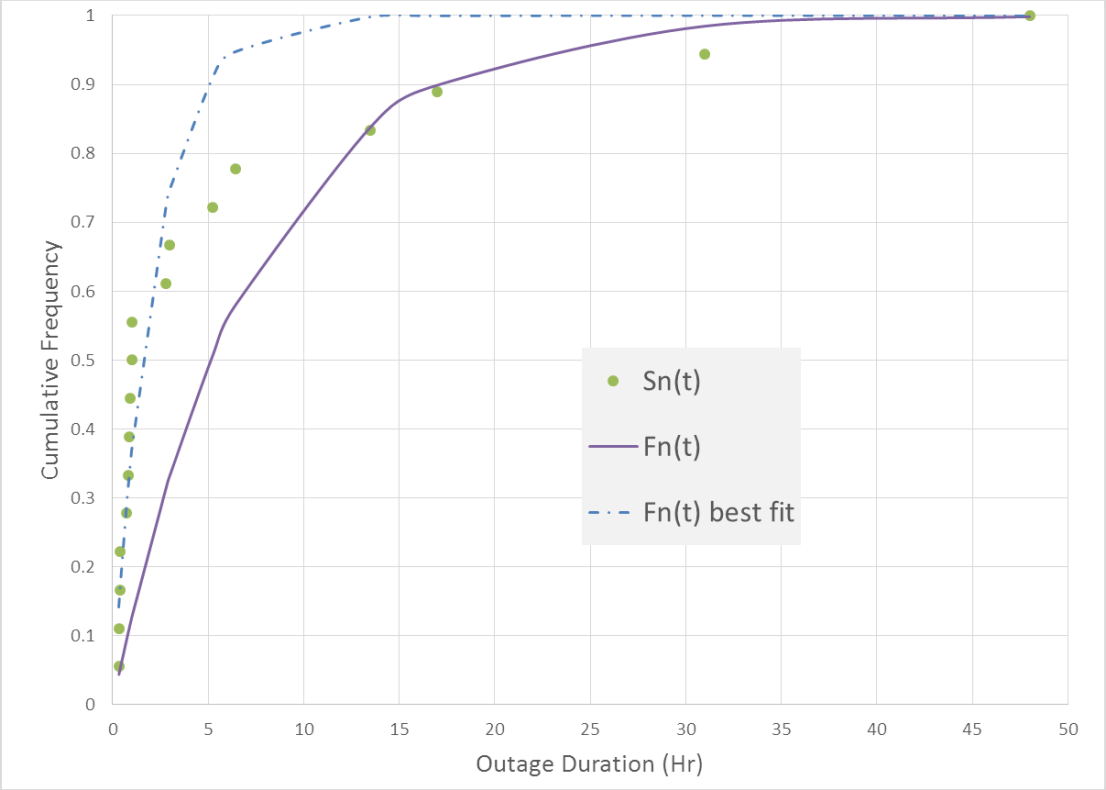

Fig. 4.2. Comparison of sample data and the MLE exponential distribution for grid repair data from Gulu, Uganda.

4.1.2 Develop methods to incorporate unavailable grid simulations into microgrid analysis

To model an unavailable grid, we compare three system configurations. As a baseline we use the microgrid architecture model developed by Twaha et al. [48] that did not consider grid failure as a possibility, hence the grid was assumed to be 100% available as shown in Fig. 4.3. The system architecture consisted of a solar PV connected to the grid with the battery as backup. We updated this work in 2014 when we considered the element of grid outages [47]. As noted, a proxy generator was used to simulate an unavailable grid, as the modeling tool (HOMER) does not include provision for modeling grid failures. This architecture is shown in Fig. 4.4 obtained by modifying some parameters in model 1 but with the same load profile, solar resources, and economics. We develop another method

with the proxy generator eliminated and replaced with a modeling method that inserts an infinite price for grid electricity during simulated outages, as indicated in Fig. 4.5. This "Infinite Price" method allows for incorporation of peak and off peak pricing and selling power back to the grid, both of which are unavailable in the "grid proxy generator" method.

4.1.2.1 Additional Detail on the Infinite Price Model

As an alternative method for incorporating grid outages, we insert an infinite price for grid electricity during simulated outages as indicated in Fig. 4.7. This allows for incorporation of both purchase from and sales to the grid. An effectively infinite price for electricity from the grid of (10^{20}/kWh is set during periods of simulated outages; during the same periods, a sellback price of $(-1)/kWh is assigned, preventing electricity from being sold to the grid while the grid is down.

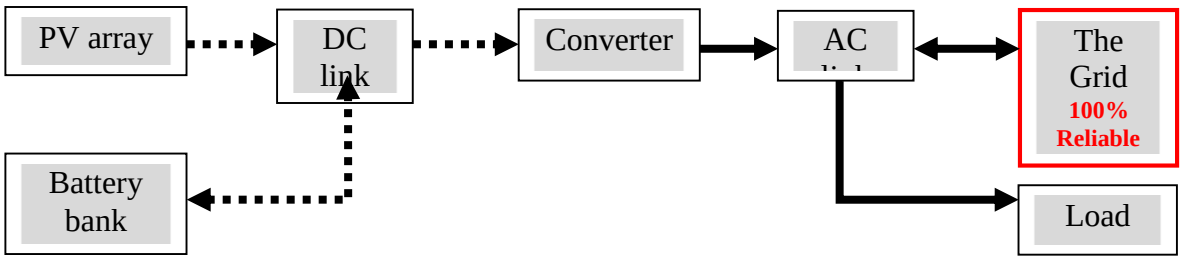

Fig. 4.3 Model 1: Grid-connected solar PV system design layout [48]

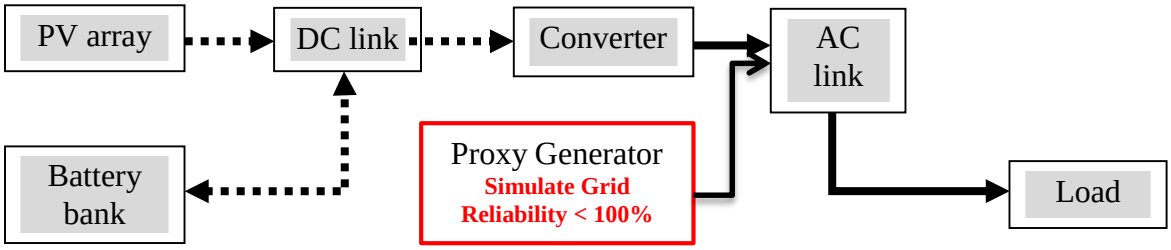

Fig. 4.4 Model 2: Grid-connected solar PV system with proxy generator [47]

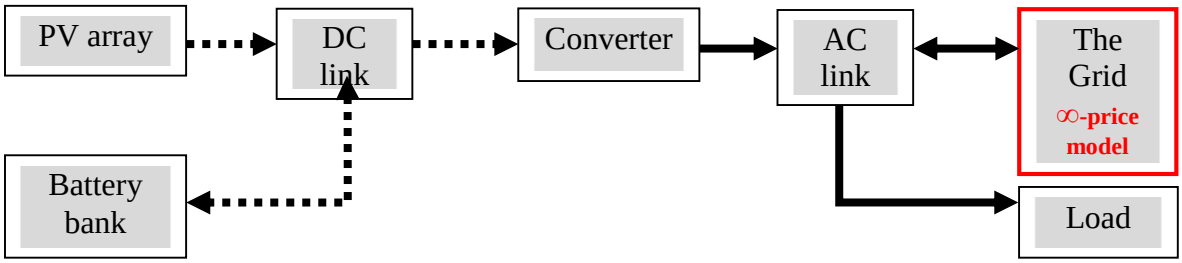

Fig. 4.5 Model 3: Grid-connected solar PV system with proxy generator replaced with a novel method for simulating an unavailable grid in HOMER

4.1.3 HOMER Simulation

Simulation focuses on three tests: (1) a maximum capacity shortage requirement (availability constraint), (2) impact of grid availability on cost of electricity with availability demand A =1; and (3) impact of grid availability and distance from the grid on cost and EDL calculation.

4.1.3.1 Demand Availability.

Demand availability is compared in 9 scenarios, with allowable downtime percentages of 0.20, 0.15, 0.10, 0.05, 0.04, 0.03, 0.02, 0.01 and 0.00. The existing unreliable grid in Uganda meets the 0.20 threshold, while storage or additional generation is required to meet the more stringent end user availability requirements, with an expected increase in LCOE to meet increased availability requirements.

Allowing a capacity shortage greater than zero enables the HOMER optimizer to shed short duration, high peak loads in order to deliver a less expensive system. For example, a 0.05 capacity shortage ratio means that a system that meets 95% of the annual electric load plus the operating reserve is considered acceptable [9].

4.1.3.2 Grid availability and grid extension distance impacts on LCOE and EDL

In this analysis, we develop 7 different scenarios for grid MTBF and MTTR with the allowable downtime set to 0. In addition to the World Bank data for Uganda MTBF and MTTR, we simulate six additional scenarios for comparative analysis across a range of availability levels. Table 4.4 summarizes these scenario inputs and the expected value of Availability (*E[A]).*

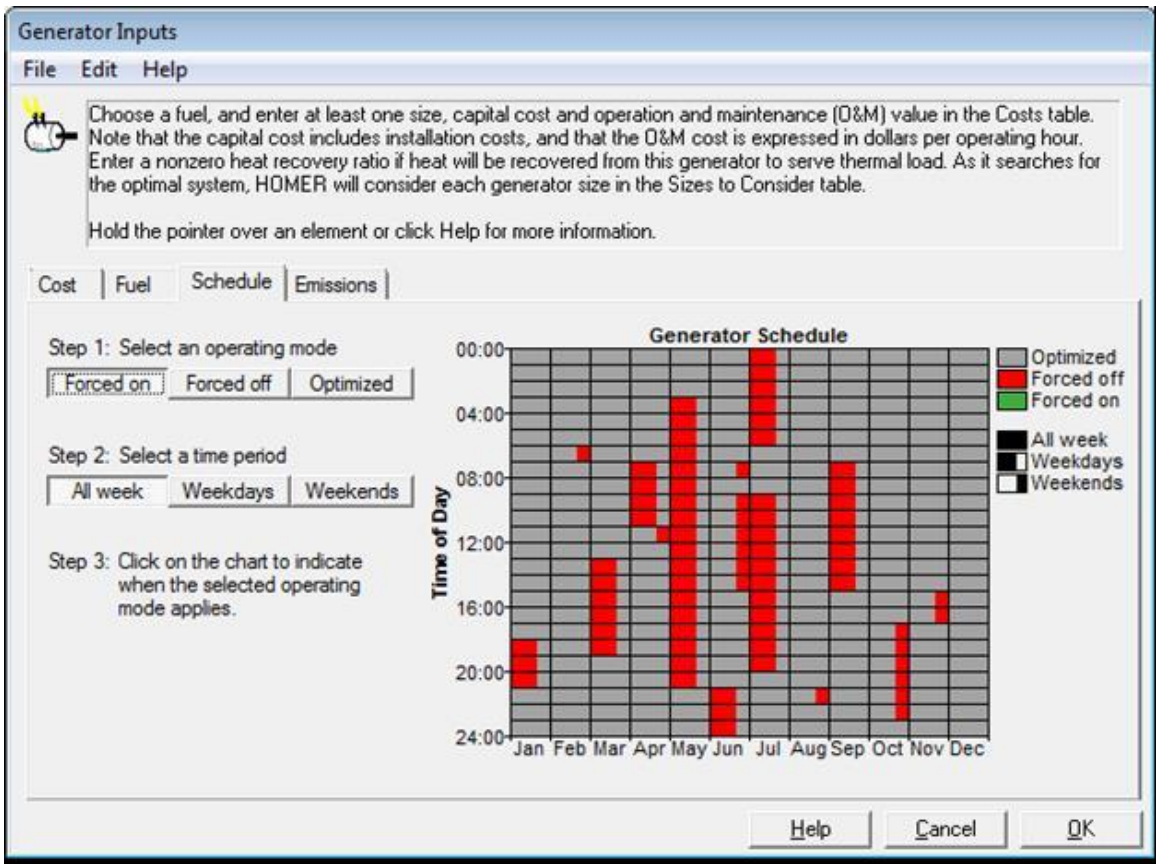

Fig. 4.6 Simulating grid outages in HOMER by scheduling down time on a 'Grid Proxy' Generator.

Table 4.4 Data input values for MTBF, MTTR, Expected Value of Availability (*E[A]*) for Scenarios (a) - (g)

Scenario	***MTBF***	***MTTR***	***E[A]***
a	∞	~0.00	1.00
b	58.10	10.10	0.85
c	58.10	20.20	0.74
d	29.05	20.20	0.74
e	14.50	10.10	0.59
f	6.00	18.00	0.25
g	~0.00	∞	0.00

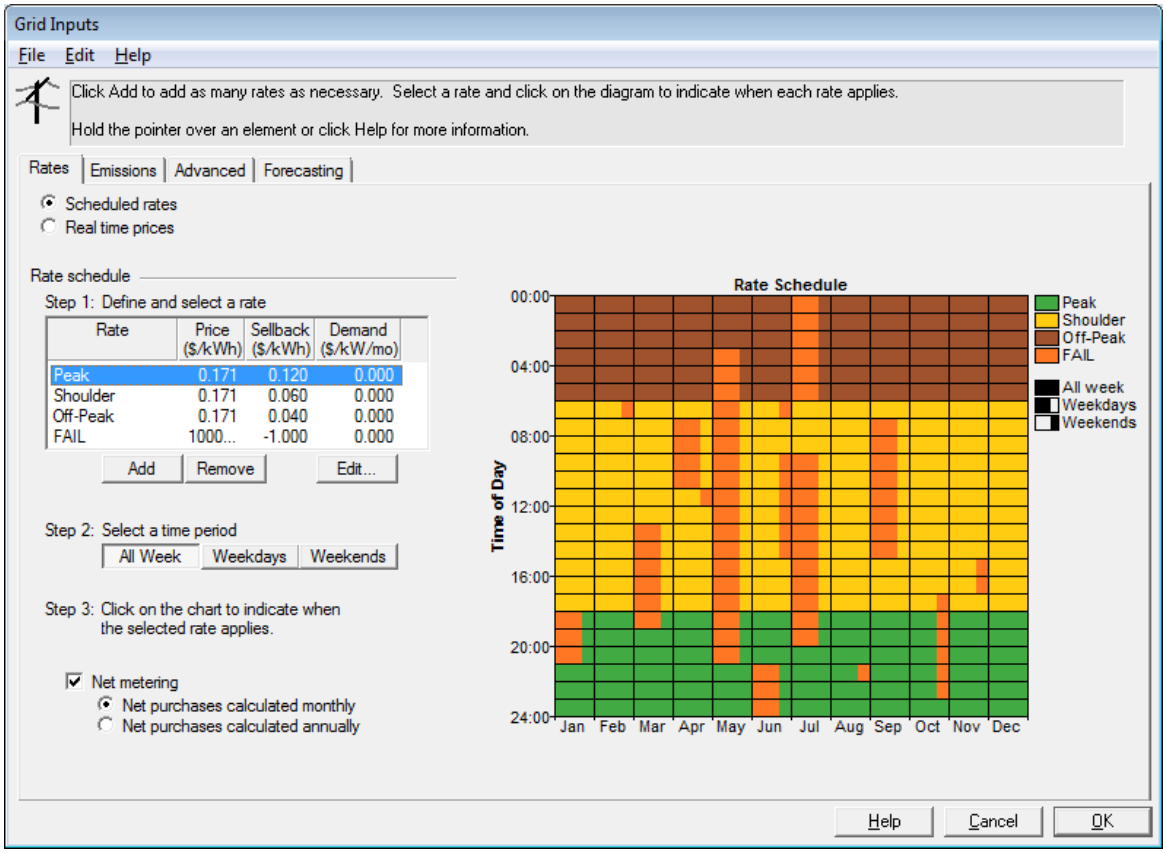

Fig. 4.7 HOMER input for simulating grid failure using the infinite/negative price model for Scenario (b), Uganda base case. Different rates for peak (green), shoulder (yellow) and off-peak (brown) can be used. Orange indicates a failed grid.

We then simulate various grid extension distances by varying the cost of a grid connection from $0 to $1,400,000. Grid extension costs are a function of distance from the grid, and can range from $50,000 to $150,000/km [42]. We use $100,000/km in this analysis, with the maximum distance considered being 14 km at the selected maximum $1.4M grid extension cost. We then run simulations with the 7 different MTBF and MTTR combinations from Table 4.4.

