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by

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GRID PARITY ANALYSIS OF STAND-ALONE HYBRID MICROGRIDS: A COMPARATIVE STUDY OF GERMANY, PAKISTAN, SOUTH AFRICA AND THE UNITED STATES

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Abstract

Grid parity for alternative energy resources occurs when the cost of electricity generated from the source is lower than or equal to the purchasing price of power from the electricity grid. This thesis aims to quantitatively analyze the evolution of hybrid stand-alone microgrids in the US, Germany, Pakistan and South Africa to determine grid parity for a solar PV/Diesel/Battery hybrid system. The Energy System Model (ESM) and NREL's Hybrid Optimization of Multiple Energy Resources (HOMER) software are used to simulate the microgrid operation and determine a Levelized Cost of Electricity (LCOE) figure for each location. This cost per kWh is then compared with two distinct estimates of future retail electricity prices at each location to determine grid parity points. Analysis results reveal that future estimates of LCOE for such hybrid stand-alone microgrids range within the 35-55 cents/kWh over the 25 year study period. Grid parity occurs earlier in locations with higher power prices or unreliable grids. For Pakistan grid parity is already here, while Germany hits parity between the years 2023-2029. Results for South Africa suggest a parity time range of the years 2040-2045. In the US, places with low grid prices do not hit parity during the study period. Sensitivity analysis results reveal the significant impact of financing and the cost of capital on these grid parity points, particularly in developing markets of Pakistan and South Africa. Overall, the study helps conclude that variations in energy markets may determine the fate of emerging energy technologies like microgrids. However, policy interventions have a significant impact on the final outcome, such as the grid parity in this case. Measures such as eliminating uncertainty in policies and improving financing can help these grids overcome barriers in developing economies, where they may find a greater use much earlier in time.

Dedication

I dedicate this thesis to my loving family, whose prayers and support have helped me achieve everything. I also dedicate this to my friends who have always been there for me.

I dedicate this to the people of Pakistan who continue to persevere in the face of many hardships and challenges including terrorism.

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List of Abbreviations

AC	Alternating Current
AEO	Annual Energy Outlook
AEP	American Electric Power
BDEW	Federal Association of Energy and Water Industries Germany
BOS	Balance of System
CSR	Climatological Solar Radiation
DC	Direct Current
EEG	Renewable Energy Sources Act
EIA	Energy Information Administration
EPA	Environmental Protection Agency
EPIA	European Photovoltaic Industry Association
ESM	Energy System Model
GHG	Greenhouse Gas
HOMER	Hybrid Optimization of Multiple Energy Resources
IEA	International Energy Agency
IPP	Independent Power Producer
IRENA	International Renewable Energy Agency
ITRPV	International Technology Roadmap for Photovoltaics
JRC-EC	Joint Research Center of the European Commission
LCOE	Levelized Cost of Energy
LR	Learning Rate

MYPD	Multi-Year Price Determination
NEPRA	National Electric Power Regulatory Authority
NERSA	National Energy Regulator of South Africa
NREL	National Renewable Energy Laboratory
NTDC	National Transmission and Despatch Company
PR	Progress Ratio
PSI	Peak Solar Intensity
PV	Photovoltaic
RAF	Road Accident Fund
WACC	Weighted Average Cost of Capital
WEC	World Energy Council

List of Symbols

η_{PV}	Solar PV efficiency
b	learning parameter
C_0	Cost of cumulative production at t = 0
CC_t	Capital Costs
CO_2	Carbon Dioxide
C_t	Cost of cumulative production at time t
F_t	Fuel expenses
H	Solar Insolation at a given location and time
H_0	German Standard Electric Load Profile
i	Interest Rate
kWh	kilowatt-hours
M_t	Maintenance Costs
P_0	Cumulative production at t = 0
P_t	Cumulative production at time t

Introduction

The current models for electricity generation in the world are predominantly based off of centralized power plants with vast transmission and distribution networks covering a wide variety of terrains to provide electricity coverage to people in far flung areas. Power at these power plants is typically generated through combustion (coal, oil, natural gas) or nuclear fission. In addition to transmission distance issues, these systems contribute to greenhouse gases, nuclear waste, inefficiencies and power loss over the lengthy transmission lines (Distributed Generation Education Modules, 2007). With increasing electricity demand across nations, increasing oil prices, costs of transmission line expansions and maintenance, and rising levels of concern for greenhouse gas emissions, the importance of a re-evaluation of this conventional centralized energy generation system has grown over the years. (Hafez & Bhattacharya, 2012).

In response to these challenges, energy developers and researchers have increasingly shown interest in the possibility of having numerous smaller generation systems allowing for reliable and more efficient electricity. Commonly termed as distributed generation, microgrids have emerged as technological implementations of such distributed generation systems.

Microgrids are modern, small-scale versions of the centralized electricity system (The Galvin Project Inc., n.d). They make use of small scale, site specific technologies such as solar and wind to generate power so that they can be located close to the end users. They generate, distribute, store and regulate the flow of electricity on a local scale, most of the time making use of renewable energy sources. By making use of such small-scale site-specific renewable technologies, they help achieve specific local goals such as reliability and carbon emission reduction. They can be connected to the main grid, working in coordination with the power utility as grid-tied distributed generation systems. In this mode of operation, they offer many advantages of distributed generation including reduced line losses and transmission congestion, improved reliability and cleaner energy.

They can also operate autonomously as stand-alone off-grid power producers, commonly referred to as an 'islanded operation'. In this case, making use of a local renewable energy source in conjunction with storage and a conventional power source like a diesel generator, these microgrids operate as local stand-alone hybrid power systems independent of the main grid. In recent times, such stand-alone systems have found applications in the provision of electricity to small communities, particularly in rural and remote areas of less-developed countries. With their ability to operate independently, they are frequently pitched as an alternative to grid extension for providing electricity to communities currently without power. Moreover, their ability to make use of cleaner alternative sources for power generation makes them a greener option.

As a result, microgrids are popping up all over the world, from systems that can connect or disconnect from the larger 'main' grid, to tiny informally wired connections between a few users (Schnitzer, et al., 2014). With fast paced evolution in technology as well as their increasing applications, researchers and energy developers are considering them to be important power systems of the future.

However, like most emerging technologies, stand-alone microgrids in particular face a number of challenges which have somewhat limited their penetration in energy markets of the world (Distributed Generation Education Modules, 2007). With widespread use of conventional grids developed over many years, these smaller versions of the grid (which may eventually become alternatives to the former) face a steep resistance from the status quo. Moreover, due to their reliance on renewable sources of energy, they face challenges such as high capital costs and intermittent nature of power output from these renewables. As a result, the costs to produce energy from these off-grid microgrids are frequently reported to be significantly higher than the electricity costs from the conventional main grids. Since the adoption of a new alternative in energy markets heavily depends on costs and economics of the technology, one of the more important economic concerns with these stand-alone grids is the cost of energy generated from them.

Grid parity is defined as the milestone when the cost of a renewable energy technology becomes competitive with the conventional grid-supplied electricity (Yang, 2010). This parity point for renewables and emerging power generation technologies like stand-alone microgrids is considered to be important because many believe this could lead to grid defection. It is argued that once consumers are offered environmentally friendly, reliable electricity produced from a renewable resource at an equal or lower price than that from the grid, they would choose the cleaner more reliable option. For renewables like solar PV in particular, this is considered as a tipping point for their dominance in the energy mix (Yang, 2010).

Given their use of alternatives, growing applications particularly in the developing world, and the ability to potentially compete with the conventional grids in energy markets around the globe, off-grid microgrids are definitely evolving into important building blocks of the future energy infrastructure. With a fast paced evolution of this technology, similar to the case of emerging alternative sources like solar PV and wind, one can expect for the associated energy costs from these systems to reduce gradually over time. This expectation, along with their current high costs of power generation leads to an important question that is in need of an answer: when do these stand-alone systems hit grid parity in the future?

Literature review suggests that even though there have been economic analyses regarding such systems, with parity studies conducted sometimes, most of them are limited in scope and analysis methodology. Moreover, much of the research on microgrids implicitly refers to grid connected systems. Therefore, they do not answer this specific question of grid parity for hybrid stand-alone microgrids, which this study aims to address.

Microgrids and Public Policy

Microgrids aim to improve the existing energy infrastructure by providing people with smaller, cleaner, reliable and more efficient grids to fulfill their energy needs. Therefore, their importance to policy can be chalked out from the arguments underlying energy's importance in public policy. Since most governments around the globe are either pushing for cleaner forms of energy or extending electric grids to people without power, they have every reason to consider this technology important.

Energy by far is one of the most important engines of economic growth and social development, on which both poverty reduction and shared prosperity are highly dependent (World Bank, n.d.). Most economic activity today is impossible without energy, which is essential for business development, job creation, income generation and international competitiveness (World Bank, n.d.). All of which are important public policy metrics. Therefore energy and its future is of great importance to policy makers.

Given this, governments around the world continue to invest time and resources in such a major driver of the economy. However, the level of this government intervention varies across countries. For most developing countries like India or those in Africa, government regulation of the energy sector is significant, with the responsibility to provide energy residing with the government. In contrast, for European countries, this government control is limited to safeguarding public interests with policies such as those for climate change. Even for US markets driven by corporations and utilities safeguarding private goals, public interests are left vulnerable, forming a firm basis for government involvement.

Since microgrids may evolve into important building blocks of the future energy infrastructure, and in turn economic development, they become important to public policy. Moreover, with their potential to compete and offer a cleaner substitute to the existing grid, the adoption of stand-alone microgrids may lead to conflicts of public values. As a result, they can assume an even greater importance at the policy level. Historically, the case of renewable sources of energy has been quite similar around the world where government subsidies and policies for renewables like solar and wind have mostly helped them compete with fossil fuels (Beck & Martinot, 2004). With a heavy reliance of such stand-alone systems on local renewable sources, public policy becomes and important aspect of their future growth and evolution.

Past literature points at this heavy reliance of emerging energy systems and renewables on public policies as well. An examination by (Yang, 2010) reveals that the growth in solar PV is limited in a small number of countries where the demand is largely policy driven. The German and Spanish feed-in tariffs are good examples of this for grid tied solar PV systems. A similar investigation by (Wiser & Pickle, 1998) shows that energy costs from renewable systems are heavily dependent on effective renewable/energy policies.

Because these grids offer a clean and more efficient alternative to the conventional grid, they have the potential to address some key energy sector externalities of climate change as well. Therefore, they have the ability to offer governments around the globe a policy opportunity to improve on environmental protection.