The relationship between the simulated outage schedules is clear in Table 4.4. Two are deterministic: (a) with 100% grid availability and (g) stand-alone/no grid, with 0% grid availability. Random scenario (b) is simulated as the average grid outage frequency and repair time in Uganda based on the World Bank statistics, and serves as the baseline.

Scenarios (c) through (f) have decreased availability as compared to Scenario (b). Scenario (c) has the same average outage duration as Scenario (b), but twice the number of outages. Scenario (d) has the same number of outages as (b), but the outages average twice the duration. As a consequence, the grid availability for Scenarios (c) and (d) are expected to be the same at $E[A] \sim 0.74$; the optimal system for each scenario are not identical, despite having the same overall availability as different techniques are optimal for longer, less frequent outages than for shorter, more frequent outages. Scenario (e) doubles both the duration and frequency of outages from the baseline Scenario (b). Finally, Scenario (f) decreases the availability further to 0.25, to provide data to analyze the trend toward lower and lower grid availability.

We prefer to run hundreds of unique simulations with each of the availability rates, but the set up processes for the generator grid-proxy and infinite random failure simulation is onerous and not truly stochastic; this level of rigor must wait for an update to the HOMER simulation tool, or for the development of alternative tools.

4.1.3.3 Grid sellback prices impact on LCOE and EDL

Finally, we examine the impact of grid sellback prices on LCOE and EDL. While many countries, including Uganda, have sellback markets with different rates for peak, off-peak and shoulder, we focus on a single rate that holds 24 h/day all year in order to simplify the analysis of the impact of sellback prices. Prices for selling electricity back to the grid range from \$-0.05/kWh (effectively prohibiting sales) to \$0/kWh (allowing excess capacity to serve the bulk grid, but not providing economic incentive), up to grid parity (\$0.171, the same price as electricity from the grid). We limit PV and local generation capacity array size such that (1) the sellback power does not exceed twice the peak load at the site and (2)

that grid sales are no more than twice grid purchases, annually, as is common with net zero metering (Florida Power and Light, 2008).

4.2 Data Collection

The bulk of the output data comes from HOMER simulation, but first we develop the input data sets for HOMER, including availability data for various electric grids, system configuration, and component costs.

4.2.1 Input data

4.2.1.1 Availability data from World Bank on international statistical sources, with limited confirmation from data collection

World Bank outage data serves as the basis for simulating grid outages [2].

4.2.2 System configuration baseline from literature, using Uganda village as the baseline

The microgrid architecture for this analysis remains consistent with the loads and sources in Twaha et al. [48], but the actual cost of PV hardware has decreased since the original work in 2010. As such, in parts of the analysis we keep the cost the same for baseline comparison, while for other parts we decrease the cost of a solar PV system from $6000/kW to $2000/kW to reflect more current PV module prices. Key inputs are described in Table 4.5

4.2.3 Experimental data from HOMER Simulation

HOMER provides detailed system configuration, economic and time series data for analysis of alternative system configurations and optimization. The biggest challenge is

that comparison across various grid availability levels is not included in the tool, and must be performed post-hoc.

Table 4.5 HOMER inputs, modified data on option sizing and other parameters for considering an unavailable grid

Options	***Sensitivity Range***	***Additional Information***	
Diesel Generator (Community Backup Gen)	0-100 kW	Capital Replacement Diesel price	= $250/kW = $200/kW = $1.3/L = UGX 3400/L
Solar PV	0-300 kW	Capital De-rating factor	=$2000/kW =$6000/kW = 80%
Converter	0-100 kW	Efficiency	= 95.5%
Battery	0-512 strings (1024 total batteries)	Surrette 6CS25P batteries Nominal voltage Nominal capacity Usable capacity	 = 6V = 1156 Ah = 8523 kWh

4.3 Analysis Procedure

HOMER serves as the primary analytical tool for generating optimal microgrid systems and economic results for the various scenarios listed in Table 4.6. We perform three distinct sets of analysis: (1) Consideration of an unavailable grid on the Twaha et al. [48]; (2) Study of LCOE as a function of demanded electricity availability based on optimal solutions considering the Twaha et al. [48] systems configuration; and (3) determination of highly available electricity cost as a function of grid availability and distance from the existing grid.

After re-creation of the Twaha et al. [48] model and an update considering unavailable grid electricity, the results from Group A1 and A2 shown in Table 4.6 are analyzed to

determine the impact of DER on end user electricity availability, the cost of increased availability.

4.3.1 Demand availability

As the systems configurations from Twaha et al. [48] were not optimized with respect to an unavailable grid, we will analyze the HOMER results to determine optimal microgrid configurations of Group B1 and B2 from Table 4.6, and analyze cost of availability under these optimized configurations, with some configurations unrestricted by environmental concerns and others with an additional constraint to use no fossil fuel (diesel).

4.3.2 Grid availability and grid extension distance impacts on LCOE and EDL

Group C in Table 4.6 allows us to calculate and compare LCOE as a function of grid availability and as a function of grid extension distance. Subsequent calculations of EDL are then possible.

4.3.3 Grid sellback prices impact on LCOE and EDL

Group D in Table 4.6 allows us to study and compare the impact of various grid sellback prices on LCOE and EDL. Sell-back prices vary from $(-1)/kWh (effectively prohibiting sellback) to $0/kWh (net metering) to $0.171/kWh (grid parity).

Table 4.6 Simulation scenario summary

Scenario ID	*Group ID*	*Group*	*Scenario*	*Purpose*
1T 2T 3T	A1	Twaha et al. [48] original scenario, with perfect grid	Perfect grid baseline Grid tied Solar Grid tied Solar/Battery	Baseline for comparisons
1M 2M 3M	A2	Same as Twaha, et al. [48] but unavailable grid	Grid only, no DER Grid tied Solar Grid tied Solar/Battery	Determine unmet load, availability/cost of availability.
1a 2a 3a 4a 5a 6a 7a 8a 9a	B1	Using one simulated unavailable grid with Grid A = 0.85, calculate cost for various levels of availability demand; no restrictions on diesel	Demand A > 0.80 Demand A > 0.85 Demand A > 0.90 Demand A > 0.95 Demand A > 0.96 Demand A > 0.97 Demand A > 0.98 Demand A > 0.99 Demand A >= 1.0	Analyze cost of availability, unrestricted by environmental concerns.
1b 2b 3b 4b 5b 6b 7b 8b 9b	B2	Same as B1, but no diesel allowed.	Demand A > 0.80 Demand A > 0.85 Demand A > 0.90 Demand A > 0.95 Demand A > 0.96 Demand A > 0.97 Demand A > 0.98 Demand A > 0.99 Demand A >= 1.0	Analyze cost of availability, with additional constraint to use no fossil fuel (diesel).
a b c d e f g	C	For Demand A = 1, using multiple simulated unavailable grids, calculate LCOE for various levels of grid reliability at various grid extension distances	Grid A = 1.0 Grid A = 0.85 Grid A = 0.74 Grid A = 0.74 Grid A = 0.59 Grid A = 0.25 Grid A = 0	Determine LCOE as a function of grid availability and grid extension distance; determine EDL
a b c d e f	D	Same as C, but vary sellback prices from none allowed through $0.171/kWh	Grid A = 1.0 Grid A = 0.85 Grid A = 0.74 Grid A = 0.74 Grid A = 0.59 Grid A = 0.25	Determine LCOE and EDL as a function of grid sellback prices

5. Expected Findings

5.1 Planned Descriptive Statistics

Statistical description of simulated outages comparing input vs. achieved MTBF, MTTR, and Availability.

5.2 Planned Inferential Statistics

5.2.1 LCOE

Determining the cost of electricity considering an unavailable electric grid, but that meets availability constraints is the foundation of this analysis. LCOE is determined as a function of

- demanded availability given a grid that cannot meet that demand
- varying grid availability
- grid availability and grid extension distance
- grid availability, grid extension distance and sellback prices

5.2.2 EDL

Electricity stand-alone generation cost and grid cost impact EDL. After determining LCOE< we use it to calculate EDL as a function of

- grid availability and grid extension distance
- grid availability, grid extension distance and sellback prices

5.3 Expected Conclusions

Providing reliable and eventually clean and renewable electricity to the 20% of the world's population that lack access to a grid is a daunting challenge. The method developed here demonstrates how consideration of the existing grid availability can be included in cost benefit analyses of various systems for electricity production, and for selecting optimal configurations for grid tied DER, and for making decisions between self-generation and grid extension.

The analysis results in more accurate calculations of LCOE considering DER optimized for improved end user availability and reliability. Results indicate increased LCOE to meet increased availability demand because some additional capital equipment must be added to the system to meet the demand that unavailable grids cannot meet.

The new methods to estimate the cost of reliable electricity and EDL will enable better comparison between grid-tied and stand-alone generation economics where the grid is not reliable. Using the methods to be developed in this effort, we expect to see increasing cost of electricity for users with low grid availability. In addition, EDL will decrease as grid availability decreases, as there is little value in extending a grid that functions poorly. While calculated LCOEs will increase, this increase illustrates the cost of availability, and will enable more informed choices for grid-tied and stand-alone electricity generation.

6. Conclusions

6.1 Observations and Results

6.1.1 Develop methods to simulate grid failure

The method for simulating failure schedules for integration with HOMER remains the same as described in Twaha et al. [47], and Section 4.1.1, using an exponential pseudo-random variable generator in Excel. The method is consistent with outage simulations based on a Poisson arrival process, as the exponential arrival times simulated generate Poisson distributions for outages and repairs [55] [56] [53] [54]. To populate the HOMER "infinite price" model outage schedule, the Excel simulator was used to generate 24 unique schedules of 24 hours each for up-time (normal price) and down-time (effectively infinite price of grid electricity, shown in orange in Fig. 4.7). Twenty four schedules of 24 hours each is the maximum schedule variation allowed in HOMER, as we can enter unique schedules by month for weekdays and weekends (January weekdays, January weekends, February weekdays, etc.) of 24 h each. From the random schedule simulation method, the results of the Excel model for the base case in Uganda (MTBF = 58.1 hr, MTTR = 10.1 hr) are shown Fig. 6.1, where green/1 indicates an operational grid and red/0 indicates a grid failure.

For analysis of LCOE and EDL as a function of grid availability, we develop 7 different scenarios for MTBF and MTTR. In addition to the scenario shown in Fig. 6.1 for World Bank data for Uganda, we simulate six additional scenarios for comparative analysis across a range of availability levels. Table 6.1 summarizes these scenario inputs and the expected value of Availability ($E[A]$) and the achieved value for availability in simulation($\hat{A}$); the resulting schedules are shown in Fig. 6.4.

	Jan		Feb		Mar		Apr		May		Jun		Jul		Aug		Sep		Oct		Nov		Dec	
Hr	wk	wknd	wk	wknd	wk	wknd	wk	wknd	wk	wknd	wk	wknd	wk	wknd	wk	wknd	wk	wknd	wk	wknd	wk	wknd	wk	wknd
0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
5	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
6	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
7	1	1	1	1	1	1	0	1	0	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1
8	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1
9	1	1	1	1	1	1	0	1	0	1	1	0	0	1	1	1	0	1	1	1	1	1	1	1
10	1	1	1	1	1	1	0	1	0	1	1	0	0	1	1	1	0	1	1	1	1	1	1	1
11	1	1	1	1	1	1	1	0	0	1	1	0	0	1	1	1	0	1	1	1	1	1	1	1
12	1	1	1	1	1	1	1	1	0	1	1	0	0	1	1	1	0	1	1	1	1	1	1	1
13	1	1	1	1	0	1	1	1	0	1	1	0	0	1	1	1	0	1	1	1	1	1	1	1
14	1	1	1	1	0	1	1	1	0	1	1	0	0	1	1	1	0	1	1	1	1	1	1	1
15	1	1	1	1	0	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1
16	1	1	1	1	0	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1
17	1	1	1	1	0	1	1	1	0	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1
18	0	1	1	1	0	1	1	1	0	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1
19	0	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1
20	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
21	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	1	0	1	1	1	1
22	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	1
23	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1

Fig. 6.1. Simulated outage schedule, Ugandan base case.

While the achieved availability in each scenario ($\hat{A}$) is consistent with *E[A]*, the limits of HOMER with respect to a stochastically failing grid are still apparent in deeper analysis of the MTBF and MTTR achieved in simulation. Table 6.2 summarizes the Achieved MTBF, MTTR and some additional descriptive statistics from the simulated scenarios for comparison.

Only in Scenario (f) do we observe an achieved avg.MTTR and avg.MTBF with 95% CI consistent with the input MTBF and MTTR; similarly, this is the only scenario where the 2 sided Z-tests for the population mean indicates we could reject the hypothesis that the means are not equal. Fig. 6.2 and Fig. 6.3 illustrate, for MTBF and MTTR respectively. The avg.MTBF for each scenario other than Scenario (f) is lower than the input MTBF, because the input MTBF results in failure durations that are often greater than the length of the day, but the schedule is defined per day, and the weekly and weekend schedules are repeated. It is therefore difficult to model long duration grid uptime and grid downtime in

this method, as the resulting lower than expected avg.MTBF indicate. If avg.MTBF is lower than the input MTBF, in order to achieve $E[A] \sim \hat{A}$, avg.MTTR is also lower than the input value for MTTR. As noted above, we see that the explanatory variable of interest is grid Availability, so for this analysis, the simulation method suffices.

Table 6.1 Data values for MTBF, MTTR, Expected Value of Availability (E[A]), and simulated value of availability (Â) for Scenarios (a) - (g)

Scenario	*MTBF*	*MTTR*	*E[A]*	*Â*
a	∞	~0.00	1.00	1.00
b	58.10	10.10	0.85	0.83
c	58.10	20.20	0.74	0.75
d	29.05	10.10	0.74	0.76
e	14.50	10.10	0.59	0.62
f	6.00	18.00	0.25	0.24
g	~0.00	∞	0.00	0.00

Table 6.2 Simulated scenario achieved values for MTBF, MTTR including average (avg.), standard error (se), and 95% confidence interval for upper (ub) and lower (lb) bounds of the avg.MTBF for Scenarios (b) - (f)

	MTBF					*MTTR*				
Scen -ario	*avg. MTBF*	*se. MTBF*	*lb. MTBF*	*ub. MTBF*	*Z Test in.MTBF = avg.MTBF*	*avg. MTTR*	*se. MTTR*	*lb. MTTR*	*ub. MTTR*	*Z Test in.MTTR = avg.MTTR*
a										
b	31.2	4.3	22.7	39.8	0.00	6.2	0.3	5.6	6.8	0.00
c	26.2	4.6	17.0	35.5	0.00	8.7	0.5	7.8	9.7	0.00
d	19.4	2.6	14.2	24.5	0.00	6.1	0.2	5.6	6.6	0.00
e	11.7	0.8	10.0	13.4	0.06	8.4	0.4	7.7	9.1	0.00
f	5.9	0.4	5.2	6.6	0.74	18.0	1.4	15.2	20.9	0.98
g										

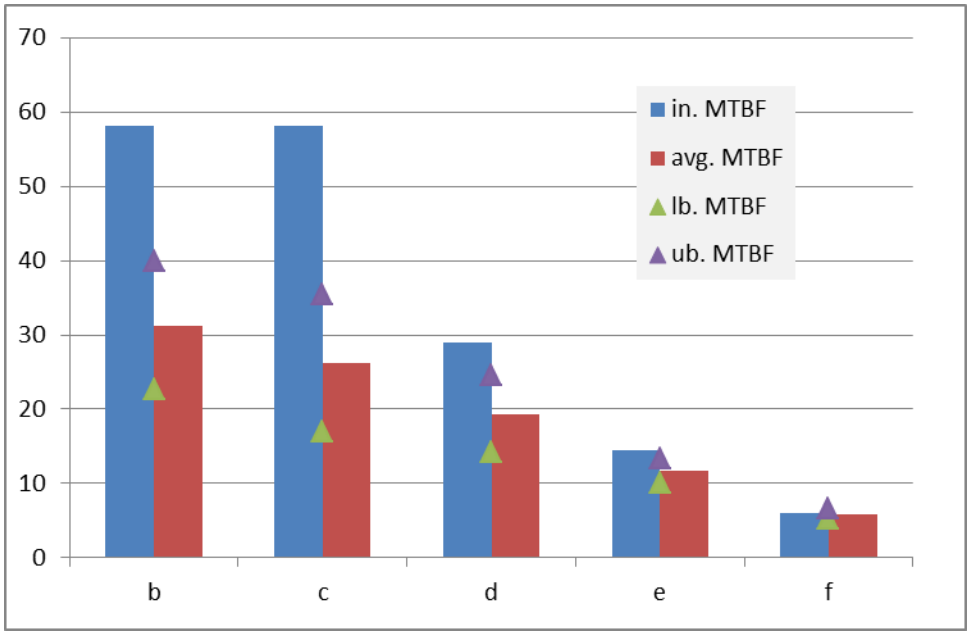

Fig. 6.2 Input MTBF compared with achieved, along with 95% upper and lower bounds.