Keeping in mind that energy systems are inflexible (Collingridge, 1992), a switch to a more novel technology like these grids themselves will always be challenging. Energy and power infrastructure is both time and resource intensive. Energy systems are inflexible systems (Collingridge, 1992) – they have high upfront costs, long lead times, are big scale projects and have a high dependence on other infrastructure. Moreover, their environmental impacts are long term. For instance, coal power plants built throughout the 20th century in America took considerable amount of resources and time to generate power and their environmental impacts were witnessed when a considerable amount of them were already operational. This may well be true for environmental and societal impacts of such hybrid microgrids as well. Thus they are prone to be at the center of future policy discussions and debates, especially when they do hit grid parity.

While the energy market is a global market, the very motivation and reason to support or block these microgrids would vary significantly across different countries of the world depending on varying economic and regulatory frameworks as well as the local energy market. It is this diversity that this research aims to investigate, which could further highlight policy paths for the countries considered.

Literature Review

When it comes to research, a lot has happened regarding distributed energy systems, microgrids and renewable energy technology. Current and past research focus on both, technological and economic aspects of their integration in to the energy markets. These have assumed importance because techno-economic as well as environmental feasibility assessments for such emerging energy systems are imperative for them to develop into satisfactorily functioning systems. Moreover, most of these efforts have led to further research into the field, helping these systems evolve over time.

Research on the technical aspects of these microgrids is concentrated on relevant power electronic devices, efficient energy storage devices and systems, effective control and protection systems and algorithms, and microgrid management systems (Ustun, Ozansoy, & Zayegh, 2011). In each of these areas, research is being conducted at both the device and system levels to improve their reliability, stability and power quality. Over the past decade, various microgrid projects have been undertaken in different parts of the world to address some of these technical challenges. The following provides a short list of some of these projects/research initiatives with their respective research domains conducted in different parts of the world (Ustun, Ozansoy, & Zayegh, 2011):

- *Microgrids project* – National Technical University of Athens: To develop strategies for control algorithms and protection schemes
- *ISET Microgrid* - Germany: Research on various microgrid control methodologies
- *More Microgrids Projects* – National Technical University of Athens: To study alternative methods, strategies along with universalization and plug-and-play concepts in microgrids.
- *NEDO* funded renewable energy systems microgrid projects in Japan to study ways microgrids help solve intermittent nature of solar/wind sources as well as to study different service levels to customers. The projects also aimed at determining optimum operation and control systems for microgrid integration.
- *Microgrid Pilot Project* in Korea to study and test all technical aspects of microgrids.
- *Consortium for Electric Reliability Technology Solutions* – CERTS USA and their research to facilitate easy connection of small distributed generators.

- *Microgrid Analysis software tools* being developed for their efficient deployment at Georgia Institute of Technology.
- *Distributed Energy Resources Customer Adoption Model (DER-CAM)* - UC Berkley, USA.
- *Virginia Polytechnic Institute Consortium on Energy restructuring* - Research dealing with the design and management of distributed generation technologies. This covers research and development of technologies, power engineering, grid interface systems as well as the social, political environmental and economic dimensions, and business, marketing and pricing of such systems. (Distributed Generation Education Modules, 2007)
- Research on the Design of microgrid integrated power systems in Australia.

Apart from the technical aspects of distributed generation, researchers have spent considerable time on the economic impediments affecting the development of these microgrids. There have been studies conducted to understand and quantify the economic and environmental impacts of such systems (Farzan, et al., 2013). Others have focused on power markets and various outcomes under different policies and microgrid penetration levels (Marnay, Asano, Papathanassiou, & Strbac, 2008). Research has been done to model each microgrid component over time, in order to calculate operational costs (Whitefoot, Mechtenberg, Peters, & Papalambros, 2011). Other studies have focused on cost effectiveness (Rangarajan & Guggenberger, 2011), their cost variations to energy prices (Zhang, et al., 2013), and the development of appropriate economic regulation frameworks (Costa, Matos, & Lopes, 2008). All of these have helped provide valuable insights on the economics of such distributed systems and grids.

There are many research efforts reported in literature that discuss the economic viability of both grid connected and stand-alone microgrids. Most of these are techno-economic analyses attempting to determine technical feasibility and economic viability for such systems. These have been mostly conducted to demonstrate the use of renewables as stand-alone power alternatives to conventional sources like diesel generators. Such comparisons have helped identify various approaches to study the economics of microgrids and highlighted the potential as well as challenges of these systems. More importantly, they have laid the foundation for further research like this thesis.

Considering stand-alone systems, even though many studies conduct analysis similar to the approach adopted in this study, their scope is usually limited in time and/or space. Work by (Shahid & Elhadidy, 2007) uses NREL's HOMER micro-power optimization model to carry out a techno-economic viability for stand-alone hybrid solar PV-diesel-battery power systems for a desert environment like Saudi Arabia. They use their results to discuss the potential of harnessing solar energy for places like Saudi Arabia and present basis for the design of such hybrid systems in similar climates. For their study, (Dekker, Nthontho, Chowdhury, & Chowdhury, 2012) investigate the economic feasibility of solar PV diesel hybrid off grid systems in different geographies in South Africa. They identify variations in system performance and associated costs with changes in geographic and climate conditions. Based on their Net Present Cost (NPC) estimates for these hybrid systems, they determine the ideal locations for their installation in South Africa, while stressing the need for government subsidies and feed in tariffs to encourage investments in renewables. With their analysis, (Bakos & Tsagas, 2003) determine technical and economic feasibility of a hybrid solar/wind installation to provide residences in Greece with thermal and electrical energy (Kaundinya, Balachandra, & Ravindranath, 2009).

They use simulation models, the Life Cycle Costing (LCC) methodology and payback period to demonstrate the use of grid connected hybrid systems to meet the typical residential load while realizing savings on energy expenses.

Other studies compare stand-alone photovoltaic systems with conventional options like diesel power systems for particular locations. These help highlight the competitiveness of renewable based stand-alone systems with conventional power sources like diesel generators, and mostly help form the basis for the quantitative secondary analysis conducted for this thesis. Work by (Kolhe, Kolhe, & Joshi, 2002) determines the economic viability of stand-alone solar PV with a conventional diesel system for India using a life-cycle cost computation and sensitivity analysis. Their results show that solar PV-powered stand-alone systems are economically competitive with diesel generators up to a specific daily energy demand in India. However, their results are limited to a solar PV system without storage or an auxiliary power supply. More importantly, their analysis reveals the sensitivity of solar PV economic viability to discount rates, diesel fuel prices, PV system costs and solar insolation, which is later investigated in this study as well. In a similar study, (Ahmad, 2002) designs a complete stand-alone photovoltaic system with storage, for a rural family house in Egypt and compares the economics of this system with a conventional diesel system. The study concludes that the use of PV + storage systems in rural zones is beneficial and competitive with diesel stand-alone systems with the added advantage of cleaner energy. The data conditioning approach used in the study partially feeds into the input data processing for this thesis.

In a similar analysis, (Dalton, Lockington, & Baldock, 2008) conduct a feasibility study for a stand-alone renewable energy system using HOMER, HYBRIDS and RES assessment tools. The study compares optimal system results for different combinations of diesel and solar

PV (diesel only, solar PV only, hybrid) configurations. The assessment criteria used in the study are similar to those used here: net present costs, renewable factors and payback times. The modelling results demonstrate that renewable energy systems have the adequate potential to reliably meet power demand in large scale stand-alone operations. They also reveal that a hybrid configuration yields the lowest net present costs while significantly reducing greenhouse gas emissions in comparison to diesel-only systems. They conclude that such stand-alone renewable systems have significant potential to meet large scale stand-alone power requirements. The overall analysis feeds into the working for this study and forms the basis for the use of multiple optimization tools to validate and compare results.

Similar economic analyses have been conducted for rural electrification in various developing and developed countries. These not only highlight the capability of such systems to provide power to remote locations, but also investigate their competitiveness with conventional stand-alone power sources. In their economic evaluation, (Vallve, Gafas, Mendoza, & Torra, 2001) conduct an analysis of the investment and operating costs of PV-hybrid systems which highlights the challenge of high up-front costs and concludes that rural electrification with such renewable hybrid systems requires government subsidies. For this analysis, they consider several rural villages of the Amazonia region, Argentina, Spain and Ecuador. In a similar study, (Nouni, Mullick, & Kandpal, 2006) use results of their techno-economic evaluation to determine financial viability for distributed stand-alone PV power systems in rural areas of India and conclude that financial incentives are imperative to make these power systems viable.

It is important to mention here that the aforementioned economic studies provide valuable insights to the use of renewables in stand-alone distributed power systems in various individual energy markets. Although some of these research efforts use an analysis approach similar to the one in this study, most of them limit the scope to single locations at current times. However, this research builds on the methods and approaches used in such studies to broaden the scope of these techno-economic analyses to four different markets. More importantly, many of these research efforts help gather technical and economic details of various system components which serve as inputs to the optimization models used for this thesis.

Even though there have been some studies covering cost parity for particular standalone renewable based power systems– like solar PV or wind, their workings are also mostly limited to specific countries. For the US, (Bronski, et al., 2014) conduct a similar techno-economic analysis to determine grid parity for off-grid solar PV systems in various residential and commercial markets within the United States. Making use of NREL's HOMER software they analyze off-grid solar-plus-battery operations, sizing and economic value to determine grid parity points for five different locations in the US. Their study results conclude that solar PV systems hit cost parity in some parts of the country well within 30 years (Bronski, et al., 2014). However, they make use of optimistic assumptions for interest rates and cost forecasts for system components. Using experience curves to conduct a grid parity analysis for Germany, (Bhandari & Stadler, 2009) determine solar PV prices in a way quite similar to the one used in this study. However, their research determines PV electricity generation costs on a kWh basis for coming decades using initial investment, replacement and variable costs. More importantly, their analysis implicitly assumes a grid-tied system. They compare these costs with grid electricity prices to determine parity points and conclude that parity for such grid-connected systems occurs before the year 2020.