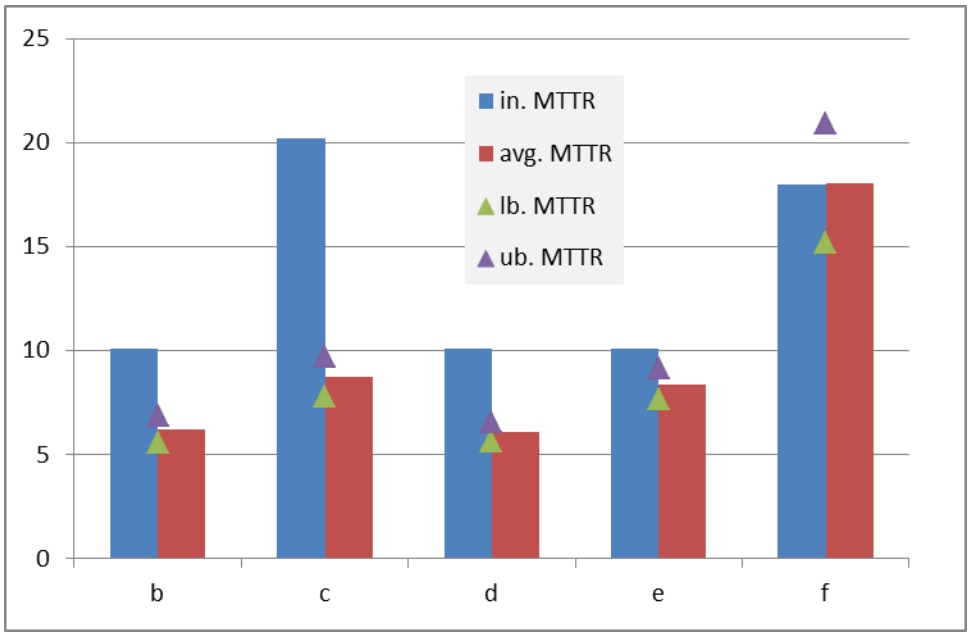

Fig. 6.3 Input MTTR compared with achieved, along with 95% upper and lower bounds.

6.1.2 Develop methods to incorporate unavailable grid simulations into microgrid analysis

To simplify incorporation and comparison of grid availability simulations and integration with EDL calculations, we have chosen not to use the "grid proxy generator" method from Twaha et al. [47]. Instead, we use the grid component of HOMER and the "infinite price" model shown in Section 4. To simulate grid failure, we insert a FAIL setting in the Grid Inputs as shown section 4. Note that in analysis of LCOE and EDL as a function of grid availability analysis, all sellback prices are set to $(-1)/kWh to allow focus on the variation in grid availability and grid extension distance. This allows us to eventually compare various grid sellback prices, which would not be possible using the grid-proxy method.

Basic comparisons were performed in Twaha et al. [48] with updated simulation considering an unavailable grid in Murphy et al. [47]. Twaha et al [48] only considered a perfectly available grid; this is now Scenario (a) in this study. Murphy et al [47] considered the Uganda base case grid availability, now explored in Scenario (b). The various scenarios are shown in Fig. 6.4, following the same format and simulation method previously described. The expanded analysis moves beyond the Ugandan example to explore the seven scenarios of varying unavailability.

All seven simulated outage scenarios from Table 6.1 are illustrated in Fig. 6.4. The relationship between the various simulated outage schedules is clear in both. Two are completely deterministic: (a) with 100% grid availability and (g) stand-alone, with 0% grid availability. Random scenario (b) was simulated and shown in Fig. 6.1 as the average grid outage frequency and repair time in Uganda based on the World Bank statistics.

Scenarios (c) through (f) have decreased availability as compared to Scenario (b). Scenario (c) has the same average outage frequency as Scenario (b), but twice the outage duration. Scenario (d) has the same average outage duration as Scenario (b), but the outages are twice as frequent. The availability for Scenarios (c) and (d) are expected to be the same at A = 0.74, and in the random simulations both are consistent with this value. Scenario (e) and (f) decrease the availability even further, as shown in Fig. 6.4. Different electricity rates for peak (green), shoulder (yellow) and off-peak (brown) can be used, but for this analysis only the single rate of $0.171/kWh is used. As noted, orange indicates a failed grid. We would prefer to run hundreds of unique simulations with each of the availability rates, but the set up process for the generator grid-proxy random failure scheduler is onerous; this level of rigor must wait for an update to the HOMER simulation tool, or for the development of alternative tools.

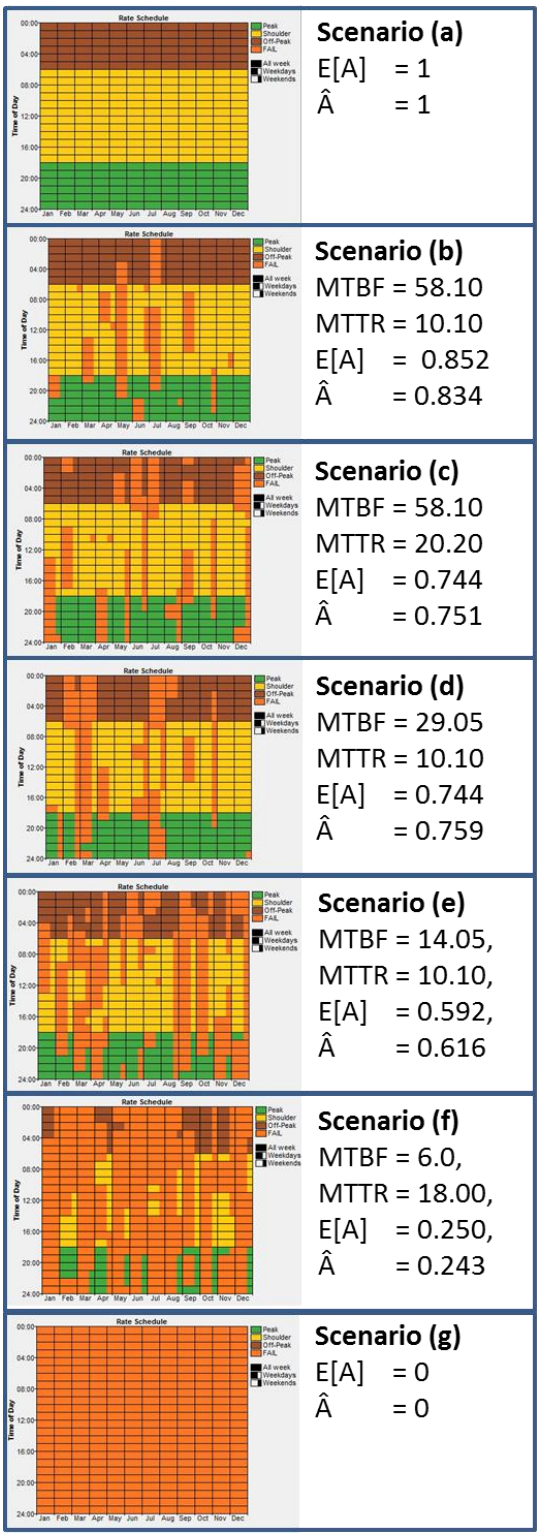

Fig. 6.4. Grid electricity modeling with failed grid, orange indicates infinite price and failed grid.

6.1.3 HOMER Simulation

The microgrid architecture for this analysis remains consistent with the loads and sources in Twaha et al. [48] and Murphy et al. [47], but the actual cost of PV hardware has decreased since the original work in 2010. As such we have decreased the cost of a solar PV system from $6000/kW to $2000/kW to reflect more current PV module prices.

6.1.3.1 Demand Availability.

Nine levels of maximum demand availability were compared in 9 scenarios, with allowable downtime ratios of 0.20, 0.15, 0.10, 0.05, 0.04, 0.03, 0.02, 0.01 and 0.00. The existing unreliable grid meets the 0.20 threshold, while storage or additional generation is required to meet all of the more stringent availability requirements, with an expected increase in LCOE.

The purpose of a DER system is to provide available electricity in an affordable and sustainable manner. In this analysis we consider sustainability as a secondary concern, and treat the current lack of electricity as a much greater economic and development crisis than greenhouse gas emissions and other pollutants. Renewable DER may help to address the lack of availability and reliability of the bulk grid, but they may not provide a cost-effective solution, and ultimately fossil fuel based DER may be necessary to achieve availability and reliability goals.

6.1.3.1.1 Baseline Comparison

First, we describe the impact of an unavailable grid on the results from Twaha et al. [48]. We recreate the system from previous work based on the information in Twaha et al.

[48], including PV prices remaining the same at $6/W for comparison to previous results, and use this as the baseline for comparison to new results with an unavailable grid. The key outputs from the re-created results of three systems discussed in previous work are shown in Table 6.3 (Options 1T, 2T, 3T) and results from three parallel systems modeled against an unavailable grid (Options 1M, 2M, 3M).

The optimal system from Twaha et al. [48] was the grid, with no backup, offering power at $0.171/kWh. The grid-only solution from that analysis is still available with consideration of an unavailable grid, but is only optimal if 17.7% or more unmet load (downtime) is allowed. With the electricity availability conditions described in Fig. 6.1 and input into HOMER as per Fig. 6.4, in Scenario (b), 17.7% or 39,835 kWh/yr of the load is not be served as no DER is available while the grid is down. Twaha et al. [48] also discussed two other options as comparatives: a system including 100 kW PV without battery storage (Option 2T), and a system including 100 kW PV and battery storage bank of 8 batteries (Option 3T). Table 6.4 identifies the selected system components and sizes.

These configurations are not optimized for economics and performance under either perfect grid or unavailable grid scenarios; the systems are only shown for comparison with Twhaha et al.'s [48] earlier results. Table 6.3 also highlights the key difference between assuming the grid is reliable and the new consideration of unreliable grid electricity. The actual load served, unmet load ratio and the unmet load when grid availability is considered shows the additional value of DER, in that it provides backup when the grid has failed.

Table 6.3 Simulation results from previous work, now considering an unavailable electric grid.

Option	*PV (kW)*	*Batt (#)*	*Inv (kW)*	*Load Served (kWh/yr)*	*Grid Sales (kWh/yr)*	*Achieved Unmet Load Fraction*	*Achieved Unmet Load (kWh/yr)*	*LCOE ($/kWh)*
1T	-	-	-	225,570	-	-	-	0.171
2T	100	-	100	225,570	68,439	-	-	0.220
3T	100	8	80	225,570	68,160	-	-	0.222
1M	-	-	-	185,735	-	0.177	39,835	0.171
2M	100	-	100	201,271	52,882	0.108	24,299	0.243
3M	100	8	80	204,353	51,639	0.094	21,217	0.245

6.1.3.1.2 Inter-relation of Energy demand, unmet energy demand and the unmet load ratios.

These variables and equations are interrelated, and are presented for clarity and completeness:

$$E_d = E_s + E_u \tag{6.1a}$$

$$E_s = E_d(1 - r_u) \tag{6.1b}$$

$$r_u = \frac{E_u}{E_d} \tag{6.1c}$$

Where

E_d = the desired total energy load
E_u = the unmet energy load
E_s = the actual energy load served, and
r_u = the unmet load ratio

As we continue to discuss improved availability as a goal for DER, we note that the unmet load ratio r_u would be equal to one minus the availability (1-A) if the average instantaneous power load was consistent across the served and unserved loads, such that:

$$\bar{P}_d = \frac{E_d}{T_{total}} = \bar{P}_s = \frac{E_s}{T_{up}} = \bar{P}_u = \frac{E_u}{T_{down}} \tag{6.2}$$

Where

$\bar{P}_d$ = the average power demand
$\bar{P}_u$ = the average unmet power
$\bar{P}_s$ = the average load served

Then by Eqns. (4.1), (6.1c) and (6.2), the unmet load ratio is:

$$r_u = \frac{\bar{P}_u T_{down}}{\bar{P}_d (T_{up} + T_{down})} = \frac{T_{down}}{(T_{up} + T_{down})} = (1 - A) \tag{6.3}$$

Even if the average power equivalencies in Eqn. (6.2) do not hold, if the failure and recovery events are truly random and of sufficient number, then by the Central Limit Theorem, we can take Eqn. (6.2) and (6.3) as approximate equalities such that $r_u \sim (1 - A)$ [54]. In the case of the simulation example this holds, as $r_u = 0.171 \sim 0.166 = (1 - 0.834) = (1 - \hat{A})$.

What is most interesting in the differences between the results from Twaha et al. [48] and the results incorporating grid outages is the additional availability provided by the PV generation and battery storage. In Twaha et al. [48], it would be difficult to justify the higher LCOEs for hybrid grid tied microgrids in Options 2T and 3T without some additional constraint or objective, for example a limit on emissions. The importance of considering grid unavailability is shown in Options 2M and 3M, which illustrate that the benefit of the renewable DER can be measured in local electricity availability and additional load served.

The question becomes: is it worth a higher price (in these cases an additional \$0.07/kWh) to cut the unmet load ratio from 0.177 to 0.095, effectively increasing the availability from 82.3% to 90.5%? We explore the cost of availability in more detail in the next section, with system configurations optimized to meet availability constraints.

6.1.3.1.3 Optimal Systems and Performance at Various Levels of Required Availability

As noted, it is impossible to economically justify grid-connected solar Options 2T or 3T in Table 6.3 without additional constraints or objectives. We now study in detail whether and how the DER options can provide value toward meeting demand availability objectives. By executing nine (9) scenarios in HOMER with the same input data and changing only the Allowed Capacity Shortage, we find the optimal systems to achieve capacity shortages of no more than 0.20, 0.15, 0.10, 0.5, 0.4, 0.3, 0.2, 0.1 and 0, despite dependence on an unavailable grid that would be able to meet only the 0.20 level of allowed capacity shortage. We add additional scenarios between 0.5 and 0 in order to observe more detail in non-linear behavior of the LCOE when renewable energy only constraints were applied.

While no cost of emissions nor fuel tax penalty beyond market price is included in the simulation, we add a constraint in the analysis to identify solutions without diesel use to illustrate the potential additional cost of green solutions. The resulting data, compiled in Table 6.4, shows the potential benefit of DER in terms of availability and the cost of availability, and the tradeoff between diesel generator-based and renewable options for achieving more electricity availability.

Starting from the lowest demanded availability requirement in Scenario 1 with 0.20 allowable capacity shortage, Option 1M from previous work satisfies the constraint. Grid power without backup is capable of serving a load E_s = 185,735 kWh/yr of the demand E_d = 225,570 kWh/yr, dropping an un-served load E_u = 39,835 kWh/yr with an unmet load ratio by Eqn. (6.1c) of r_u = 0.177.

Options 2M and 3M both provided increased availability with unmet load ratio near 0.1, but neither were optimized against an availability constraint. For Scenario 2 with a maximum unmet load ratio of 0.15, Option 2 adds a 10 kW diesel generator to provide generation for 14,451 kWh that were left unmet in the grid only solution. Option 3 adds 20 kW of PV and a 50 kW inverter to further increase the load served. Options 4 through 9 in Scenarios 4-9 increase the size of the diesel to 50 kW, drop the PV and inverter, and all achieve the same load at the same cost per kWh. The LCOE increases linearly as the unmet load ratio decreases. From an alternate perspective, as more reliable electricity is provided the cost per kWh of that electricity increases linearly with Availability A, as shown in Fig. 6.5. The solar and solar battery solutions from previous work (Options 2M and 3M in blue squares) are shown for comparison, and are clearly above the minimum price for the achieved availability, and so are not efficient solutions to the availability optimization.

Scenarios 1b-9b, with no diesel allowed are also shown graphically in Fig. 6.5 (green triangles). Below a demand availability of 0.98, the LCOEs increase linearly, but at a higher rate than for the diesel allowed solutions. Above demand availability of 0.98, the price per kWh increases rapidly. The capital infrastructure (PV panels, batteries, and inverters) drives the cost increase as additional capital investment is required to meet the short term peak loads that were otherwise shed with lower availability constraints. Observe in Table 6.4 and Fig. 6.6, the four bands of capital investment, grouped and defined by the number of batteries required. To meet the 0.20 and 0.15 unmet load requirement, no batteries were needed. To meet the 0.15 unmet load ratio constraint, 20 kW of PV and a 50 kW inverter were required.