In a similar parity study at a much greater scale, (Breyer & Gerlach, 2013) conduct a grid-parity analysis for solar PV using a grid parity model based on the LCOE and experience curves. They determine capital expenditures for PV power plants using experience curves, and arrive at the LCOE making use of these and other variable expenses. Their results show grid parity for over 150 countries in order to present a global overview. However their research model is limited in terms of the uniform assumptions applied to determine parity points on a kWh basis, making their working overly simplified. More importantly, they implicitly consider a grid-tied system by not considering battery storage in the analysis. They cover different market segments but only consider large scale PV power plants, rather than off-grid or on-grid distributed systems. They base their PV power plant system costs on prices for roof-top and industrial roof-top systems from the German market, which are one of the lowest in the world. Their use of a single weighted average cost of capital and uniform learning rates for the experience curve approach fail to capture diversity across different countries as well. For parity point determinations, they use average retail price figures at a regional level, thus not accounting for the true retail price trends. Their scope is limited to only 10 years and even though their parity study covers a lot of countries, it simplifies and generalizes the investigation.

Similar grid parity work is reported by (Perez, 2014) for both the residential and commercial sectors for multiple countries. Even though their work accounts for many variations between countries, their analysis is only limited to a PV system with no storage and diesel back-up. Additionally, the analysis mostly covers previous years rather than a prognosis into the future. Moreover, rather than modeling the operation of such a system to determine the optimal system configuration and LCOE, they calculate PV generated electricity mathematically using an approach similar to an experience curve analysis. Thus their working fails to capture the true time series operation of such a system to meet the electric load. Based on this simplified approach, they conclude that grid parity is already here for solar PV in many of the considered locations.

A common conclusion from most of these grid parity studies is their fairly optimistic parity results primarily based on future technological advancements. In his study, (Yang, 2010) discusses these ‘unrealistic’ expectations for solar PV, indicating that in most cases this is due to the fact that not all elements of the costs to the end consumers are amortized. Moreover, (Yang, 2010) concludes that cost-effectiveness alone would not be sufficient for solar PV systems and the importance of public policy cannot be ignored. On a similar note, (Kaundinya, Balachandra, & Ravindranath, 2009) assert that the implementation of such energy systems can be successful only if policies are clearly stated and presented to stakeholders. They summarize literature on policy aspects of stand-alone systems and highlight that they can be only successful if there is local, institutional and government support (Kaundinya, Balachandra, & Ravindranath, 2009).

Considering the developing world, numerous studies discuss these microgrids as viable solutions to rural electrification in developing economies. In most cases, they highlight the importance of such distributed systems in achieving universal power access as well as augmenting a strained centralized grid. A recent study published by the United Nations Foundation uses microgrid case studies from developing countries around the world to assess the progress and success of these grids in underprivileged villages without access to electricity. They recognize the technical and financial inefficiencies associated with connecting the remote areas to the main grids and present benefits of microgrid use (Schnitzer, et al., 2014). Similar challenges of grid extension at remote locations in developing countries are discussed by (Bhattacharyya & Palit, 2014). They assert that with insufficient generating capacities in many developing countries, even urban areas remain poorly supplied. Therefore, grid extensions may only worsen the energy shortfall. Moreover, with grid extension being capital-intensive and highly dependent on geography and remoteness, the poor financial health of utilities in such developing economies limits its importance. They maintain that microgrids may be a suitable solution in such situations, offering reliable power at a much smaller/local scale.

Apart from just rural electrification, other studies have pointed at the use of such systems to off load the central grid in places where power demand exceeds supply. In their research, (Ravindra & Iyer, 2014) identify the challenge of reliably matching electricity supply with demand in developing countries like India, where traditional policy measures of load shedding and/or increasing supply centrally have been insufficient. By conducting a scenario analysis for an urban residential community, they conclude that locally installed community microgrids can be suitable decentralized options to augment the centralized power systems and plug the demand-supply gap (Ravindra & Iyer, 2014).

Based on this literature, there is ample evidence to conclude that for developing markets like Pakistan/India or those in Africa, such stand-alone renewable power systems have the ability to solve some of their energy woes. For instance, considering the current energy situation in a place like Pakistan, where the existing grid is old, inefficient and unreliable while the country has significant solar/wind resources, these stand-alone systems can help plug the demand-supply gap as well as provide an alternative to grid extension in some of the most remote locations currently unserved.

Apart from this, other studies discuss how these microgrids can even help developing nations leapfrog past the conventional large scale transmission systems of the industrialized world. With examples of renewable microgrids around the developing world including places like India and Africa, (Guevara-Stone, 2013) talks about these grids supplying electricity to remote regions without power. Drawing from how mobile phone technology in such developing countries has leapfrogged past landline infrastructure of the industrialized world, she believes that these grids are capable of doing the same. This potential provides ample reasoning for such markets to seriously consider these stand-alone microgrids as important energy infrastructure options.

Given this clear diversity in the potential need and use of such grids in developing and developed countries, the question of grid parity becomes an important one. Moreover, since most of the discussed analysis studies conduct financial evaluations limited in scope, they do not address this question of grid parity using a techno-economic analysis which models the most optimal off-grid PV/Diesel/Battery system. More importantly, such an analysis is not used to compare different countries and energy markets for microgrid development. Since there is enough literature to support the claim that the development and adoption of microgrids and renewable based distributed generation systems are dependent on public policies, it is certain that different countries will have different cost parity points. Conclusions drawn from a comparative study investigating differences in solar PV system prices between the US and Germany (Seel, Barbose, & Wiser, 2014) reveal this effect of diversity on the economics of renewable energy technologies like solar PV. A similar comparison of grid parity points can thus reveal similarities and differences between the considered energy markets, which may serve as important inputs to a policy debate.

Since solar PV is considered as the renewable technology for this hybrid microgrid analysis, research on the economic aspects of solar PV assume great importance as well. In particular, studies regarding future price forecasts and cost parity help identify key forecast results and methods. Studies with experience curve analyses to determine future prices for solar photovoltaic modules (Bhandari & Stadler, 2009) help develop a method to deduce prices for areas where dependable forecasts are not available. Various international and national agencies like the Energy Information Administration from the US, the European Photovoltaic Industry Association (EPIA) for the EU, the International Energy Agency (IEA), and departments of energy in countries, all publish their respective energy industry status reports with price forecasts for renewable and conventional energy resources. Most of these reports are annually updated and help gather up to date data. Therefore, these reports and agencies are one of the main sources of data for this research.

This research is an attempt to build on past literature and conduct a techno-economic analysis for stand-alone hybrid microgrids in different energy markets of the world in order to answer the following research question.

Research Question

When do stand-alone solar PV/diesel/battery hybrid microgrids hit cost parity with the conventional power grids in different energy markets of the world?

Based on differing energy profiles, energy mix, government policies and regulations, electricity distribution networks, infrastructure, tariff and price regimes, load profiles and the use of renewable energy due to varying government subsidies and incentives, microgrids and their utility and usability will be seen differently in different countries across the globe. Due to the aforementioned factors, their deployment in countries will vary across domains such as time and location. This thesis discusses these geographical and temporal variations to identify parity points which reflect when these grids become economically competitive to the conventional grid systems in four different countries of the world. The main goal here is to get a high level view of this grid parity by considering a few diverse energy markets.

The question is an important one to answer for policy makers as well as researchers, energy developers and investors working on the integration of distributed energy systems to the conventional grid infrastructure around the world. Currently, initial capital investments in microgrids are high with long payback periods. With many people considering investments in these projects, while they are an expensive proposition compared to the conventional grid systems, the study can highlight future trends for such investors.

Moreover, it can provide both a quantitative and qualitative analysis of varying scenarios and situations across different countries. The resulting forecast figures can then help policy makers to plan and perceive the importance of steps that may be needed to capitalize on any opportunities that these grids may have to offer. For instance, due to considerable uncovered remote areas and strained power grids in developing countries, they may leapfrog past the conventional central grid infrastructures of the developed world. This means that such systems could potentially hit cost parity much earlier in these developing countries than the industrial nations. As a result, such developing countries could be huge potential markets for the relevant microgrid infrastructure and technology industries from the developed world.

More importantly, the answer to this research question may help form the basis for the next important question about what happens once they do hit grid parity. As mentioned earlier, these stand-alone grids may ultimately compete with the conventional central grid. Considering their application in both developing and developed countries, this could result in different outcomes. For developed countries, the disruptive effects of these grids could ultimately lead to what is termed as ‘cascading natural deregulation’ (Bass, 2013) by the Hawaiian Electric Company. With grid parity, such microgrids would become more attractive alternatives to the main grid, which will eventually lead consumers to leave the main grid. With fixed costs of these main grids spread across fewer users, electricity rates would increase. This in turn would further promote grid defection so that ultimately the central grids adapt to the change. Recent drops in grid electricity demand in Hawaii are seen by many as cascading natural deregulation.

For developing countries however, this grid defection may have an entirely different outlook. Instead of challenging the main grid, these microgrids could in fact help ease congestion in markets where there is an energy shortage, or improve access to power by providing energy to remote areas. For markets with consumers experiencing massive power cuts, a more reliable power option could lead consumers to leave the grid. In either case, this could result in a paradigm-shift which may have important consequences for the energy sectors around the world.

Based on this discussion, it can also be concluded that the research can help highlight and identify spatial and temporal variations in energy markets and how these impact evolution and acceptance of novel energy technologies like stand-alone microgrids. For instance, in terms of user acceptance, one may expect consumers in developing countries with strained energy sectors to have a higher willingness to pay for reliable power. This is in fact reported by (Phuangpornpitak & Kumar, 2011) where they investigate the user acceptance of diesel/PV hybrid systems in an island community. Their results show that islanders in a community in Thailand were willing to pay for electricity from a hybrid system even though it was eight times more expensive than the grid power in the mainland. Grid parity results from this study may in fact help lay the foundation for such future investigations into the local energy markets and their susceptibility to evolving technologies like microgrids. By providing a high level view of when researchers may expect things to change in individual markets, the study can form the basis for further policy analysis, especially in locations where they hit grid parity much sooner.

Methodology

The following two energy system modeling tools are used to predict the future of microgrids and when they hit economic parity with the grid in four different economies of the world.

- Energy System Model (ESM) developed here at RIT
- NREL's Hybrid Optimization Model for Electric Renewables (HOMER)

The use of two tools helps validate results, since their optimization algorithms are different. Also, it helps reinforce the work because this study involves a prognosis of many parameters, most of which are based on simplifying assumptions.

For this research, a co-located off-grid /PV/Diesel/Battery hybrid microgrid system is considered. A hybrid energy system generally consists of a primary renewable source working in parallel with a standby secondary non-renewable module and storage units (Khan & Iqbal, 2005). A hybrid system, as suggested by (Khan & Iqbal, 2005), offers a potential solution to the problems of stand-alone systems like low capacity factors, excess battery costs and limited capacity to store extra energy (Kaundinya, Balachandra, & Ravindranath, 2009). The analysis is driven by a cost predictive modelling of various energy resources deployed in microgrids in different countries with different energy policies governing prices of fuel, solar PV, batteries and installation/labor, all of which serve as inputs to the models. Future forecasts for these are used to determine the Levelized Cost of Energy (LCOE) values for the optimal microgrid systems.