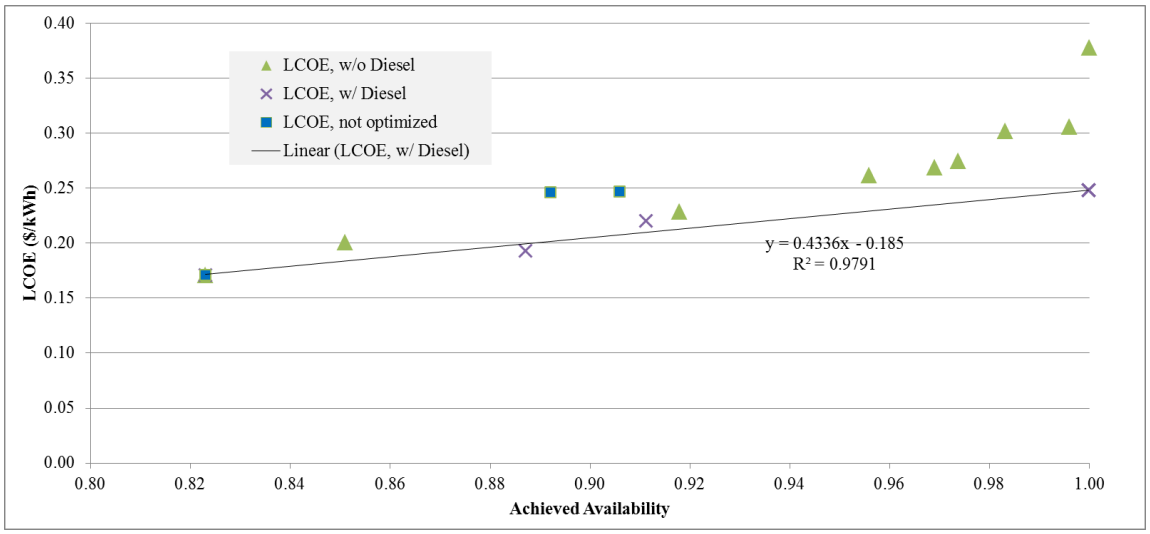

Fig. 6.5. Cost of availability results. Previous results from non-optimized systems (LCOE, not optimized) compared to optimal systems showing the lowest cost solutions for each demanded availability level (LCOE w/ Diesel), and optimal systems not allowing diesel (LCOE w/o Diesel) showing renewable only solutions.

For unmet demand ratios of 0.10 through 0.03, 64 batteries were required, with increasing larger PV and inverter solutions required at each increased demanded availability level. For unmet demand ratios of 0.02 and 0.01, 128 batteries met the need, along with 50 kW and 80 kW PV arrays. Finally to achieve 100% available power, 256 batteries and a 100 kW PV array were required to augment the unreliable grid.

Another consideration of cost for availability is in terms of the cost in \$/*kWh of the additional load served*, versus the previous price, with amortizes the increased cost across every kWh used. Thus, the LCOE provides the cost for all electricity, or the weighted average of grid and backup power. The cost of additional load served is the average cost of each additional kilowatt hour provided by Option j as compared Option i, which we note as $C_a^{j,i}$ and is given by:

$$C_a^{j.i} = \frac{C_t^j - C_t^i}{L_s^j - L_s^i} \tag{6.4}$$

Where

i = baseline option

j = comparative option

C_t^i = total cost per year for Option i, and

L_s^i = load served for Option i

Eqn. (6.4) for Option 2 as compared to Option 1M is calculated as:

$$C_a^{2.1M} = \frac{C_t^2 - C_t^{1M}}{L_s^2 - L_s^1} = \frac{38{,}636 - 31{,}761}{200{,}186 - 185{,}753} = \frac{6{,}875}{14{,}451} = 0.476$$

The resulting calculations of $C_a^{j.1M}$, the cost for the additional load served as compared to Option 1M, for each of the other options are presented in Table 6.4 as Cost of Additional Load Served, and displayed in Fig. 6.7.

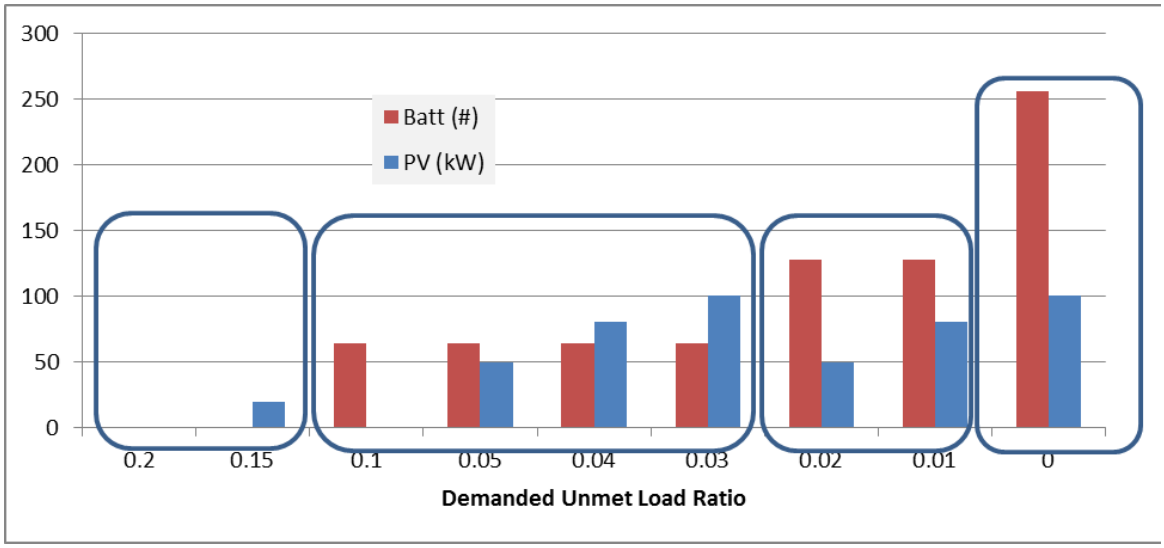

Fig. 6.6 The increasing capital investment required to meet increased availability demand. Four bands defined by the number of batteries required are apparent, each with an increasing amount of solar PV capacity required as the unmet load ratio constraint is tightened.

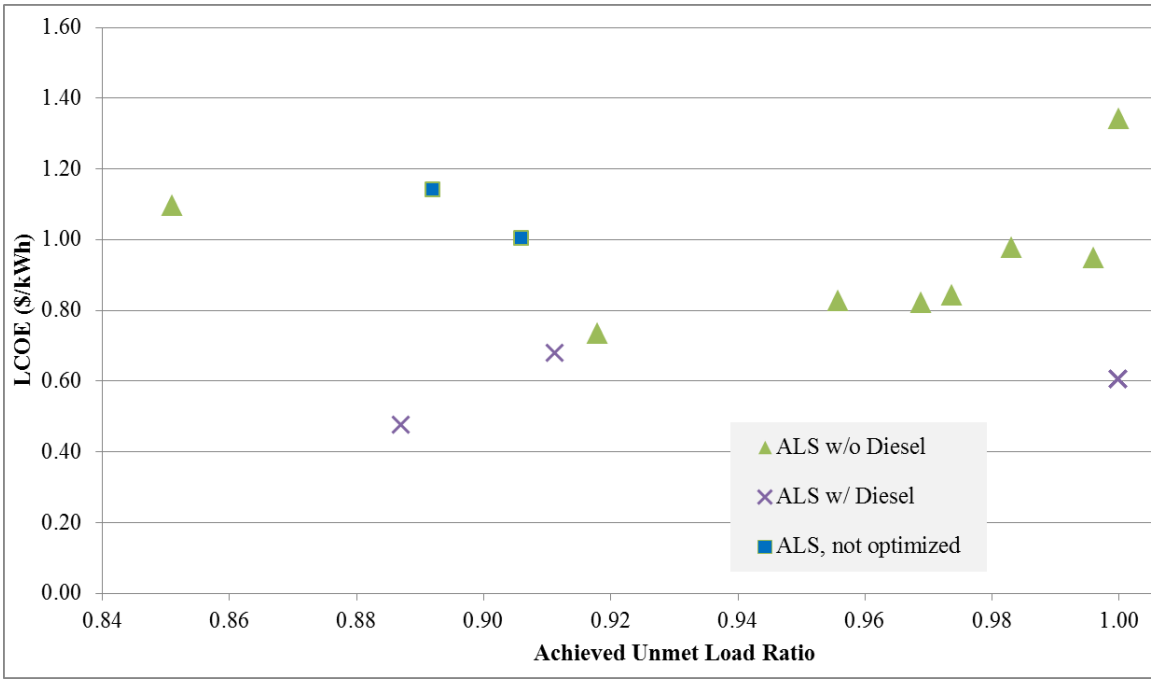

Fig. 6.7 Cost of additional load served beyond that provided by an unavailable grid (Option 1M) for minimum cost and renewable only options.

Table 6.4. Simulation results for optimal configurations to meet various availability and environmental requirements

Opt.	Allowed Cap. Shortage Ratio	Achieved Unmet Load Ratio	PV (kW)	Batt (#)	Inv (kW)	Gen (kW)	Load Served (kWh/ yr)	Grid Purchase (kWh/ yr)	Grid Sales (kWh/yr)	Additional Load Served (vs. Grid Only) (kWh/yr)	Cost Ops + Capital ($/yr)	LCOE ($/ kWh)	Cost of Additional Load Served ($/kWh)
1=1M	0.20	0.177					185,735	185,735	0	0	31,761	0.171	NA
2	0.15	0.113				10	200,186	185,735	0	14,451	38,636	0.193	0.476
3	0.10	0.0888	20		50	10	205,547	164,084	0	19,812	45,220	0.22	0.679
4	0.05	0.0003				50	225,509	185,735	0	39,774	55,926	0.248	0.608
5	0.04	0.0003				50	225,509	185,735	0	39,774	55,926	0.248	0.608
6	0.03	0.0003				50	225,509	185,735	0	39,774	55,926	0.248	0.608
7	0.02	0.0003				50	225,509	185,735	0	39,774	55,926	0.248	0.608
8	0.01	0.0003				50	225,509	185,735	0	39,774	55,926	0.248	0.608
9	0.00	0.0003				50	225,509	185,735	0	39,774	55,926	0.248	0.608
1b	0.20	0.177		0	0		185,735	185,735	0	0	31,761	0.171	NA
2b	0.15	0.149	20	0	50		191,953	164,084	1	6,218	38,583	0.201	1.097
3b	0.10	0.0821	0	64	50		207,046	214,930	0	21,311	47,414	0.229	0.734
4b	0.05	0.0442	50	64	50		215,607	159,723	6,684	29,872	56,489	0.262	0.828
5b	0.04	0.0311	80	64	75		218,563	148,680	28,826	32,828	58,793	0.269	0.823
6b	0.03	0.0263	100	64	75		219,641	144,220	45,815	33,906	60,401	0.275	0.845
7b	0.02	0.0169	50	128	50		221,760	165,637	4,617	36,025	66,972	0.302	0.977
8b	0.01	0.004	80	128	50		224,667	152,145	23,286	38,932	68,748	0.306	0.950
9b	0.00	0	100	256	75		225,570	140,141	37,164	39,835	85,265	0.378	1.343

Once again, increasing availability comes at an increasing cost. From Table 6.4 and Fig. 6.5 and Fig. 6.7, we see that by reducing the allowable capacity shortage to 0.15 (demand availability greater than or equal to 0.85) in Scenario 2, the achieved unmet load ratio is reduced from 0.177 to 0.113. The LCOE increases from $0.171 to $0.193. The cost of additional load served is $0.476/kWh, which applies to the 14,451 kWh/yr additional load served in Option 2. The cost of additional load served remains relatively consistent for the diesel allowed options, averaging $0.60 across the 9 scenarios, as to serve additional load with diesel, so long as power capacities are not exceeded, simply requires the consumption of more diesel.

The increasing LCOE and cost per unit of additional load served is a function of the additional hardware and fuel required to meet the increased availability requirements. Option 3 adds solar PV and batteries to the solution from Option 2, to decrease the unmet capacity and unmet load ratios. To achieve a maximum capacity shortage ratio of 0.05 (Scenario 4), the minimum cost solution requires a larger diesel generator and more diesel generation, as shown in Option 4 Table 6.4. The economically preferred option for Scenario 4 – Scenario 9 are the same, each allowing near zero downtime; all 6 data-points are co-located on Fig. 6.7 at (0.9997, 0.608).

The no-diesel constraints in Options 2b-9b results in more variation in system configuration and electricity costs across the range of capacity shortage constraints. The initial hardware to improve availability above that provided by the grid costs more than $1/kWh for the additional load served. At every level, the no-diesel constraint results in a higher cost than when diesel is allowed, given these prices and no environmental costs or benefits accounted for.

6.1.3.1.4 Observation on Grid and Environment Interactions.

For the diesel allowed options, there is no change in grid demand and no sales of electricity back to the grid. In effect, the DER in these scenarios are purely local solutions. They do not decrease consumption from the grid because when the grid is operational, it is still the cheapest source of electricity in these scenarios, so diesel does not offset grid use while the grid is operational.

For Scenarios 3 Option 3b, grid consumption actually increases to 214,930 kWh/yr. The increase in grid consumption occurs because battery storage enables the systems to shift grid power to times when the grid has failed, which increases the hours of consumption and the total consumption. Battery use also incurs energy loss in the round-trip conversion to and from battery storage, and so can even increase the total consumption beyond the original demand.

As a result, each of these options may be viable local solutions, but broadly applied could actually decrease regional grid availability as they increase consumption from an already underpowered grid, but do not provide any increased generation capacity to the grid. This creates new grid outages from generation shortfalls. The local utility would likely force such installations to become stand-alone micro-grids as to avoid the negative consequences on the grid system, such as changing the system from a passive to an active network, increasing system losses, lowering the voltage profile below the allowable limit, and thus decreasing the overall availability and operation of the power system network [35]. This would in effect force the implementation of Scenario (g) - stand-alone microgrids for these communities, with the associated increase in cost.

For Scenarios 4b-9b, as the solar PV/battery infrastructure increases to augment the unreliable grid and meet the availability demand, it also reduces grid demand and provides some electricity for sales back to the grid. These solutions could potentially mitigate local and broader regional electricity capacity shortages. Once installed, the marginal cost of solar electricity is near zero, and so the Options 4b-9b can economically offset some grid purchases, and even sell power back to the grid. The broader grid impacts bear further analysis, but are outside the scope of the HOMER tool and this paper.

In addition, solar and battery alternatives are of great importance in decreasing the level of greenhouse gas (GHG) emissions and therefore these options might come cheaper in the future if the cost of emissions is accounted for with the introduction of emission costs. This is possible since it is now widely recognized that GHG emissions resulting from the use of a particular energy technology need to be quantified [60].

6.1.3.1.5 Observation on Hybrid Solutions to Adapt to Changing Energy Prices

Especially with high-availability constraints, renewable options in this analysis are much more costly than the diesel only solutions. The difference is particularly stark in the 100% availability requirement for Scenario 9. LCOE for a PV system in Scenario 9 (Option 9b) is $0.13/kWh more than the Option 9 (diesel allowed) LCOE at $0.248/kWh. On a per additional kWh served basis, Option 9b costs $0.74/kWh more than Option 9 at just over $1.34/kWh for Option 9b. This highlights the economic challenge for renewable-only solutions at the prices in this analysis.

The result, though, is based on a fixed price for grid, diesel and solar over the 20 year lifecycle analysis in the HOMER simulation, but prices for solar have been decreasing while diesel has become more expensive [61]. To replicate the data from previous work,

we used the $6/Watt from that analysis, but high quality panels are available in Kampala, Uganda for less than $3/Watt in 2013, and this is consistent with world prices [48] [62]. Meanwhile, diesel and grid electricity prices are expected to rise over the 20 years of this system lifecycle, with a baseline expectation of a 30% increase and a high-side estimate of a 60% increase in diesel prices by 2030 [13] [63]. Szabó notes that the optimal system is extremely sensitive to diesel fuel costs and diesel subsidies, and that PV electricity is at the margin to become competitive with diesel and with grid electricity for larger populations in remote areas [43].