Levelized Cost of Energy (LCOE)

The Levelized Cost of Energy (LCOE) is a primary metric for the cost of electricity produced by a generator over its lifetime. It is determined by dividing the discounted total costs by the energy generated. These include all lifecycle costs including initial investment or capital costs, operations costs and cost of fuels. It is typically used to compare relative costs of energy produced by different sources. This makes it an important metric for energy policy since it helps compare and evaluate different energy sources, thus allowing to determine the most cost-effective one. Units are typically cents/kWh or $/kWh. The following mathematical relation defines the LCOE:

$$LCOE = \frac{\sum_{t=1}^{n} \frac{CC_t + M_t + F_t}{(1+i)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+i)^t}}$$

where

CC_t are the capital costs in the year t

M_t are the operation and maintenance costs in the year t

F_t are the fuel expenditures in the year t

E_t is the energy generated in the year t

n is the life of the system

i is the discount rate

The Four Locations

The four countries considered in this comparative study are: United States, Germany, Pakistan and South Africa. They are chosen keeping in view the availability of relevant input data and the need to maintain diversity in both economic and geographic terms. Of the four, the United States and Germany are both developed countries with mature energy markets, ample energy resources, and policy frameworks which have helped develop their respective energy sectors. At the same time, they are significantly different in terms of the use of renewable energy, especially when it comes to solar PV. In contrast, South Africa and Pakistan are developing economies with strained energy sectors and poor governance. Their energy sector problems along with their good renewable energy resources make them interesting potential candidates for microgrid solutions.

It is worth mentioning here that only specific locations in each country, which are representative of the respective energy market, are considered for the analysis because of the limitations of time, resources and scope. The choice of cities is primarily governed by the availability of relevant data. However, it is important to highlight that the chosen locations are representative of conditions suitable for the use of a solar PV-hybrid system in each country. These are shown in the table below:

Table 1

The four countries and their respective locations considered in the analysis. The choice of locations is governed by the availability of necessary data.

Country	Location
United States	Columbus, Ohio
Germany	Munich
Pakistan	Hyderabad, Sindh
South Africa	Johannesburg

The following sections provide brief overviews of the electricity markets in each country.

United States. The United States is one of the biggest, most diverse electricity markets of the world. About 80% of the electricity in the US gets generated by private utilities, while the remaining power is generated by federal agencies (REEEP, 2013). Generally, competitive wholesale electricity markets function across the US, using distinct models in different regions. As a result there are many retail electricity providers in the country. Several agencies within the government share jurisdiction over the production, transformation, transmission and consumption of energy (REEEP, 2013). Of the total generation capacity, renewables only provide a small percentage with wind and solar as the most adopted alternatives. However, the US federal and state governments have developed policies to incentivize the use of renewable energy in order to increase this share of alternatives in the energy mix. Currently, retail electricity prices are low in most places.

Germany. Germany is a frontrunner in renewable electricity. The recent growth in renewable energy sources for electricity (RES-E), which contributed up to 17% of the electricity supply by 2011, has helped the country in significantly diversifying its electricity sources. At the same time, future large-scale deployments of renewable energy are at the heart of Germany's energy concept, Energiewende (REEEP, 2013). Currently, most of this renewable electricity generated is connected to the distribution systems. With feed-in tariffs from the Energy Sources Act (EEG) in place, network operators are required to purchase electricity generated by renewables, which has increased the diversity of power generators in the country. This has allowed a steady revenue stream for a large number of producers who have set up and connected renewable systems like solar PV to the grid. However, it has come at the expense of retail electricity prices, which have considerably risen in real terms over the last decade. In terms of the market, a significant number of power plants are owned and operated by four incumbent power producers. Competition is not that high with regional and local companies ensuring supplies, although the German local authorities tend to play a role in transmission and distribution of electricity (REEEP, 2013). In terms of solar PV, even though Germany has one of the lowest costs associated with solar PV systems, the average solar irradiation is less than many southern European countries.

Pakistan. Pakistan's energy sector is in a state of crisis with a significant electricity shortfall. The government-controlled power sector is facing growing problems due to a tariff not reflective of costs, high inefficiencies, low payment recovery and the government's inability to manage its subsidy mechanisms (REEEP, 2013). Despite investments in generation capacity, electricity demand continues to exceed supply, resulting in blackouts of about 8-10 hours per day (commonly referred to as *load shedding*) in cities and almost double in rural areas (REEEP, 2013). The current energy mix heavily relies on imported gas and fuel oil which is unsustainable, given the countries developing economy. The power sector is regulated by the government and mostly relies on public utilities and some independent power producers (IPPs) for power generation. Owing to its geographical location, the country has a huge potential for renewable energy. It lies in a region of high solar irradiance and is ideally suited for solar energy projects. However, the current utilization is still at a development stage with several large scale pilot projects being implemented (REEEP, 2013).

South Africa. The South African economy is one of the most energy intensive economies of the world (REEEP, 2013). However, the residential use of electricity only accounts for 16-18% of the country's electricity consumption. Eskom, the main utility in South Africa provides almost 95% of the country's electricity, with the rest supplied by independent power producers. Around 73% of the population has access to this power (REEEP, 2013). Presently, the power grid in South Africa is constrained as the margin between demand and supply is narrow, resulting in power outages or *load shedding* during some months of the year. Moreover, existing grid infrastructure problems have been surfacing, which Eskom has been unable to effectively address because of limited finances. Low electricity tariffs not reflective of the cost of generation and maintenance backlogs are severely affecting progress. With most of the power currently generated from coal, the country aims to develop renewable energy sources to increase diversity. For solar PV, with most areas in South Africa averaging more than 2500 hours of sunshine, it has good solar resources to harness energy from (Department of Energy South Africa, n.d.)

Research Methodology

Data collected is conditioned to serve as inputs to both the ESM and HOMER. A combination of various economic and technical inputs help define a microgrid system and feed into calculations for the LCOE. Some of the more important ones considered in this research are:

Economic

- Capital costs for the diesel generators, solar PV, lead acid batteries and inverters
- Diesel fuel prices
- Operating costs for the diesel generator, solar PV, lead acid batteries and inverters
- Cost of Capital rate (i.e. discount rate)

Technical

- Electric Load Profile time series data
- Solar Radiation time series data
- Temperature time series data (in case of the ESM)

Other technical inputs for both models are set at default values and kept constant throughout the analysis. Using these inputs, HOMER and ESM help complete the optimization to determine the cheapest optimal system design. Optimization routines are run at 5 year intervals with input values for the years 2015 till 2040. Economic inputs are updated for each of these six optimization runs at a particular location, while some of the technical system parameters are kept constant for the entire analysis at that location. For a new location, both technical and economic inputs are updated. The 5 year interval runs at each location render LCOE values with the optimal system configurations for the next 25 years, allowing a fair comparison with the retail grid electricity prices to determine parity points. These base case results are further analyzed for discussion using a one way sensitivity analysis. The following figure summarizes the flow of work in this study.

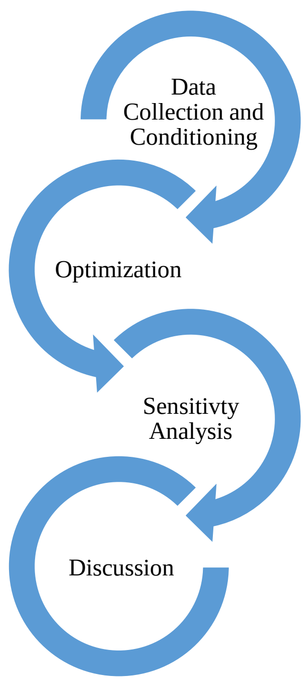

Figure 1. Research workflow diagram. Data collected from various sources is processed in the required input format for the models. Optimization using these renders the LCOE results. Base case analysis is followed up with a sensitivity analysis to investigate the impact of variations in important inputs. It also helps draw necessary conclusions and policy implications.

The Optimization Models

This section describes the two modelling tools used in this analysis

The Energy System Model (ESM). The ESM is an engineering-economic model that inputs a particular system configuration, load time series and solar resource time series to determine the time-series operation of each component and calculates the Levelized Cost of Electricity (LCOE) and other relevant financial information (Hittinger, Wiley, Kluza, & Whitacre, 2015). It is flexible enough to allow for changes in the microgrid design used for such calculations. Within input constraints, the model iterates to choose the most optimal system under the given set of parameters (such as PV costs or diesel prices) and can be used to study how changes in these parameters affect the optimal system configuration (Hittinger, Wiley, Kluza, & Whitacre, 2015). It has been implemented in MATLAB and is a specific engineering-economic model for a co-located off-grid diesel generator/PV/Battery microgrid system. The following figure shows a snapshot of the MATLAB interface for the ESM.

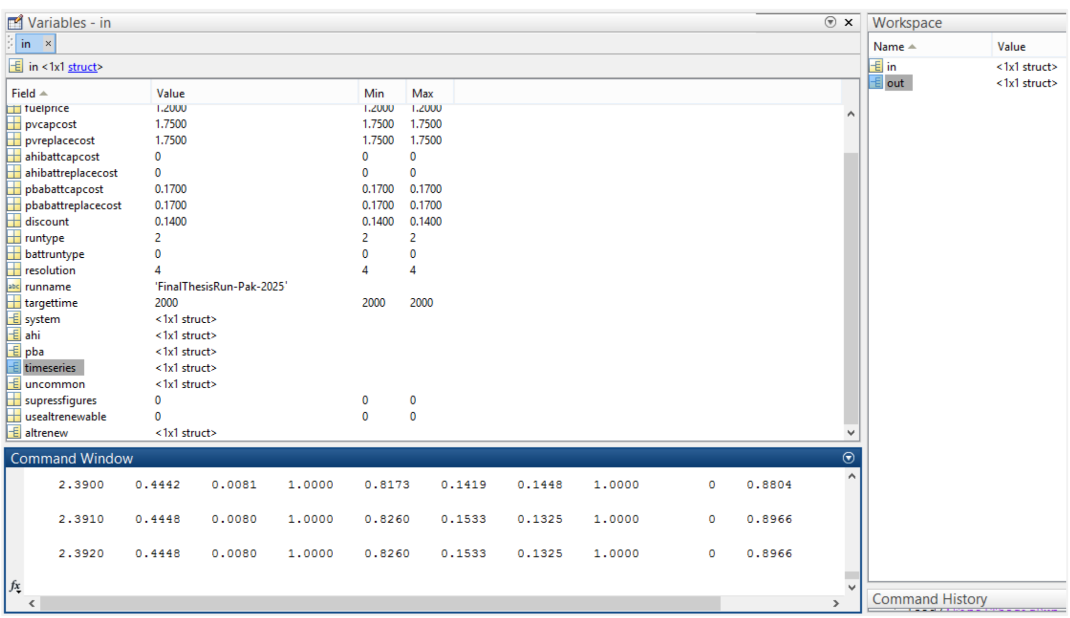

Figure 2. MATLAB Interface of the ESM. The figure shows the input structures and the main command window during an optimization run

The model can currently be used to determine:

- The cost of meeting a certain load by a specified system configuration
- The cheapest system configuration to meet a certain load
- How changes in parameters like fuel prices, capital costs, electric loads etc. affect the LCOE as well as the optimal system configuration

It uses a combination of ‘simulated annealing’, ‘uphill climb’ and ‘brute force optimization’ techniques to find the optimal system (Hittinger, Wiley, Kluza, & Whitacre, 2015). By varying the four parameters: generator size, PV size, battery size and a binary flag that determines whether the battery can be charged by the generator, the optimizer starts off with a random search picking diverse systems, most of which may be inferior ones. However, it gradually improves the search by only choosing systems that have a lower LCOE than the current choice, such that by the end of the simulated annealing routine it finalizes a local optimum. This local optimum is further improved with an ‘uphill climb’ search, examining 54 nearby neighbor systems, transitioning to the one with the lowest LCOE system at a given resolution level. In case it does not find a cheaper system, it moves to the next level of resolution and repeats until it progresses through all the resolution levels without finding a better system. The output of the model is a time series data for each of the system components i.e. PV, diesel generator, batteries and the corresponding financial information for the best chosen configuration. These include present values for fuel costs, generator costs, PV costs and battery costs as well as an LCOE figure.

The model gives the user, choice between three types of search routines. The simplest routine takes as input a microgrid configuration and runs the optimization once to calculate the LCOE as well as other relevant financial and technical information. The ‘improver’ routine starts off the search from the initial system configuration input to the model and seeks to find a nearby lower cost system that is a local minimum. The ‘global’ search routine ignores any initial system configurations and attempts to find a globally optimal system starting off with the ‘simulated annealing’ algorithm. The good systems are then fine-tuned using the ‘improver’ routine to determine the local minimum. It is important to distinguish these three types of search routines in the ESM since they have been used in the analysis at different occasions.

NREL’S Hybrid Optimization Model for Electric Renewables (HOMER). Hybrid Optimization Model for Electric Renewables or HOMER, created by the National Renewable Energy Laboratory (NREL) in the US, is used to validate analysis results obtained from the ESM in this study. It is a general-purpose hybrid system design software that facilitates the design of electric power systems for stand-alone applications (Shahid & Elhadidy, 2007). It simulates a PV/Diesel/Battery hybrid system based on the hourly load data profile and the solar irradiation data of the specific location over a period of 1 year. Therefore, similar to the ESM, HOMER takes as inputs three forms of data:

- Estimated electric load data in the form of load profile time series
- Environmental/Climate data such as the annual solar resource profile
- Financial and technical data for system components.

Based on these inputs, it performs hourly simulations to determine how different systems can be used to meet the load. It offers the user as input, a search space for the system component sizes. With the input information and the choice of component sizing and pricing, HOMER is able to simulate the most economically and technically feasible solution at a specific location (Dekker, Nthontho, Chowdhury, & Chowdhury, 2012). The following figure shows the

HOMER model schematic as well as the optimization results for a single run. The total number of simulations in each run is governed by the search radii specified for each component.

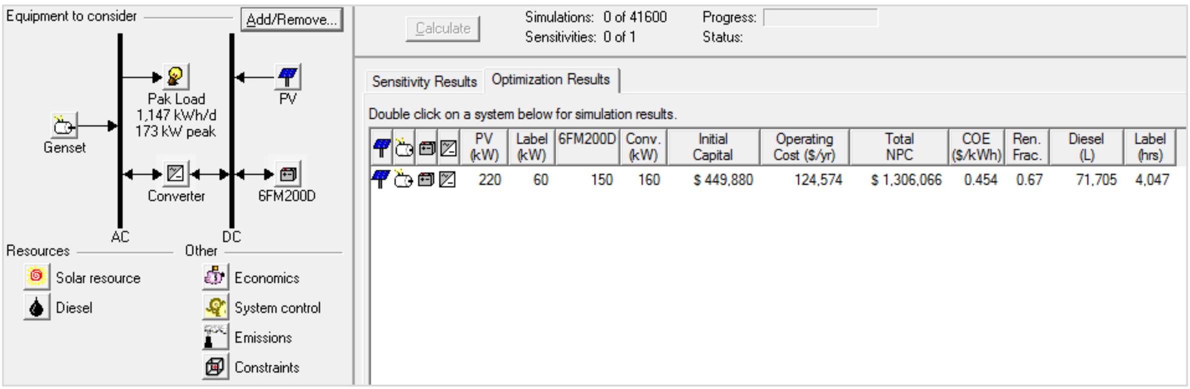

Figure 3. HOMER’s user interface, showing optimization results obtained from a single run for Pakistan. A schematic of the hybrid PV/Diesel/Battery microgrid is also visible

It is important to point out that HOMER is only used in this study to validate results obtained from the ESM. Therefore, the following discussion on data conditioning pertains mostly to the ESM. However, it is worth mentioning that for most inputs both tools have very similar input formats so that data conditioned for either one can be used for the other (slight modifications may be required at times).

Data Collection and Conditioning

Since both the models have a fairly large number of input parameters which need to be conditioned in the format acceptable to the software, the study involves extensive data collection and conditioning. Data from multiple sources is gathered and prepared to serve as input for all locations.

In most cases, power sector forecasts from the respective countries are the primary sources of. In case of unavailable forecasts, historical trends are extrapolated into the future.

There is ample literature on microgrid economics as well as renewable cost parity projections (for solar PV) specific to countries such as India, Germany, and South Africa. These studies also help identify other sources of information. Extensive studies have already been done in the areas of renewable technology pricing forecasts. Studies like the Global Renewable Energy Market Outlook (Masson, Orlandi, & Rekinger, 2014) provide future forecasts for energy production from renewables. They provide an outlook for different places around the world and forecast renewable energy use, prices and penetration in the markets based on a number of factors. These are used in this study to deduce inputs such as renewable technology and storage device prices. For cases where forecast studies are not present, current figures collected from recent research are extrapolated. In many cases, quotations from major market suppliers are used to form the basis for any extrapolations. Some of the important resources used to gather data include:

- EPA Renewable Energy Cost Database: the database is a compilation of renewable energy costs for electricity generation in America. It consists of existing cost data, historical costs and projected costs for wind, solar PV, solar thermal and geothermal. (EPA, 2012)
- Black and Veatch Cost and Performance Data for Power Generation Technologies: report completed for the NREL which provides the power generating technology cost and performance estimates till 2050. (Black and Veatch, 2012)
- Reports from the NREL Strategic Energy Analysis Center: the *Renewable Electricity Futures Study* report which investigates the extent to which renewable supplies can meet the electricity demands in the US over the next several decades (NREL, 2012).
- EIA and their *Annual Energy Outlook 2014* with projections till 2040 (EIA, AEO 2014 Table Browser, 2014).

- *Development of Energy Markets – Energy Reference Forecast*. A study commissioned by the German Federal Ministry of Economics and Technology (Schlesinger, Dietmar, & Lutz, 2014).
- *Photovoltaic Electricity – The localization potential of Photovoltaics and a strategy to support the large scale roll-out in South Africa* (EScience Associates, Urban-Econ Development Economists, 2013).
- *Integrated Resource Plan for Electricity South Africa 2010-2030* (NERSA, Integrated Resource Plan for Electricity 2010-2030, 2013).
- *NTDC Electricity Demand Forecast 2011-2035* for Pakistan (NTDC, 2011).

Other than these, the main sources of data are journal articles, as well as reports published by international agencies including the European Photovoltaic Industry Association (EPIA) for the EU, the International Energy Agency (IEA), the International Renewable Energy Agency (IRENA), the International Technology Roadmap for Photovoltaic (ITRPV), the World Energy Council (WEC) and the Joint Research Center of the European Commission (JRC-EC).

It is important to mention that in most cases the data available needs conditioning to serve as input to the models. In many cases, data from multiple sources is combined to get the required information and format. Due to this extensive data processing on all inputs of the models, the author acknowledges that there is a certain level of uncertainty associated with the results of the analysis. Therefore, the main analysis is followed up with a sensitivity study to investigate the effects of variations in some of the more important input parameters.

Input Data

Of all the data collected using the aforementioned sources, most of it is processed to prepare it as an input to both the ESM and HOMER. As mentioned earlier, in either case the format is very similar.

Considering the ESM, most of the technical parameters which define the initial system are ignored since the ESM is used in the global search algorithm mode. With this, making use of the basic input parameters necessary for an optimization, the model conducts a rigorous search for the cheapest possible system. It does this by running a simulated annealing algorithm to search for good systems. It then sends these best systems through an ‘improver’ routine which improves on the costs by searching for the cheapest system configuration. Therefore, other inputs like component lifetime figures and generator fuel consumption curves can be kept constant for different locations in order to maintain system level consistency.

Other basic parameters are varied along two dimensions: time and space (i.e. locations). The following table summarizes these parameters and their variations in time or/and locations. Values not varied in time have been assumed to stay constant in real 2014 US$. The actual parameter names in the ESM are not used here to avoid confusion. Appendix B contains a list of these parameters and their MATLAB variable names.

Table 2

ESM input parameters. The list identifies input parameters which are varied in space and/or time for the analysis.

Input Parameter	Varied in Time	Varied Across Locations
Generator Capital Costs	No	Yes
Diesel Fuel Prices	Yes	Yes
Solar PV Capital Costs	Yes	Yes
Battery Capital Costs	No	Yes
Inverter Capital Costs	Yes	Yes
Generator Operational Costs	No	No
PV Operational Costs	No	Yes
Installation Costs	No	Yes

The following section discusses the conditioning of raw data to prepare inputs for the ESM. All working is done in real US 2014 dollars. Wherever necessary, currency conversion factors are used to convert figures to US dollars. Exchange rates used are presented in Appendix C. It is important to highlight here that this study is being done from the perspective of the consumer rather than a social perspective. Therefore, unless explicitly mentioned, all figures reflect prices seen by the end consumers (with subsidies inclusive). This approach is adopted because the goal here is to determine grid parity as seen by the end consumer. And because this parity may very well lead to grid defection in many places, all stakeholders can consider implications of such an event keeping view the results. A similar approach has been adopted by (Bronski, et al., 2014) in their study of the US market.