While HOMER does not support the ability to simulate an inflation rate for fuel prices that is higher than the general inflation rate, we can run sensitivity analysis on the price of diesel to examine possible impacts of a 30% and 60% increase in the price of diesel against the baseline price used in simulation. Note that this price increase holds throughout the simulation, so cannot exactly replicate a fuel inflation rate, but does serve to bound the solution. For comparison, we re-examine Scenario 4 (0.05 allowable capacity shortage ratio) at various fuel prices and PV panel costs. A range of diesel costs from $1.10/L (less than current prices) through $1.30/L up through 1.6 times that to $2.10/L is considered. Solar PV costs per watt are examined from the baseline of $6/Watt using HOMER's "PV capital cost multiplier" function to study PV costs reductions of 0.667 and 0.333 times 2010 prices ($ 4/W, $2/W respectively).

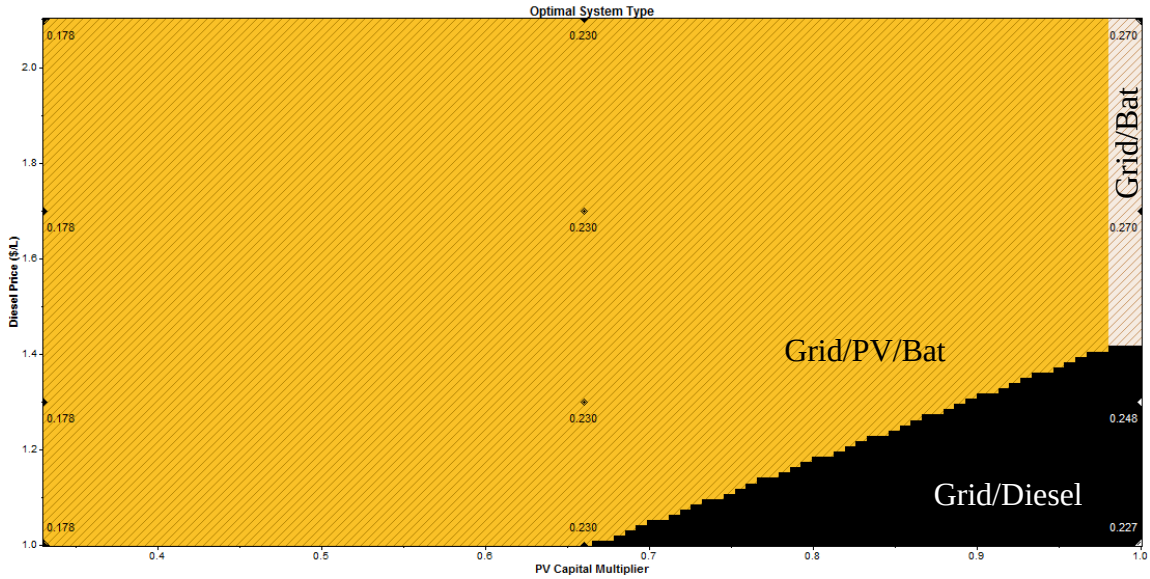

Fig. 6.8 Sensitivity analysis, optimal system configurations determined in HOMER simulation for increasing fuel prices and decreasing PV prices.

A clear summary of the impact of diesel price increases and PV price decreases can be seen in Fig. 6.8. The baseline price of diesel and PV panels is near the bottom right corner ($6/W, $1.3/L, LCOE = $0.248). Even at high PV prices, as diesel prices increase up the *y* axis, it takes only an increase in diesel to $1.4/L to move into a regime where batteries replace diesel in the optimal solution.

Leaving fuel prices alone, but considering less expensive PV, one moves left along the bottom of the chart to see that PV prices need to drop only to $4/W (66% of 2010 costs) for PV to become part of the optimal system configuration. Considering that PV prices have already (in 2013) dropped to less than $3/W, PV looks to be part of the optimal systems configuration now and in the future.

In sum, hybrid PV/diesel/battery solutions offer some adaptability to increasing fossil fuel prices, and have become more affordable and competitive as PV prices have decreased. At $2/W, the LCOE for a grid connected system in this scenario drops to $0.16/kWh for

95% availability at the end user, which is cost competitive with the $0.171/kWh cost for 85% availability from grid electricity.

6.1.3.2 Grid availability and grid extension distance impacts on LCOE and EDL

The optimal architecture for reliable electricity at a given location is a function of the cost of stand-alone generation, the cost of grid extension, the availability of the grid, and the required electricity availability at the site. For example, if the customer was satisfied with 20% downtime, the Ugandan grid would suffice and current methods for LCOE and EDL calculation and grid tie architectures would hold. Let us assume that the customers in question require more uptime, at a 100% availability rate.

To study EDL, we vary the grid extension distance from 0 to 14 km, and then run simulations with the 7 different MTBF and MTTR combinations shown previously in Table 6.1 as illustrated in Fig. 6.4.

For a perfectly reliable grid, the cost for grid extension increases linearly with the required extension distance. In the case of this analysis, connection can be made at a cost of $100,000/km, and this can be amortized across the useful lifecycle – in this analysis we will use 25 years, which we will show below results in a $0.03/km/kWh increase in LCOE.

Scenarios with an unreliable grid, but where 100% of the demand must still be met, require some form of additional local electricity generation. Therefore, we can expect that for each availability scenario, the cost in that scenario will (1) increase with decreasing grid availability, as more local generation capacity is required; and (2) increase linearly over distance at the $0.03/km/kWh as with the perfectly reliable grid.

Fig. 6.9 illustrates the resulting LCOE for each scenario at grid extension distances from 0 to 10 km. EDL at various grid extension distances for each scenario is also indicated where the parallel sloped lines for Scenario (a) through Scenario (f) intersect the horizontal line at \$0.456/kWh, the price from Scenario (g) for stand-alone generation. The EDL and LCOE values are also shown in Table 6.5. 'LCOE(A,0)' is the generation cost at a grid extension distance of 0 for the various availability rates, which are also the *y*-intercepts of the LCOE for each scenario shown in Fig. 6.9. The slope of the LCOE in the grid extension distance plot is shown as '$\partial LCOE/\partial D$,' and it's consistency between \$0.0308-0.0309/kWh indicates the linear increase with distance from the grid, as expected.

Simulation results for EDL and $\partial LCOE/\partial D$ can be confirmed mathematically, using data from a subset of the HOMER optimization results. Consider the optimal (minimum) LCOE(A,D) from HOMER simulation as a function of grid availability, A, and distance from the grid, D. LCOE (1,0) is simply the cost of grid electricity where the grid already extends (D=0) and is reliable (A=1). Without a grid connected DER providing sales back to the grid, this cost would be the price for electricity from the grid at \$0.171/kWh. For this analysis, we will not allow sales back to the grid, in order to focus on the impacts of grid availability and extension distance.

Table 6.5 Simulation results for LCOE, $\partial LCOE/\partial D$ and EDL for Scenarios (a) – (g)

Scenario	***Â***	***LCOE(A,0) ($/kWh)***	***∂LCOE/∂D ($/kWh/km)***	***EDL (km)***
a	1.00	0.171	0.0308	7.04
b	0.83	0.233	0.0308	5.03
c	0.75	0.267	0.0308	3.93
d	0.76	0.271	0.0309	3.79
e	0.62	0.301	0.0308	2.82
f	0.24	0.366	0.0308	0.72
g	0.00	0.388	na	

LCOE (0,D), or the LCOE of the stand-alone system from Scenario (g) where grid availability A = 0, is independent of distance, and is found from HOMER to be $0.388/kWh. Assuming that components scale linearly in cost, then the minimum LCOE at a grid connection distance of zero for any availability rate (the *y*-intercepts in Fig. 6.9) are given as the availability weighted average of the stand-alone generation cost and the price from a perfectly reliable grid:

$$LCOE(A,0) = [LCOE(1,0) - LCOE\ (0,D)]A + LCOE(0,D) \tag{6.5}$$

Which in this case gives LCOE(A,0) = [-0.217]A + 0.388.

Fig. 6.10 shows the comparison of this calculated LCOE(A,0), the actual simulation results from HOMER, and a linear regression along with 95% confidence bounds for the regression on the HOMER simulation results. The results from Eqn. (6.5) (blue line) are consistent with the HOMER simulation results (red squares), and well within the confidence bounds.

To calculate the LCOE as a function of distance, we next calculate the annual cost per kilometer of the grid extension over the lifecycle. The cost/year/kilometer is given by [64]:

$$k_{GE} = K_{GE}\left[\frac{i(1+i)^n}{(1+i)^n-1}\right] \tag{6.6}$$

where

K_{GE}= the capital cost per kilometer = 100,000
i =the interest rate = 4.8%/yr
n = the number of periods in the lifecycle = 25

which in this case Eqn (6.6) gives k_{GE} = $6,954/km/yr.

Next we determine the $\partial LCOE/\partial D$, the increase in LCOE per kilometer of grid extension. To calculate the grid extension cost in terms of LCOE, we divide the annualized cost of grid extension per kilometer (k_{GE}) by the amount of electricity demand per year,

and this gives the cost per kilometer of grid extension per kilowatt hour of electricity. We then update Eqn. (6.5) with the addition of a distance term:

$$LCOE(A,D) = [LCOE(1,0) - LCOE(0,D)]A + LCOE(0,D) + Dk_{GE}/e \quad (6.7)$$

where

D = distance from existing grid
A = availability
e= the total energy consumption per year = 225,570 in this example

which, in this case becomes LCOE(A,D) = [-0.217]A + 0.388+ [0.0308]D. The calculated $\partial LCOE/\partial D = k_{GE}/e$= \$0.0308/kWh, which is consistent with the values of \$0.0308-\$0.0309 shown in Table 6.5.

To calculate the EDL, one must first remember that the EDL occurs where the standalone electricity cost equals the electricity cost for grid extension, or LCOE(0,D) = LCOE (A,EDL). Substituting D=EDL to into Eqn. (6.7), then subtracting LCOE(0,D) from both sides, and rearranging terms, we get$[LCOE(1,0) - LCOE(0,D)]A = - [EDL]k_{GE}/e$. Solving for EDL gives:

$$EDL = [LCOE(0,D) - LCOE(1,0)]eA/k_{GE} \quad (6.8)$$

In this case the EDL is calculated as: EDL = [7.04]A, which is equivalent to the simulated EDL at $\hat{A} = 1$, and consistent with the remaining results shown in Fig. 6.11. This is also consistent with the linear assumption in Mahapatra and Dasappa [65]. In general we can say that EDL as a function of grid availability, A, is less than the EDL that would be calculated assuming a perfect grid, by a factor of A:

$$EDL(A) = [EDL_{A=1}]A \quad (6.9)$$

where

$EDL_{A=1}$ is the EDL assuming a perfectly reliable grid.

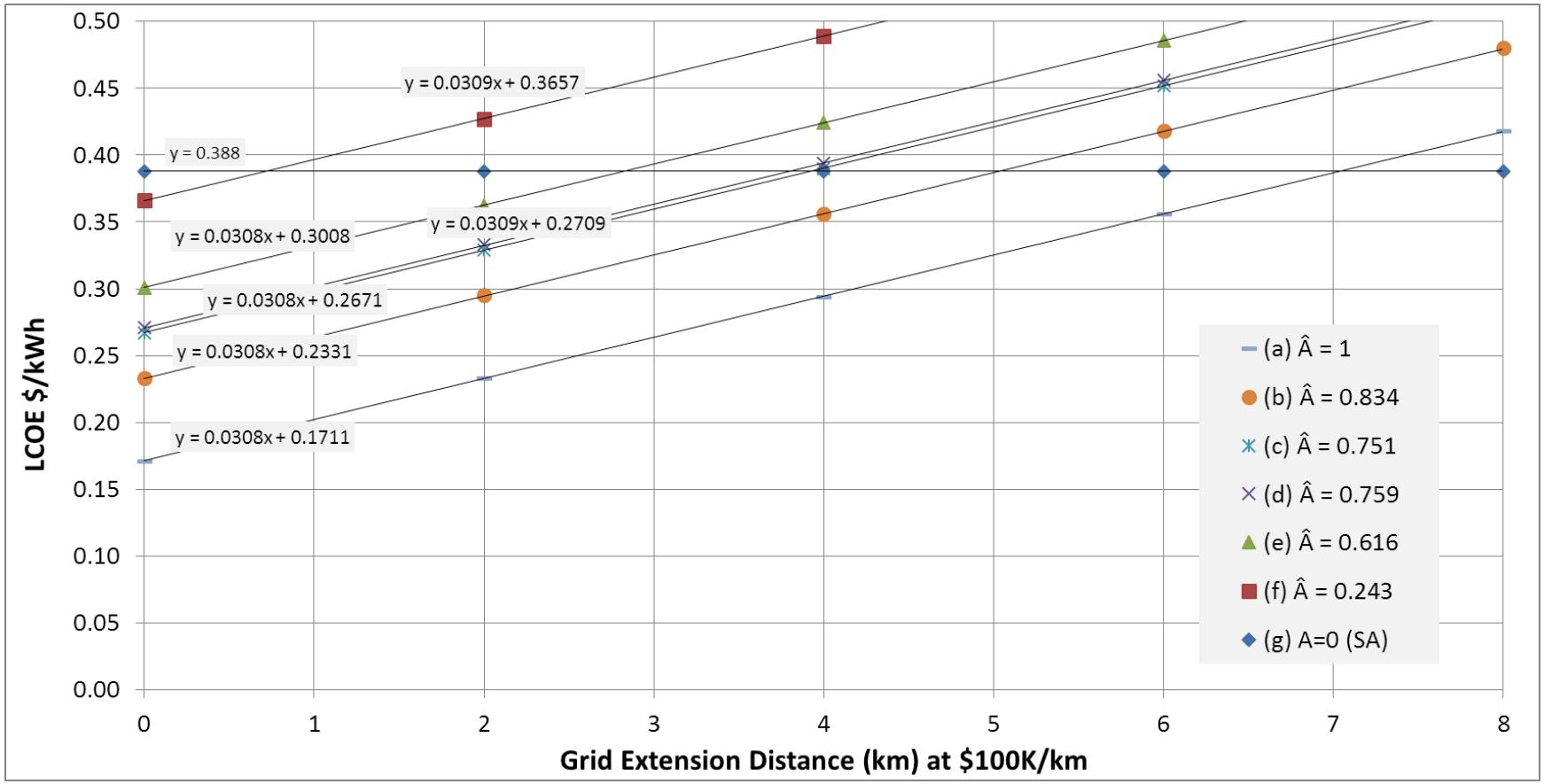

Fig.6.9 Grid extension distance versus LCOE for Scenarios (a) – (g)

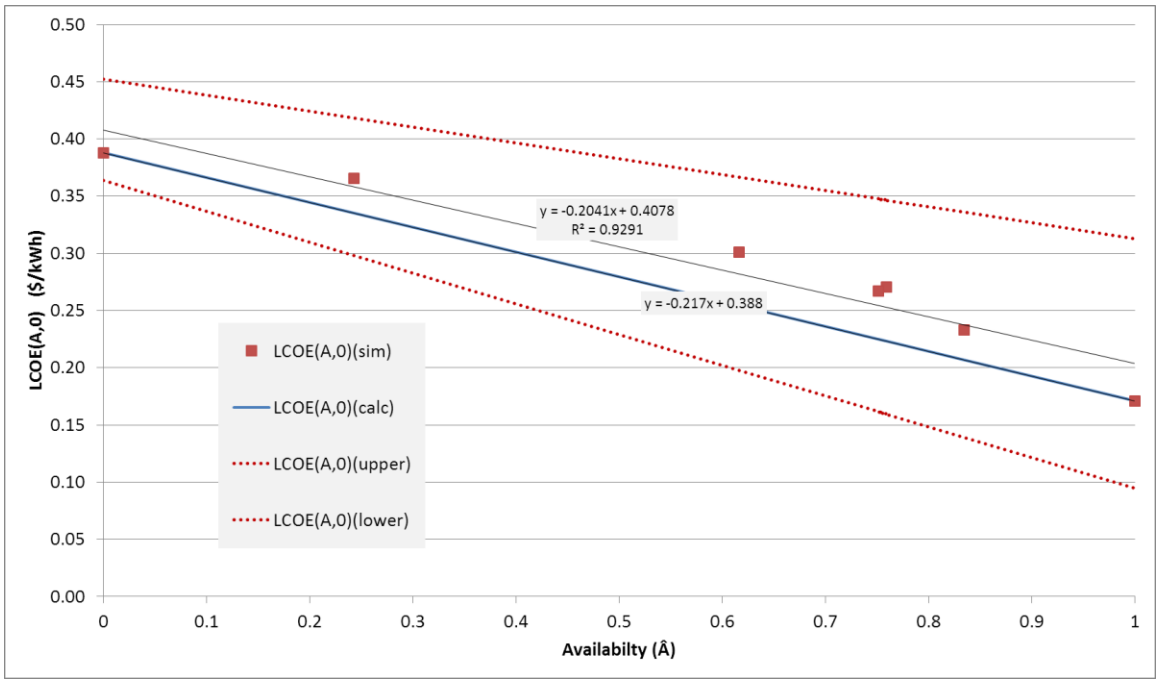

Fig. 6.10 LCOE (A, 0) (as a function of availability, with grid extension distance = 0) vs. Availability

Performing a linear regression on the EDLs using Â as the explanatory variable gives a slightly different result, as shown in Table 6 and the regression line in Fig. 6.11. The linear regression gives EDL = [5.79]A, with a regression coefficient $R^2 = 0.85$, and a 95% confidence interval for the coefficient to be between 4.66 and 6.93. For the regression, we set the constant to zero, as we fail to reject the hypothesis that the constant is zero with P-value on the constant term of 0.09. Fig. 6.11 shows the linear regression of the EDL versus Â along with the 95% confidence interval, the calculation from Eqn. (6.8) and Eqn. (6.9), and the observed data from simulation. The regression rejecting the hypothesis that the constant term is zero is also shown for comparison. Of note, this regression would indicate that at A ~ 0.2, it no longer makes sense to extend the grid. But because we have failed to reject the constant term = 0, despite the weak justification for the constant term, the 95% confidence interval on the mean becomes very wide – 95% confidence interval on the

constant term ranges from (-3.8, 0.4) with the resulting uselessly wide confidence interval shown in blue (EDL_c (lower) and EDL_c (upper)).