Inflation rate. For cases where data is available in nominal dollars, a relevant inflation rate is used to convert this to real 2014 dollars. The following table summarizes the inflation rates used. These are average figures for the last few years gathered from multiple sources. They are assumed to stay constant over the entire study period.

Table 3

Inflation rates.

Location	Inflation Rate
UNITED STATES	2%
GERMANY	2%
PAKISTAN	10.9%
SOUTH AFRICA	6.5%

For the US, the 2% figure is an average for the last one decade. Historical figures retrieved from the website *trading economics* are used to calculate this average. Multiple recent studies use a 2% inflation rate for Germany. In their study, (Fraunhofer ISE , 2013) use the same number to calculate WACC figures for solar PV Systems. Similarly, (Perez, 2014) use the same 2% inflation rate for Germany in ECLAREON's solar PV grid parity study from 2014. For South Africa, the average inflation rate for the period 2009-2013 from the World Bank (The World Bank, 2015) is used. In the case of Pakistan, the 2013 Pakistan Economic Survey 2013 (Government of Pakistan, 2012) inflation figure of 10.9% is used.

Cost of capital rate. The cost of capital, which signifies the discount rate for present worth calculations, is input as the interest rate parameter in both the ESM and HOMER. It is an important input parameter governing present value calculations in the optimization routine. Given the nature of the two energy sources being used (solar PV and diesel generator) in the hybrid system, the cost of capital is an important determinant of the final optimal system configuration because both technologies are different when it comes to the distribution of expenses. While solar PV has high capital costs, the largest share of costs for a diesel generator are spread in time in the form of fuel expenses. Therefore, the choice of interest rates is important for the analysis and is further investigated in the sensitivity analysis. The following table lists the interest rates used in the base case analysis. Note that the three words, discount rate, interest rate and cost of capital rate are used interchangeably in the study because of the way it is inferred by the ESM. Therefore, all three are one and the same thing within this study.

Table 4

The Cost of Capital or 'Discount rate' for present worth calculations in the ESM and HOMER

Location	Cost of Capital
UNITED STATES	8%
GERMANY	5%
PAKISTAN	14%
SOUTH AFRICA	10%

An interest rate of 8% is used for the US. The recent EIA’s AEO 2014 Assumptions document uses a 7% interest rate for residential consumers in the US (U.S Energy Information Administration, 2014). A recent study out of Stanford, *The prospects for cost competitive Solar PV power* (Reichelstein, 2012) uses an interest rate of 8% for commercial scale solar PV in the US. Based on these figures, an 8% cost of capital rate figure is used for the US.

Generally, literature suggests a 4-6% range of discount rate for energy investments in Germany. In their recent study on solar PV, (Fraunhofer ISE , 2013) calculate a WACC range of around 4-5% for Germany. An RWTH Aachen study (Merei, Berger, & Sauer, 2013) also uses a

5% interest rate for calculations. ECLAREON's *Grid Parity Monitor* document (Perez, 2014) determine a 3.6% rate for commercial cases in Germany. The European Climate Foundation's technical analysis report *Roadmap 2050* (European Climate Foundation, 2010) uses a 7% WACC figure for all places in Europe. Using this range reported in previous works, a 5% figure is used for Germany.

In a recent study, (Ondraczek, Komendantova, & Patt, 2015) calculate real WACC figures for solar PV power in 143 countries. For Pakistan and South Africa, they calculate real WACC figures of 13.8% and 11% respectively. Given the rates of inflation in these countries, and the immature energy markets involving a certain level of risk, both numbers are plausible and are used as the basis for the choice of interest rate in the two countries. For Pakistan, a real 14% cost of capital figure is used in the base case. In case of South Africa, other than the study mentioned earlier, there are multiple resources which help validate the real 11% figure from (Ondraczek, Komendantova, & Patt, 2015). A United Nation's Environment Program Research Project from 2010 (Edkins, Marquard, & Winkler, 2010) uses a 10% interest rate for future projections. South Africa's primary power utility, Eskom uses an 8% real discount rate for utility scale power, which has been approved by the National Energy Regulator of South Africa (NERSA). NERSA uses the same 8% figure in their Integrated Resource Plan for Electricity 2010-2030 Document (NERSA, 2013). Therefore, a 10% real interest rate is deemed plausible for South Africa.

Generator costs. Diesel generator replacement costs are kept equal to the initial capital costs in each location. Both the upfront and replacement costs are assumed to be constant in real 2014 dollars over the entire period of the study. Since the capital costs for a generator are small compared to the operating costs of fuel, this assumption does not affect the final optimization results.

For the US, the upfront cost used is from the work of (Bronski, et al., 2014). However, 2012 US dollars are adjusted to US 2014 real dollars. For Germany, South Africa and Pakistan, generator prices are obtained through quotes and websites of relevant market sellers. Relevant installation costs are incorporated to these prices to make up the final figures used in the base case analysis. Details of this working are presented in Appendix D.

Diesel fuel prices. Diesel fuel prices for each location are conditioned carefully to omit any taxes for its use as a transportation fuel. For the US, Germany and South Africa, government imposed taxes for the fuel's use in transportation are deducted to capture the true cost of the fuel for energy production.

For the US, diesel fuel prices are taken from EIA's Annual Energy Outlook 2014 data table (U.S Energy Information Administration, 2014). Constant 2012 dollars are converted to 2014 US dollars. In order to account for state and federal motor fuel taxes, they are deducted separately from these values. Ohio State's federal and state motor fuel tax values of 24.4 cents and 28 cents respectively (Ohio Department of Taxation, 2014) are subtracted to obtain final values. For oil importing countries like Pakistan and South Africa, the same future trend as that of the US is applied to the current fuel prices. This is because their oil prices are linked to the price of oil in international markets and are influenced by changes in it. Hence the use of EIA's future projections is plausible. For South Africa, current price used is from (Shell, 2014). However, it is adjusted for the road accident fund levy (RAF), 100 South African cents at the time of the analysis, which is exclusive to the use of diesel for transportation in South Africa

(Road Accident Fund, n.d.). For Pakistan, the current price used is the October 2014 figure taken from (Product Prices, 2014).

Following from the work of (Fraunhofer ISE , 2013), as well as email correspondence with Dr. Matthias Lang, Partner at Bird & Bird LLP (Lang, 2014), it is concluded that the fuel price for stationary power applications in Germany is lower due to low taxes. Heating oil, which is chemically the same as diesel and is used in electricity generation, has lower taxes and is bought in bulk amounts for stationary applications (Federal Statistics Office, Germany, 2014) . Future price projection figures for heating oil are calculated based on the forecast provided by (Schlesinger, Dietmar, & Lutz, 2014). As a basis for the calculations, heat oil prices for the year 2011 from (TESCON, 2014) are used. The percentage change trend is applied to this 2011 value to determine projected results, which are then converted to 2014 constant dollars. For Euro to dollar conversions, a constant conversion rate is used.

Details of the projection working are presented in Appendix E. The table below shows the final prices used for the analysis.

Solar PV costs. Solar PV capital costs, like diesel fuel prices, are one of the more important input factors which determine the final results obtained from the optimization in both the ESM and HOMER. With multiple solar PV price figures available for Germany and the US, and very limited sources of data for developing places like Pakistan and South Africa, it is hard to maintain consistency. Moreover, future price projection studies are limited to developed countries with most of them using different projection methodologies.

Therefore, in order to maintain uniformity across the analysis and given the importance of solar PV price projections, learning curves are used to forecast future prices.

Learning curves describe how costs decline with cumulative production, where the cumulative production is used as an approximation for the accumulated experience in producing and employing technology (Bhandari & Stadler, 2009). This decline in cost is a constant percentage with each doubling of the total number of units produced, characterized by the learning rate LR. The learning curve equation is written as:

$$C_t = C_0 \cdot \left(\frac{P_t}{P_0}\right)^b$$

where,

C_t is the cost of cumulative production at time t;

C_0 is the cost at initial level of production at $t = 0$;

P_t is the cumulative production at time t;

P_0 is the cumulative production at $t = 0$;

b is the learning parameter defined as $\frac{\log(1-LR)}{\log 2}$

Typically in learning curve analyses, the learning parameter is presented as a progress ratio PR, which is defined as unity minus the learning rate or$(1 - LR)$. As seen from the above equation, any future estimates based on the learning curve analysis depend on this learning parameter (or progress ratio) as well as current and projected levels of cumulative solar PV production. Therefore, the three parameters needed for the extrapolation of learning curves to determine future prices are:

- The learning rate which determines the learning parameter/Progress Ratio
- Current and future estimates of cumulative solar PV systems
- Current estimate of system costs

Considering the importance of the learning parameter in the analysis methodology, the choice of a learning rate is rather challenging. For PV industry, learning rates of about 20% are reported frequently in literature (Kersten, et al., 2011). However, most of these studies often discuss learning curves for PV at the module level and ignore any other system associated costs.

Given a PV system, it can be broadly defined by two subsystems – PV modules and all system components other than the modules as the balance of system (BOS). The BOS typically include controllers, cables, connectors, combiners, inverters and any mounting hardware. At times, batteries are also considered part of the BOS. For this study, batteries and inverters are not taken as part of the BOS based on the input structure of both the ESM and HOMER. The total cost of a solar PV system comprises the solar PV module price, the Balance of System (BOS) and the installation costs (GlobalData, 2012). Recently, PV module prices have declined at a pace faster than the BOS costs, mainly due to plunging costs among Chinese suppliers (GlobalData, 2012). As a result, the BOS costs have assumed a greater share in the total cost of PV systems, accounting for more than 50% (greentechsolar, 2012).

Therefore, it is important for a learning curve analysis to distinguish and take into account any cost learning associated with the BOS as well. One simple approach to define learning parameters for each country in this study could be to identify PV module and BOS cost learning separately, and apply them to the respective system components. However, the cost learning of BOS has not been studied as widely as that for PV modules and is not readily available (Bhandari & Stadler, 2009). Moreover, as (Shum & Watanabe, 2008) assert, cost learning in individual BOS components is mostly exhausted due to mass production and so BOS learning can mostly be attributed to experiences gained through system design and installation. This further makes it difficult to identify and segregate this component of system learning.

Another approach could be to use the solar PV module learning as the system learning. However, with globalization of PV module manufacturing, learning at the PV module level alone does not help distinguish between global and local learning since there is extensive exchange of scientific information in module technology (Bhandari & Stadler, 2009). And given a comparative study such as this, the choice of learning parameters needs to capture and distinguish the differences between the four markets to translate any of its effects into the final LCOE results.

Therefore, a system level learning parameter approach is used in this study. In their work, (Kersten, et al., 2011) determine a global average for the consolidated solar PV system level learning rate at 14% (PR of 86%). This learning rate is used as the basis for all the learning curve analyses done in this study. The figure is however adjusted for each country, considering the maturity and future potential of solar PV markets determined from existing market situation and relevant policy frameworks. This is mentioned by (Bhandari & Stadler, 2009) in their research, where they make note of a similar approach for individual countries and talk of the price decline in PV modules for Germany. The following table summarizes the learning parameters for each country. The rate is assumed to stay constant over the considered time period.

Table 5

Learning rates for all 4 countries

Location	Learning Rate LR
UNITED STATES	20%
GERMANY	10%
PAKISTAN	15%
SOUTH AFRICA	15%

For the US, considering the level of penetration of solar PV in the market, favorable policies and ample potential for market consolidation (Seel, Barbose, & Wiser, 2014), a learning rate higher than the average rate is applied. On the other hand, considering a much more mature market in Germany with a greater level of consolidation (Seel, Barbose, & Wiser, 2014), the learning parameter is chosen to be the lowest amongst the four countries. For both the developing countries, lack of favorable policies along with a strong potential of growth given good solar resources and troubled energy markets, an almost average learning parameter is used.

The cumulative solar PV production figures are the other important piece necessary for the learning curve analysis. In their study, (Seel, Barbose, & Wiser, 2014) show that local solar PV system prices are well correlated to the global cumulative growth of these systems. The choice of a system level learning parameter therefore also allows the use of global cumulative solar PV production forecasts. The European Photovoltaic Industry Association (EPIA) in their report, (Masson, Orlandi, & Rekinger, 2014) project global solar PV cumulative installed capacity up until the year 2018. Their 'Low Scenario' projection figures are extrapolated till 2040 to get conservative estimates of future global solar installations. These are then used in the learning curve analysis to determine solar PV prices up until 2040.

Another system level price distinguishing factor in this case turns out to be the current solar PV system price. For the US, the recent SEIA/GTM research report, (SEIA/GTM, 2014) helps determine this number. For Germany, (Solar, 2014) provides a figure for the solar PV system costs. In their report, (EScience Associates, Urban-Econ Development Economists, 2013) provide a good estimate for system prices in South Africa. For Pakistan, solar PV system prices are obtained from a solar systems entrepreneur company, T.S.K Engineering International (Pvt.) Ltd. The following table summarizes these values.

Table 6

Total PV 2014 $/W system costs borne by the end user. Costs include PV modules, BOS components, inverter, and installation costs. These are used as the starting point for the learning curve analysis

Location	Current PV System Cost (2014 $/W)
UNITED STATES	3.80
GERMANY	2.15
PAKISTAN	2.45
SOUTH AFRICA	3.35

As seen from the above table, system costs for Pakistan and Germany are relatively lower than the other two locations. For Pakistan, this is due to a greater penetration of cheaper Chinese system components in the market as well as cheap labor. For Germany, this is because of a much more mature market and solar friendly policies of the government. South Africa has relatively higher system prices owing to the lack of infrastructure and imported system components. The US has the highest system prices due to a large unconsolidated market with varying regulations and high non-module/soft costs, as investigated by (Seel, Barbose, & Wiser, 2014).

The results of the learning curve analysis are shown in the following figure. Detailed mathematical working is presented in Appendix F. Comparison of results with other projection studies available for the US, South Africa and Germany reveal that the analysis yields prices close to those present in previous studies.

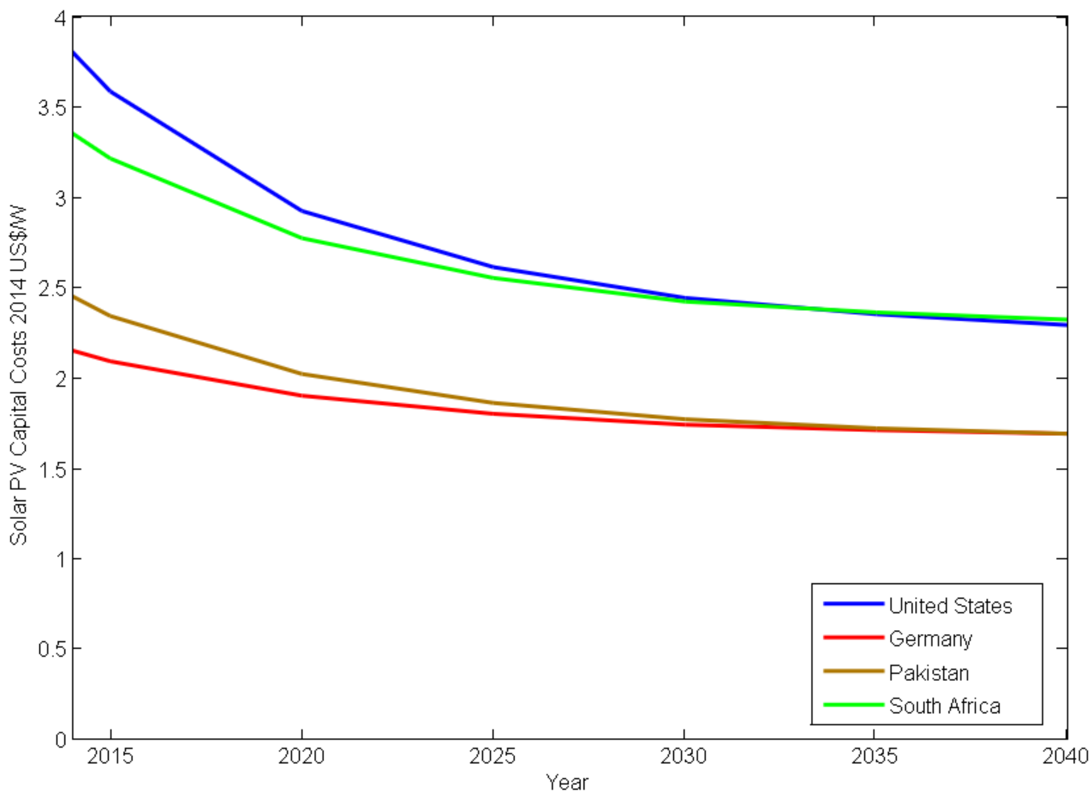

Figure 4. Future projection of solar PV system costs based on the learning curve analysis. The costs include PV modules, BOS components (including the inverter) and installation costs.

The solar PV replacement costs are kept equal to the initial capital cost figures in each case. The operational costs for solar PV are kept at 1% of the system capital costs for the year 2015. Both (Bhandari & Stadler, 2009) and (Dekker, Nthontho, Chowdhury, & Chowdhury, 2012) use the same % figure in their calculations. In their report, (EC, 2005) find that the yearly maintenance costs for solar PV lie in the 0.5% - 1% range. However, for subsequent years, this operational cost figure is kept constant in real 2014 dollars. A fixed value rather than a fixed percentage is used to neglect any learning effects that may push down the maintenance costs to unrealistically low levels. In other words, it is assumed that cost learning will not affect the maintenance of solar PV in real dollars.

Battery costs. Costs of storage used for the analysis are determined by averaging battery prices from multiple suppliers in each market. The table below summarizes the values used in the analysis. It is typically (often implicitly) assumed that learning in lead-acid battery production is "finished". The literature analyzing the price-point goal for emerging energy storage technologies refers to a static value of current lead-acid battery prices (Matteson & Williams, n.d.). Due to this and the limited amount of data available on storage device price projections, these figures are assumed to be constant in real 2014 dollars throughout the analysis.

It is important to highlight that these price figures do not capture the true costs associated with the batteries. An installation cost figure needs to be accounted to completely represent the true costs. Based on the data provided by T.S.K Engineering for Pakistan, and correspondence with their experienced engineering staff, battery installation costs account for roughly 2-3% of the total battery costs in a solar PV system. Therefore, they are ignored in the battery cost calculations and are accounted for in the installation costs variable discussed later.

Table 7

Lead Acid Battery costs in 2014 $/Wh. These do not account for any battery installation costs

Location	Battery Cost 2014 $/Wh
UNITED STATES	0.160
GERMANY	0.219
PAKISTAN	0.170
SOUTH AFRICA	0.216

Battery costs for the US are obtained from a recent work on Lead Acid Battery experience curve analysis completed here at RIT (Matteson & Williams, n.d.). For Germany, the figure is a consolidated average for lead acid battery prices from multiple suppliers, figures used by (Merei, Berger, & Sauer, 2013) and (Mulder, et al., 2013). For South Africa and Pakistan, prices are average figures from different suppliers. Battery replacement costs are kept equal to the initial capital costs. The detailed working is presented in the Appendix G.

Inverter costs. An inverter converts electricity from AC to DC and vice versa. Inverter costs are derived from the system costs by using fixed percentage figures. The same approach is used by (Bronski, et al., 2014) and is plausible looking at the relevant data available. The percentage figure allows a uniform method for inverter cost calculation across countries. The choice of system cost share considered as inverter costs is different for each country and is based on data available for local systems.

The following table presents the share of inverter costs as a % of the total system costs used for each location. For the US, figure reported by (Bronski, et al., 2014) is used. For Germany, it is estimated using system cost figures from (Seel, Barbose, & Wiser, 2014). For South Africa, the system cost breakup provided in (EScience Associates, Urban-Econ

Development Economists, 2013) is used to estimate the 13% figure. For Pakistan, T.S.K Engineering's quotation provides the necessary information to determine this cost share.

Table 8

% share of the total PV system costs considered as inverter costs. This % figure is applied to the system costs to determine inverter costs at each location.

Location	% share Inverter costs
UNITED STATES	8%
GERMANY	11%
PAKISTAN	5.6%
SOUTH AFRICA	13%

The % figure is assumed to stay constant for each location over the entire period of the analysis. Inverter replacement costs are considered equal to the capital costs for each location.

Installation costs. The ESM takes as input, installation costs separately to cover miscellaneous expenses of any civil work required to set up the system. It is expressed as a fraction of the capital costs of the total system. In this study, this parameter is used to account for these costs as well as any overlooked factors (e.g. battery installation costs). A constant 5% figure is used for all locations.