One could argue for a non-linear regression to capture the apparent curve of the experimental data, but we cannot determine the parameters of the exponential without simulation. In addition, the exponential regression would result in an EDL > 0 at A = 0, which cannot be rationally justified. As such the linear model still serves as a better estimator.

Using the linear regression without the constant term, the calculated EDL is consistent with the data from simulation, and Eqn. (6.9) serves as an upper bound estimate on EDL, which follows from the slight underestimation of LCOE from Eqn. (6.5).

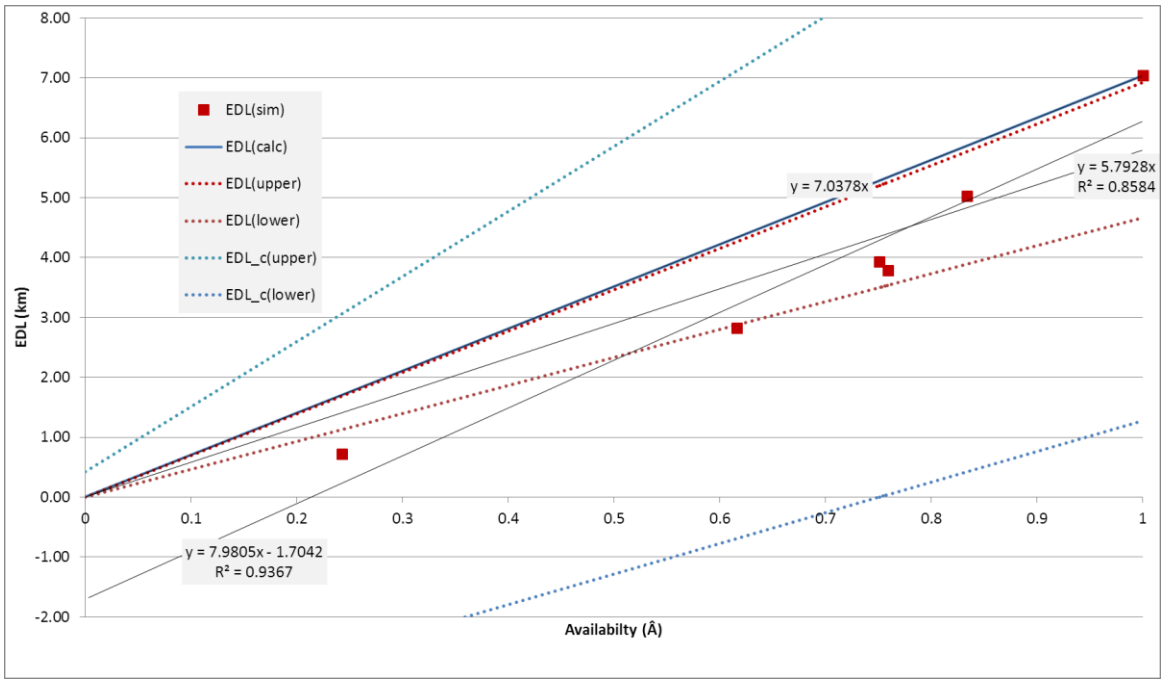

Fig. 6.11 EDL vs. Availability, including regression on simulation data and 95% confidence intervals for the regression

6.1.3.2.1 Observations on simulation and detailed design

The need to perform detailed design simulation can be seen by comparing the system configurations for each scenario at a certain grid extension distance. For a distance of 4 km, results are shown in Table 6.6. Note first that Scenario (a) meets all electrical demand with the grid, at a price of $0.294/kWh, a price $0.123 higher than at a grid extension distance of 0 km. As expected, this is 4 km*$0.031/km as per Eqn. (6.7). With grid availability in Scenario (b) dropping to 0.834, some additional generation is required, and is met by a solar-diesel hybrid, with no battery storage. Although Scenarios (c) and (d) both have grid availability on the order of A ~ 0.75, and LCOEs are similar at $0.391/kWh and 0.378/kWh, the architectures optimized for each scenario are quite different. As noted in Table 6.1 and Fig. 6.5, Scenario (c) incurs fewer longer outages compared to Scenario (d) with more frequent shorter outages. To address the longer outages, a diesel generator is part of the optimal solution in Scenario (c) while Scenario (d) forgoes the diesel generator and increases the solar and adds batteries. As the grid availability decreases in Scenarios (e) and (f), more solar and more battery are added to fill the gap left by the unavailable grid. Note that Scenario (f)'s LCOE at a 4 km grid extension distance is higher than standalone LCOE in Scenario (g). As can be seen from Fig. 6.9 and 6.11 and Table 6.4, the 4 km grid extension distance considered here is beyond the EDL for Scenario (f) of 2.9km, and the optimal architecture would be the same as Scenario (g) as a stand-alone microgrid.

Table 6.6 System architectures for 7 availability scenarios at a grid extension distance of 4 km.

Scen-ario	*Grid*	*PV (kW)*	*Batt (#)*	*Inv (kW)*	*Gen (kW)*	*Diesel Gen (kWh/yr)*	*Grid Electricity (kWh/yr)*	*LCOE ($/kWh)*
(a)	Yes	0	0	0	0	0	225570	0.294
(b)	Yes	50	0	50	50	30,843	142,890	0.357
(c)	Yes	50	0	50	50	46,513	128,657	0.391
(d)	Yes	80	128	50	0	0	145,149	0.378
(e)	Yes	200	128	50	0	0	112,119	0.435
(f)	Yes	300	256	50	0	0	2,167	0.499
(g)	No	250	512	50	0	0	0	0.487

6.1.3.3 Grid sellback prices - impact on LCOE and EDL

6.1.3.3.1 Grid sellback prices - impacts on electricity cost

For sellback price analysis, we will first focus on a grid extension distance of 0km. We have shown that grid extension simply increases the LCOE linearly as a function of distance, amortizing the cost of each kWh consumed. Depending on how sellback prices are incorporated, this will change the denominator in the third term of Eqn. (6.7).

We can predict that the ability to sell electricity back to the grid will lower the LCOE for the end user operating the microgrid, as electricity that would otherwise be excess can be exported to the grid, bringing in some revenue. If the sellback price is higher than the production cost, this could also incentivize larger and larger generation capacity in the microgrids and increased revenue, at least until distribution grid capacity constraints come in to play.

We can also predict that for availability levels A_1 and A_2, where $A_1 > A_2$, for a fixed sellback price, the LCOE for A_1 should be lower than the LCOE for A_2. Any solution available as a cost minima for a scenario with availability A_2 should also be available as cost minima for a scenario with availability $A_1 > A_2$. This prediction should hold until the

standalone generation cost is less than the price of grid electricity, in which case grid availability no longer matters and stand-alone generation is the preferred architecture.

The first result to consider is the impact of simply allowing net metering. This has a significant impact on LCOE. Net metering allows the grid-connected distributed generation system to put excess electricity (for example during peak sunlight hours) back on the grid and receive credit against grid energy usage (for example at night, when the PV system isn't producing) such that the billed amount is reduced by the amount put on the grid [66]. . The result for this analysis is shown in Fig. 6.12. First, the ability to sell power back to the grid will be a function of grid availability, as sales can only occur when the grid is functioning. The change in LCOE is shown, where the ratio

$$R(A) = \frac{LCOE_{noNM} - LCOE_{NM}}{LCOE_{noNM}} \tag{6.10}$$

is calculated for each availability level, with no net metering (noNM) and with net metering (NM) and a sellback price of $0.00 (NM). Fig. 6.12 shows that *R(A)* is a linear function of availability (*A*) such that

$$R(A) = R(1)A \tag{6.11}$$

Where in this case *R(1)* ~ 0.25. The decrease in LCOE resulting from allowing net metering will be a function of the amount of sales back to the grid, and from this it follows that this will be a function of production capacity (especially excess production capacity) and grid availability. Production capacity and excess capacity will only be known after detailed study or simulation of the specific scenario. In this analysis, only two scenarios need to be simulated – a perfectly reliable grid with and without net metering - in order to characterize the potential LCOE savings across all possible availability scenarios as per Eqn. (6.11).

Once net metering is allowed, Fig. 6.13 illustrates the impact of increasing sellback prices on LCOE. As expected, LCOE decreases as sellback prices increase and improve the economics of distributed generation. However, the effects are non-linear. For example, between $0.00/kWh and $0.104/kWh we expect and observe no impact from sellback prices. The marginal cost of generation from PV is $0.104/kWh at these capital costs and for the available solar radiation in the selected location in Uganda, there is no incentive for adding capacity to sell additional power until this marginal price is exceeded.

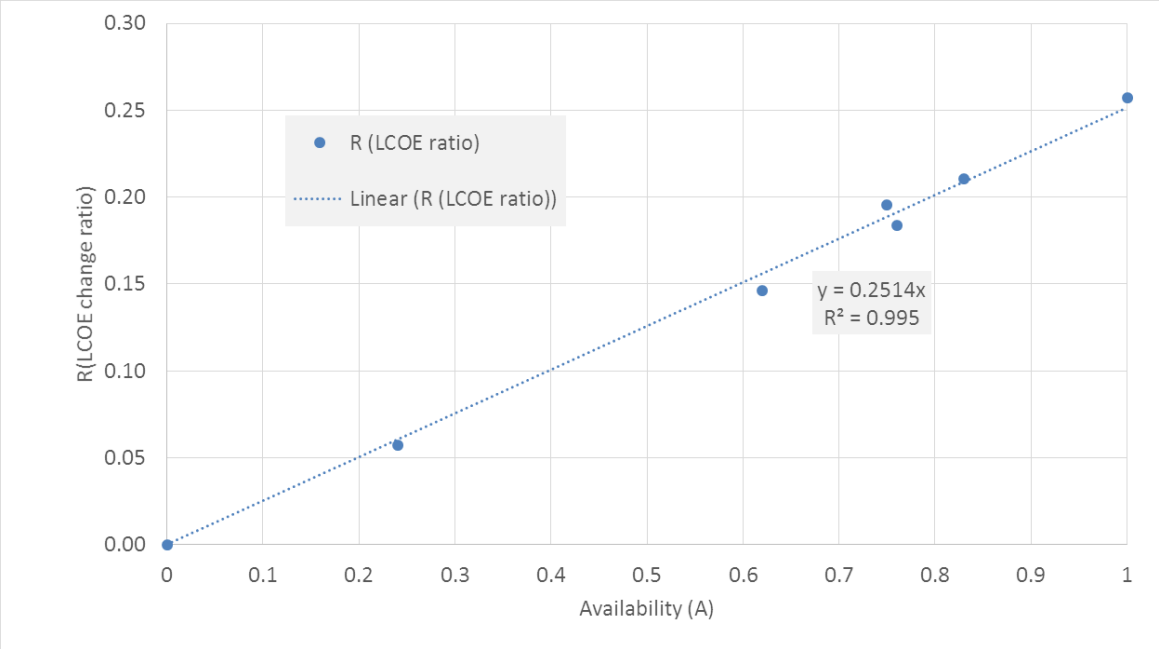

Fig. 6.12 Sales and the Ratio of the difference between LCOE with and without Net Metering vs. Availability

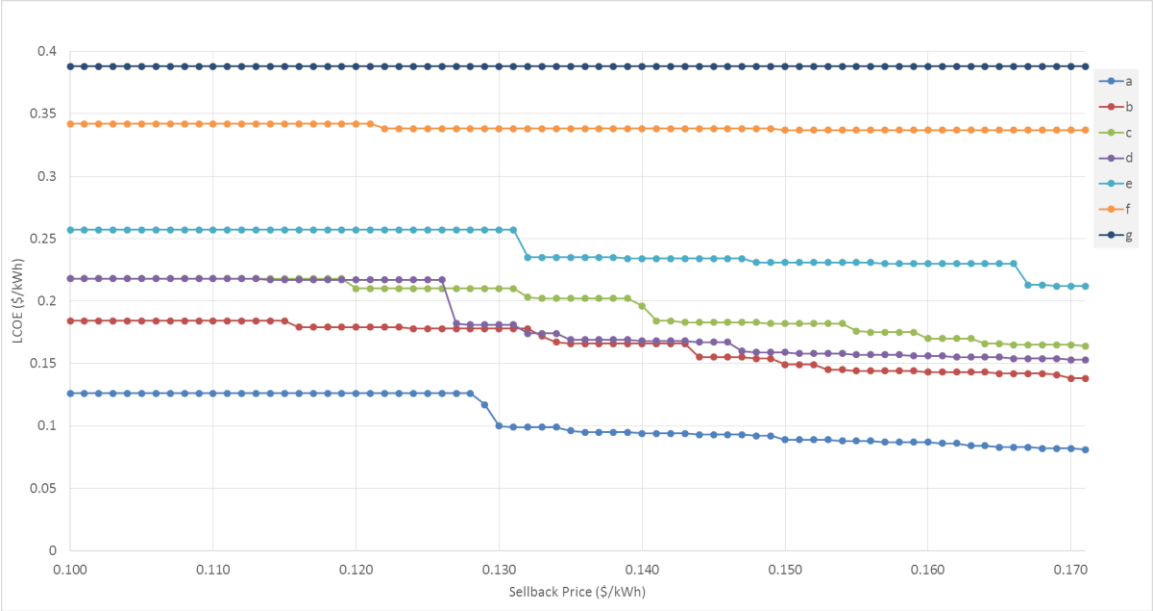

Fig. 6.13. LCOE vs. Sellback price, for the seven availability scenarios

Clearly in Scenario (g), sellback prices have no impact as no power can be sold back to a non-existent grid. Scenario (f) has such low grid availability that sellback still has very little impact with a less than $0.01/kWh difference in LCOE for sellback prices ranging from $0.00 through $0.171/kWh. Essentially, there is little benefit from increased sellback prices as the grid is not available enough for the system to sellback to it and recoup costs.

The next higher availability simulated in Scenario (e) with $A = 0.62$, sellback price does have impact on LCOE, cutting costs from $0.257/kWh at a sellback price of $0.00/kWh to $0.212/kWh at a sellback price of $0.169/kWh. The bulk of the reductions occur at discrete points, where sellback prices are $0.132/kWh and $0.167 and LCOE drops by $0.022/kWh and $0.017/kWh respectively. As can be seen in Fig. 6.14 and Fig. 6.15, the LCOE drop coincides with an increase in PV capacity and inverter capacity for the optimal system configurations. PV Capacity for Scenario (e) at sellback prices above $0.167/kWh actually exceed the PV capacity required by Scenario (f) with $A = 0.24$.

Similarly for Scenarios (a) through (d), relatively large decreases in LCOE coincide with increases in PV and inverter capacity, as increased sellback prices incentivize increased generation capacity. Inverter capacity peaking at 100kW occurs because of the limit on sellback power of 108 kW; a larger inverter is not necessary, and so not economical. Scenarios (a), (b) and (c) all obtain optimal LCOE with PV capacity of 80 kW up through sellback prices of $0.116/kWh. Above a sellback price of $0.116/kWh, Scenarios (b) and (c) follow a similar trend in PV and inverter scale, with resulting LCOE following similar steadily decreasing trend.

Conversely, Scenarios (a) and (d) both result in optimal configurations with larger step functions in PV and inverter near a sellback price $0.13/kWh, stepping PV capacity from 80 kW up to 150 kW. The optimal system in Scenario (d) cuts the LCOE to be competitive with Scenario (b), despite the difference in grid availability, and the LCOE remains lower than that for Scenario (c), despite the similarity in grid availability between Scenarios (c) and (d). The shorter duration outages for Scenario (d) vs. Scenario (c) appear to allow for more economical solutions under higher sellback prices. With only two scenarios to compare, this conclusion bears further study. For now, it is important to note that although the grid availability for Scenario (c) and Scenario (d) is almost the same, the MTBF and MTTR are quite different, and the resulting optimal systems components are not always the same.

6.1.3.3.2 Grid sellback Prices – impacts on EDL

That net metering and grid sellback impacts EDL is a given; the reasons how and by how much are twofold. First, by lowering the LCOE at a grid extension distance of 0 km

(LCOE(A,0)), net metering and sellback prices shift the entire set of LCOE vs. D curves downward. Second, the total electricity on the grid extension is increased by the amount of sales back to the grid, thus potentially decreasing the slope of the LCOE(A,D) curve.

For the first, LCOE(A,0) decreases in this case by a factor of 0.25*(A) as per Eqn. (6.10) and Eqn. (6.11) and as shown in Fig. 6.12. The 0.25 multiplier is only for this set of inputs, and would need to be simulated for the specific demand, prices and resources available at a given location. For this set of inputs, considering A = 1, or a perfectly reliable grid, this moves LCOE(1,0) from $0.171 with no net metering to $0.127/kWh with net metering, even with a $0.00/kWh sellback price. For a sellback price of $0.16/kWh, LCOE(A,0) drops to $0.087/kWh. Each LCOE(A,0) drops similarly, by 0.25(A), as shown in Fig. 6.12.

Secondly, sellback prices impact EDL by decreasing the rate of change in LCOE over distance. This occurs because with sellback prices, the total demand served increases from the local consumption e = 225,570 kWh/yr to also include grid sales from the microgrid. Determining the amount of grid sales for a given scenario requires detailed analysis and/or simulation of the scenario including sellback prices.

Fig. 6.16 illustrates the two-fold impact of sellback prices for Scenario (c) and Scenario (d). The upper 2 series for LCOE(~0.75, D, -0.05) replicate the data from Fig. 6.9 with no net metering. EDL remains the same at 4km for both scenarios. The two series in the middle illustrate LCOE(~0.75,D, 0), with net metering and a sellback price of $0/kWh. The intercept has dropped by $0.05/kWh, consistent with Eqn. (6.9). The slopes of the curves have dropped to $0.027/kWh/km; and the combined the impact extends EDL to 6km. These two slopes and intercepts hold between sellback prices of $0/kWh through

$0.119/kWh, where the two scenarios begin to have divergent optimal systems. When sellback price increases to $0.16/kWh, LCOE (~0.75, D, 0.16), the two curves have diverged significantly, with a $0.01 difference in the intercept, and a difference in slope of $0.002/kWh/km. The effect is to extend EDL to 10.0km for Scenario (c) and 11.5 km for Scenario (d).

A comparison of EDL across all 6 grid connected availability scenarios, and across the range of sellback prices is shown in Fig. 6.17 and Fig. 6.18. From Fig. 6.17, the independence of EDL from sellback prices between $0/kWh and $0.10 is apparent across all 6 scenarios. For Scenario (f) the relative independence continues, as the lack of grid availability limits the impact of sellback. Above $0.10/kWh, the trend is that the higher the availability, the steeper the slope of the EDL response to sellback prices.

Fig. 6.18 provides more detail on the trend. The data and regression for "No Net Metering" is the same as was shown in Fig. 6.11 if we reject the hypothesis that the constant term is zero. The resulting EDL = 8.0[A] – 1.7. For this set of analysis we can reject the hypothesis that the constant term is zero for S=0.18 and S=0.16, and so choose to do the same for all sellback prices.

For S=$0.00/kWh through S=$0.10/kWh, the EDL remains relatively independent of sellback prices, with EDL = 11.1[A] – 1.6, as was clear from the case in Fig. 15. This is the impact of net metering; sellback prices have not significant impact until they exceed the marginal price of production.

When sellback prices are above the marginal production price, the slope of EDL vs. Availability increases with increasing sellback price, as the increasing grid availability allows for more and more sellback until power constraints limit the amount of sales. Fig.

6.17 illustrates the impact of power constraints as the slopes all begin to level out above S=$0.14/kWh. As can be seen from converter capacity in Fig. 6.15, the 100 kW max power is being achieved above this point.

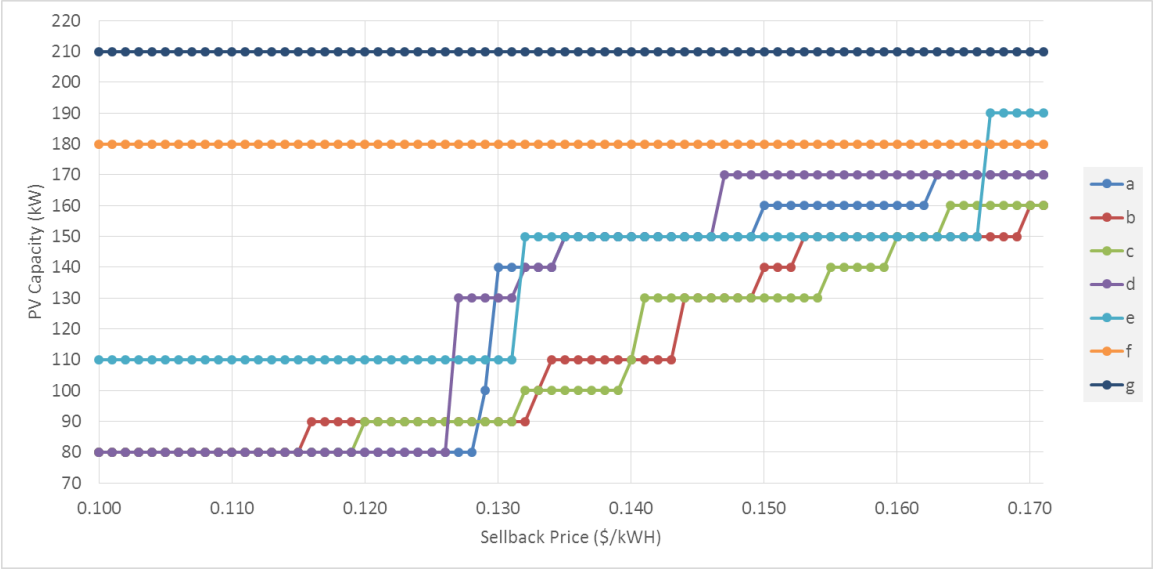

Fig. 6.14 PV capacity for optimal system configuration vs. Sellback price, for the seven availability scenarios

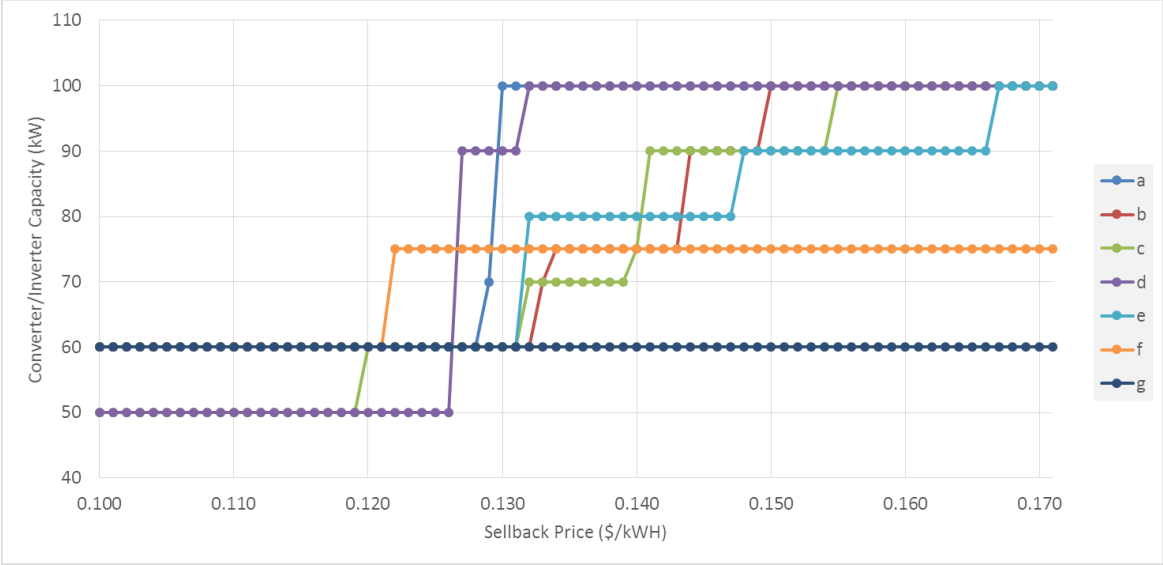

Fig. 6.15 Inverter capacity for optimal system configuration vs. Sellback price, for the seven availability scenarios

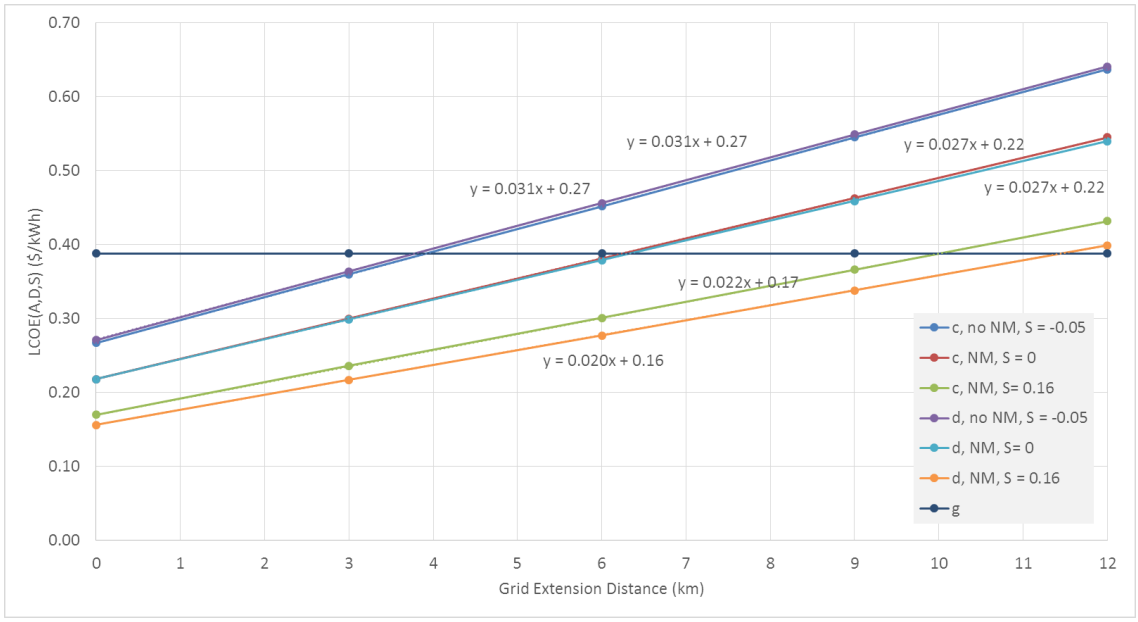

Fig. 6.16 LCOE as a function of grid availability, distance from the grid and sellback price (LCOE(A,D,S)) vs. grid extension distance for Scenarios (c) and (d)

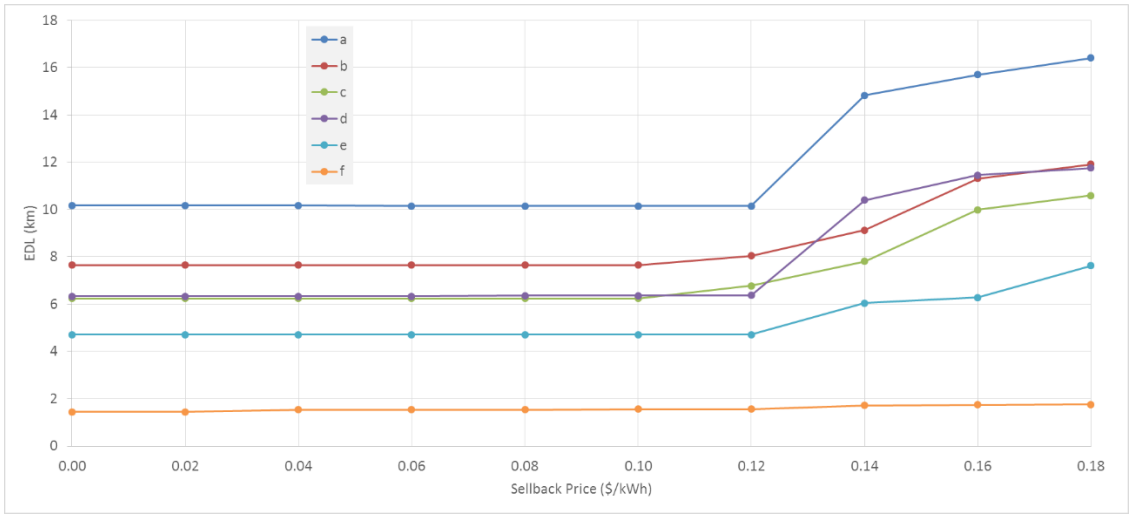

Fig. 6.17. EDL vs. Sellback prices for various availability scenarios

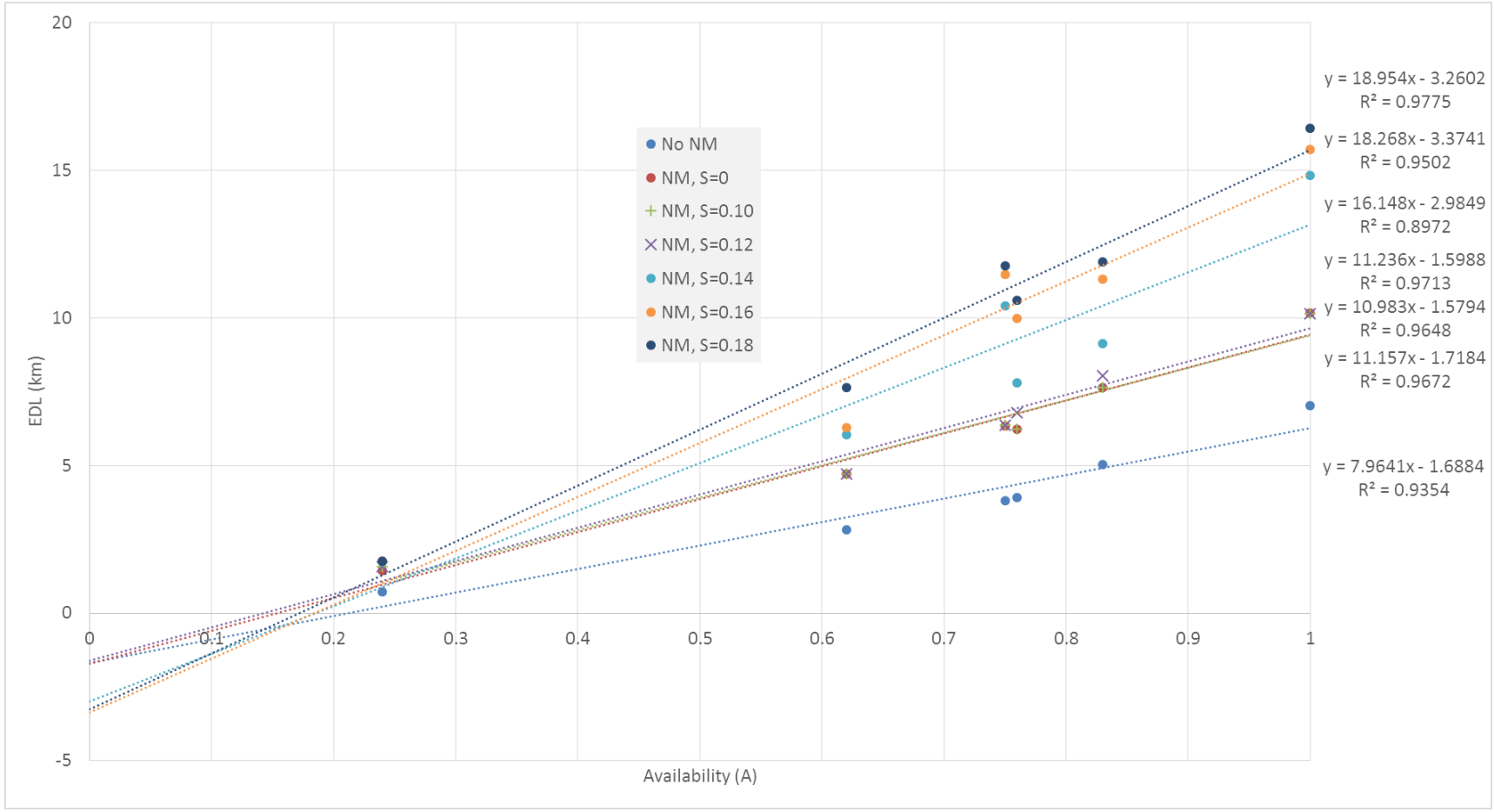

Fig. 6.18. EDL vs. Grid Availability for various sellback prices

Table 6.7. System architectures for availability scenarios at a grid extension distance of 4 km.

Scen -ario	*Grid*	*PV (kW)*	*Batt (#)*	*Inv (kW)*	*Gen (kW)*	*PV Gen (kWh/yr)*	*Diesel Gen (kWh/yr)*	*Grid Electricity Purchases (kWh/yr)*	*Excess Electricity (kWh/yr)*	*LCOE ($/kWh)*
(a)	Yes	0	0	0	0	0	0	225,570	0	0.294
(b)	Yes	60	0	50	50	87,551	29,384	139,218	27,935	0.356
(c)	Yes	60	0	50	50	87,551	44,933	125,028	29,348	0.390
(d)	Yes	50	0	50	50	72,959	49,432	125,199	19,628	0.394
(e)	Yes	90	128	60	50	131,326	24,470	121,514	27,842	0.424
(f)	Yes	160	256	60	50	233,469	19,070	64,177	56,029	0.489
(g)	No	210	256	50	60	306,428	35,376	0	71,948	0.388

6.1.3.3.3 Discussion of Grid Sellback Prices

In sum, from Fig. 6.9, Fig. 6.10 and Fig. 6.11, we see that Eqns. (6.3), (6.5), (6.6) and (6.7) hold, offering simple calculations for estimating LCOE and EDL, having to simulate neither outage schedules to enter into HOMER nor execute all of the various availability levels in simulation. Only one simulation is necessary, that for determining the standalone LCOE from Scenario (g). Although we can approximate LCOE and EDL, this method cannot identify the optimal system configurations necessary to achieve the minimum LCOE. Simulation in HOMER or other analysis tools is still required to determine optimal components.

The need to perform detailed design simulation can be seen by comparing the systems configurations for each scenario at a certain grid extension distance, even without sellback prices. With sellback prices, the systems optima vary significantly across the range, as can be seen from Fig. 6.14 and Fig. 6.15. For no net metering, at a grid extension distance of 4 km, optimal configuration results are shown in Table 6.7.

Note first that Scenario (a) meets all electrical demand with the grid, at a price of $0.294/kWh, which is $0.123 higher than the cost at a grid extension distance of 0 km. As expected, this is 4 km*$0.031/km as per Eqn. (7). With grid availability in Scenario (b) dropping to 0.834, some additional generation is required, and is met by a solar-diesel hybrid, with no battery storage. Although Scenarios (c) and (d) both have grid availability on the order of A ~ 0.75, and LCOEs are similar at $0.390/kWh and $0.394/kWh, the architectures optimized for each scenario are slightly different. As noted in Table 6.1 and Fig. 6.8, Scenario (c) incurs fewer, longer outages compared to Scenario (d) with more frequent, shorter outages. In part because of this disparity, and because of the pseudo-stochastic nature of the simulation, Scenario (c) incurs more outage hours during mid to late afternoons – when demand is peaking. To address the longer, afternoon outages, a larger PV array is part of the optimal solution in Scenario (c). As the grid availability decreases in Scenarios (e) and (f), more PV capacity is added, and batteries are included to fill the gap left by the unavailable grid. Note that Scenario (e)'s and Scenario (f)'s LCOEs at a 4 km grid extension distance are significantly higher than the standalone LCOE in Scenario (g). As can be seen from Fig. 6.9, Fig. 6.11 and Table 6.6, the 4 km grid extension distance considered here is beyond the EDL for Scenario (e) and Scenario (f) of 2.9km and 0.87km respectively. The optimal architecture would be the same as Scenario (g) as a stand-alone microgrid, as these systems are beyond the EDL. Scenario (c) and Scenario (d) are right at the EDL, and additional information would be required to determine if grid extension or stand-alone generation were optimal.

Sellback prices further justify the need for detailed analysis considering unavailable grids, as the LCOE and EDL impacts of net metering and sellback prices are significant.

Net metering can serve as an incentive for adoption of increased distributed renewable generation capacity, as it lowers the cost of electricity for the operator. Sellback prices below the marginal cost of generation are of little value to the operator, and have little or no impact on the capital and operations cost for the end user.

6.2 Conclusions

Providing reliable and eventually clean and renewable electricity to the 20% of the world's population that lacks access to a grid is a daunting challenge. The methods presented here demonstrate how consideration of the existing grid availability can be included in cost benefit analyses of various systems for electricity production, decision making for grid extension vs. stand-alone generation, and selecting optimal configurations for grid tied DER. This paper addresses this analytical shortfall by providing new methods to estimate the cost of reliable electricity and identify optimal systems configurations to provide more reliable electricity.

Using the methods presented here to analyze potential systems configurations for a village power system in Uganda, results indicate that at 2010 prices, diesel is the most economical choice for a backup system for the village. But expected increases in diesel fuel costs and continuing decreases in solar PV prices make solar/diesel hybrid systems economically competitive with diesel backup systems in the long run.

The method presented in Murphy et al. [47] demonstrates how consideration of the existing grid availability can be included in cost benefit analyses of various systems for electricity production, and selecting optimal configurations for grid tied DER. We then elaborated to provide new methods to estimate the cost of reliable electricity and EDL,

enabling better comparison between grid-tied and stand-alone generation economics where the grid is not reliable. Using the methods described in this paper, we can perform simple calculations for estimating LCOE and EDL without having to simulate all of the availability levels and grid extension distances. Only the standalone LCOE must be determined from simulation. Simultaneous consideration of grid unavailability and grid sellback prices are incorporated, as their analysis together were not possible using earlier methods. This is especially powerful because no simulation of grid outages is necessary for estimating LCOE and EDL, and the toolset for simulating unavailable grids needs improvement. The linear approximations work well for systems without net metering and electricity sellback. It is possible now to estimate the impact of net metering on LCOE and running only one additional simulation scenario, with a perfectly reliable grid and net metering.

To determine the optimal grid-tied or stand-alone microgrid configuration still requires simulation of a grid failure scenario and implementation of that scenario in a tool like HOMER. The model and method hold for any region with an electric grid that is less than perfectly reliable. The results have direct applications to current best practices for estimating economic grid extension distances. For example:

- the algorithms in Szabo et al. [44] for determining geographic locations where grid extension is optimal should be modified such that:
    - the distances from existing grid infrastructure where grid extension is noted as optimal should be modified by the availability A in each country and region, as per Eqn (6.2); and
    - where demanded availability is greater than grid availability, the regions noted for grid extension must also include hybrid distributed generation; that is, where the grid is unreliable, grid extension is never the optimal solution by itself.
- The calculations used by Parshall et al. [67] to determine MVmax, the maximum distance for extension of the medium voltage line - effectively the medium voltage EDL - should also be reduced by a factor of availability (A) as per Eqn (6.2).

6.3 Future Work

Four areas in this analysis have been identified for future research and exploration: (1) improved tool development, (2) deeper analysis of components of Availability, (3) analysis of sell-back prices on LCOE and EDL calculations, and (4) DER impacts on overall grid stability and availability.

First, integrating improved methods for HOMER grid availability modeling to allow for truly stochastic simulation of grid outages would allow for more detailed analysis of availability, availability components and economic impacts of stochastic outages.

Second, with new tools, analysis of a large number of MTBF and MTTR scenarios with the same overall availability would allow for the determination of the importance of reliability vs. reparability and their impacts on LCOE and EDL.

Third, analysis of grid sellback prices on system economics changes the linear simplifications presented in this paper. For a given grid availability, increased sellback prices generate lower LCOE overall, but demand additional infrastructure to produce enough for the DER to have excess to sell back to the grid. Predicting how grid availability considerations interact with sell-back prices will be critical for policy recommendations on sell-back prices. For example, at what grid availability level does the investment in grid connection for purposes of sellback stop being economical? The method will incorporate feed-in tariff (FiT) schemes as per Moner-Girona's [68] Renewable Energy Premium Tariff (RPT) and identifying optimal values for RPT in various countries and regions to support local supply and regional stability.

Finally, analysis of grid tied DER adoption on overall grid availability and stability could potentially increase the economic case for DER. What are the impacts of DER and their potential to augment the unreliable grid and meet the availability demand outside the defined microgrid customer? Could the local reduction in demand prevent rolling blackouts and scheduled outages from excess demand? Under what conditions is this most viable?

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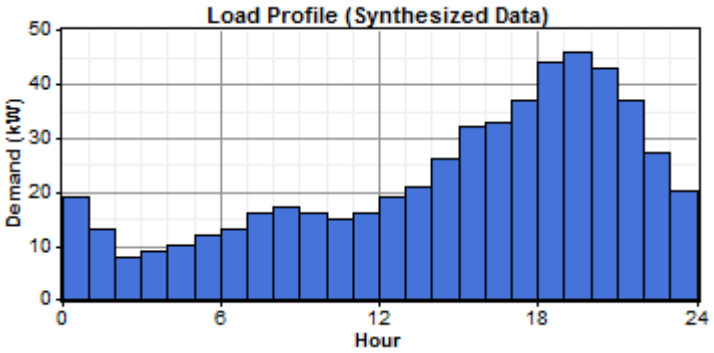
Appendix A

Homer inputs for scenarios (a)-(g)

HOMER Input Summary
AC Load: Primary Load 1



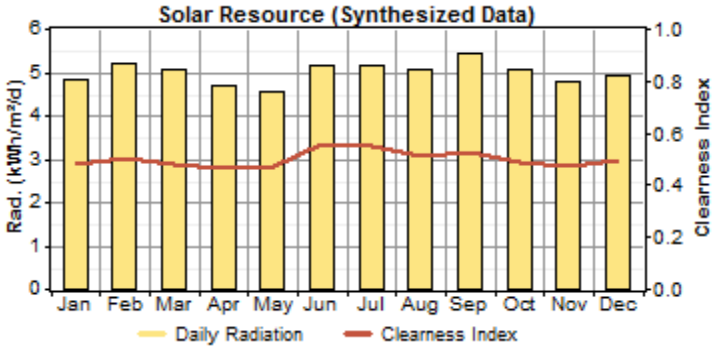
Data source:	Synthetic
Daily noise:	1.97%
Hourly noise:	1.94%
Scaled annual average:	618 kWh/d
Scaled peak load:	56.4 kW
Load factor:	0.457

PV Array (kW)	Generator (kW)	Batteries (strings of 2 each)	Converter (kW)
0.000	0.00	0	0.00
20.000	10.00	4	50.00
50.000	50.00	32	75.00
80.000	75.00	64	100.00
100.000	100.00	128	
120.000		256	
150.000		384	
200.000		512	
250.000			
300.000			

PV

Sizes to consider:	0, 20, 50, 80, 100, 120, 150, 200 kW
Lifetime:	25 yr
Derating factor:	80%
Tracking system:	No Tracking
Slope:	0.3 deg
Azimuth:	180 deg
Ground reflectance:	20%

Solar Resource



Latitude: 0 degrees 18 minutes South
Longitude: 31 degrees 42 minutes East
Time zone: GMT +1:00
Data source: Synthetic

Month	Clearness Index	Average Radiation
		(kWh/m^2/day)
Jan	0.481	4.858
Feb	0.502	5.224
Mar	0.483	5.074
Apr	0.462	4.710
May	0.474	4.559
Jun	0.555	5.149
Jul	0.549	5.163
Aug	0.510	5.052
Sep	0.528	5.453
Oct	0.490	5.083
Nov	0.475	4.808
Dec	0.495	4.924

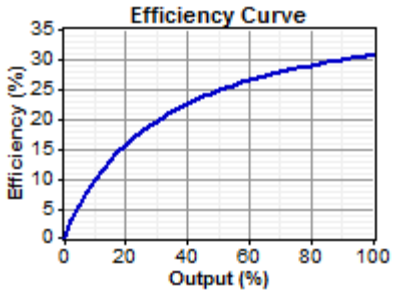
Scaled annual average: 5 kWh/m²/d

AC Generator: Cmty Backup Gen

Size (kW)	Capital ($)	Replacement ($)	O&M ($/hr)
100.000	25,000	20,000	3.000

:

Lifetime:	15,000 hrs
Min. load ratio:	30%
Heat recovery ratio:	0%
Fuel used:	Diesel
Fuel curve intercept:	0.08 L/hr/kW
Fuel curve slope:	0.25 L/hr/kW



Fuel: Diesel

Price:	$ 1.3/L
Lower heating value:	43.2 MJ/kg
Density:	820 kg/m3
Carbon content:	88.0%
Sulfur content:	0.330%

Battery: Surrette 6CS25P

Quantity	Capital ($)	Replacement ($)	O&M ($/yr)
1	1,200	1,000	10.00

Quantities to consider:	0, 4, 32, 64, 256, 512
Voltage:	6 V
Nominal capacity:	1,156 Ah
Lifetime throughput:	9,645 kWh
Batteries per string	2
Initial state of charge	100 %

Converter

Size (kW)	Capital ($)	Replacement ($)	O&M ($/yr)

100.000	42,900	40,000	0

Lifetime:	16 yr
Inverter efficiency:	95.5%
Inverter can parallel with AC generator:	Yes
Rectifier relative capacity:	100%
Rectifier efficiency:	95.5%

Grid

For each scenario (a)-(g), define rates

Rate	**Price ($/kWh)**	**Sellback ($/kWh)**	**Demand ($/kW/mo)**
Peak	0.171	0.120 / -1	0.000
Shoulder	0.171	0.060 / -1	0.000
Off-Peak	0.171	0.040 / -1	0.000
FAIL	1e+030	-1.000	0.000

Set schedule so each scenario matches images (a)-(g) below.

Net metering:	Monthly accumulation
CO2 emissions factor:	632 g/kWh
CO emissions factor:	0 g/kWh
UHC emissions factor:	0 g/kWh
PM emissions factor:	0 g/kWh
SO2 emissions factor:	2.74 g/kWh
NOx emissions factor:	1.34 g/kWh
Interconnection cost:	$ 0
Standby charge:	$ 0/yr
Purchase capacity:	1000 kW
Sale capacity:	500 kW
Prohibit any grid sales below sellback rate of	0 $/kWh

Economics

Annual real interest rate:	4.8%
Project lifetime:	25 yr
Capacity shortage penalty:	$ 0/kWh
System fixed capital cost:	$ 0
System fixed O&M cost:	$ 0/yr

Generator control

Check load following:	No
Check cycle charging:	Yes
Set point state of charge:	80%
Allow systems with multiple generators:	Yes
Allow multiple generators to operate simultaneously:	Yes
Allow systems with generator capacity less than peak load:	Yes

Emissions

Carbon dioxide penalty:	$ 0/t
Carbon monoxide penalty:	$ 0/t
Unburned hydrocarbons penalty:	$ 0/t
Particulate matter penalty:	$ 0/t
Sulfur dioxide penalty:	$ 0/t
Nitrogen oxides penalty:	$ 0/t

Constraints

Maximum annual capacity shortage:	Varies by scenario
Minimum renewable fraction:	0%
Operating reserve as percentage of hourly load:	10%
Operating reserve as percentage of peak load:	0%
Operating reserve as percentage of solar power output:	10%
Operating reserve as percentage of wind power output:	10%