Time Series Data

Both the ESM and HOMER take as inputs, time series data for the solar resource and the electric consumer load profile at a given location for one complete year. The ESM, in addition to these, also uses a temperature time series input to model the effects of changes in temperature on the lead acid batteries over an entire year of operation. Even though the ESM is capable of modeling at sub-hourly resolutions, time series data used in this study is for a complete year at 1-hour resolution, resulting in 8760 data points in each case. The 1-hour resolution provides a single basis for validating results obtained from both HOMER and the ESM, because HOMER uses a time resolution of 1 hour for system operation (Hittinger, Wiley, Kluza, & Whitacre, 2015). Moreover, availability of sub-hourly time series data for all locations is challenging, given the unavailability of hourly data for some of the locations considered. For many cases, data is not readily available in a time series format and needs conditioning. The following sections discuss this for the Solar Resource, Electric Load Profile and Temperature time series data.

Solar PV output time series. Solar Radiation data for each location is extracted from HOMER's in built solar resource data function. Based on the Longitude and Latitude positioning for a location, HOMER accesses NREL's online databases that serve data from either NREL's Climatological Solar Radiation (CSR) or NASA's Surface meteorology and Solar Energy (SSE) data set (HOMER Energy, 2011). The data is an hourly time series for an entire year and can be exported for use elsewhere. For HOMER itself, the data function loads the online searched data for the current optimization run.

The ESM, however inputs the solar resource in terms of the power output of a defined PV system. For this study, in order to maintain simplicity in calculations, the defined PV system is assumed to have a rated (nominal) peak power output of 1000 W (1kW) at an irradiation of 1000 W/m^2. The choice of such a system value allows solar irradiation data extracted from HOMER to be used directly for the ESM as well. Based on the work of (Ahmad, 2002), this is shown below:

$$PV\ Peak\ Power = PV(Area) \times Peak\ Solar\ Intensity\ (PSI) \times \eta_{PV}$$

where η_{PV} is the solar PV efficiency and PSI is the value used to define the standard conditions i.e. 1000 W/m^2

For a power system with a peak power of 1000 W at standard conditions, the PV area turns out to be:

$$1000\,W = PV(Area) \times 1000\,\frac{W}{m^2} \times \eta_{PV}$$

$$PV(Area) = \frac{1}{\eta_{PV}} m^2$$

For a given solar irradiation, the output for a solar PV system is given by the relation:

$$PV\ Output = PV(Area) \times Solar\ Irradiation \times \eta_{PV}$$

which implies that:

$$PV\ Output = \frac{1}{\eta_{PV}} m^2 \times H\ \frac{W}{m^2} \times \eta_{PV} = H\ Watts$$

where H represents the solar irradiation value at a given location and time. This is the value extracted from HOMER, however irradiation figures of kW/m^2 are converted to W/m^2 before inputting to the ESM.

Electric load profile time series. Hourly electric load profile data defines the annual electricity consumption at a 1 hour resolution and is essentially the target load that needs to be met by the hybrid microgrid system. Since the use of electricity is governed by many factors including geography, weather and any tariff policies, a single load profile cannot be used in such an analysis. Instead, electric load data typical for each location must be used to simulate a microgrid operation at that place. For this study, in most cases except the US, load profiles for the concerned locations are processed from raw data, since 1 hour resolution data is not readily available.

For the US, data is readily available for multiple locations. For Columbus Ohio, the load data used is from the American Electric Power (AEP) Ohio's webpage (AEP Ohio, 2014). This defines a typical residential consumer's hourly load pattern for an entire year. It is used as the basis for a 50 home microgrid setting.

For Germany, due to unavailability of high resolution individual household consumption data, an industry standard load profile is typically used to describe residential consumption. In their research, (Gottwalt, Ketter, Block, Collins, & Weinhardt, 2011) use such standard load profiles to evaluate and verify simulation generated results. The Federal Association of Energy and Water Industries (BDEW) in Germany provides this profile, called H_0, in a 15-minute resolution for the average electricity consumption of a norm German household (Gottwalt, Ketter, Block, Collins, & Weinhardt, 2011). The standard profile distinguishes the electricity consumed in different seasons and on different days of the week. The standard load profile used in the study is for the year 2013. Individual values in the time series are normalized and at a 15-minute resolution. In order to de-normalize these, maximum and minimum values from the sample load profile used by (Gottwalt, Ketter, Block, Collins, & Weinhardt, 2011) to verify model results, are considered. The details of the working are presented in Appendix H. The outcome is a time series describing the electric consumption pattern for an individual household in Germany. Since scaling does not affect the choice of an optimum system in both the ESM and HOMER, a 50 home load profile is considered for the microgrid system analysis to maintain consistency.

The four seasonal load profiles provided by (Kanase-Patil, Saini, & Sharma, 2011) for a remotely located village in a rural setting in India are used for the case of Pakistan. Given the similarity between the two countries when it comes to village life and the fact that such a high resolution load profile is not readily available for places in Pakistan, the use of this data series is justified. The profile is representative of a remote village with around 250 homes and an electric demand for domestic, agricultural, community and rural industry activity (Kanase-Patil, Saini, & Sharma, 2011). The 4 seasonal profiles are consolidated into one yearly profile using HOMER. Both hourly and daily variations are incorporated to the series to account for uncertainty.

For their research, (Heunis & Dekenah, 2014) revise a model that estimates load profiles for residential consumers in South Africa and present an average load profile for a typical weekday. This profile is used as a basis for the full year time series for South Africa. Even though the profile is representative of a weekday only, it is assumed to be the same for weekends and similar across seasons. This is done because load profile time series data is not readily available for South Africa.

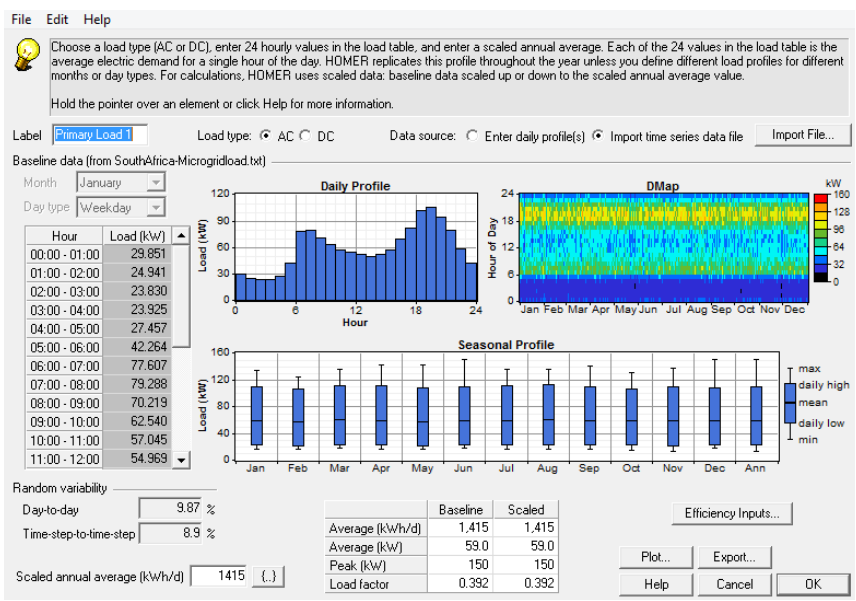

Figure 5. Load time series data input snapshot from HOMER for South Africa. The daily load profile and random variability numbers are input to generate an annual load profile

Figure 5 shows a HOMER snapshot for load data in South Africa. The *daily profile* is the estimated profile input to the software. This, with random variations added, is repeated over the entire year. Day-to-Day and Time-step-to-time-step variation figures of 9.87% and 8.9% are input to allow for this random variability. These figures are obtained from an average of the same random variations reported by HOMER for Germany and United States load data time series. This is important to avoid replication of the exact profile over the entire year. Such a replication would be unable to distinguish real life variations in load on a day to day and hour to hour basis. Also, considering that the load data already does not capture seasonal variations, such daily and hourly variations are deemed necessary.

Temperature time series. The temperature time series data may assume importance in such an analysis involving lead acid battery storage because at high temperatures lead acid batteries experience faster degradation, while at lower temperatures their ability to deliver energy is reduced (Hittinger, Wiley, Kluza, & Whitacre, 2015). However only the ESM accounts for these effects and allows a separate temperature time series data input.

In most cases, this data is readily available. Of the four locations considered in this study, average temperatures are used to construct a time series only for the case of Pakistan. Data for other locations is readily available at the required resolution. Historical monthly temperature data for Hyderabad compiled by (Hong Kong Observatory , 2012) is used to derive hourly data. Average high and low temperatures are assumed to occur at 2 PM and 4 AM respectively. Step changes are applied to these values to populate data between the two extremes, forming hourly time series for each day in a month. For an entire month, the data series is repeated. Detailed mathematical working is described in the Appendix I.

For the US, hourly temperature data for Pittsburgh Pennsylvania is readily available and thus used in this study. Since hourly temperature data for Columbus Ohio was not available, data for Pittsburgh which is 185 miles from Columbus and has a similar climate is used instead. Data is available with the National Weather Service Forecast Office, Pittsburgh (NWS, 2014). In case of Germany, the Deutscher Wetterdienst (DWD) have hourly temperature data for multiple stations within Germany (Wetterdienst, 2014). For South Africa, results from Meteonorm 7, a global meteorological database product by METEOTEST Genossenschaft, Bern are used.

It is important to note that in some microgrids, batteries can be stored in a climate-controlled area at little or no cost and so temperature effects would not be a concern. However, developing places like Pakistan and South Africa, where microgrids would target mostly rural remote areas, temperature control would be a challenge (Hittinger, Wiley, Kluza, & Whitacre, 2015). Since there is no right way to account for such costs for these places, maintaining uniformity becomes a challenge. Therefore, for the base case in the ESM, actual temperature time series data is used. A temperature controlled environment, modelled by a constant temperature time series is later used in the sensitivity analysis to highlight the impact of this on the LCOE and parity points.

Utility Electricity Price Projections

In order to determine a parity point for microgrids, the utility electricity prices for each location are used for comparison with the LCOE. These prices are projected such that they help define a ‘parity region’ into the future. This grid parity area enclosed by lower and upper future estimates helps give a fair idea of the range of years when one could expect parity at a particular location. A range rather than specific year estimates is a more appropriate result for this study, given the uncertainty and assumptions involved in the optimization. The ‘high’ and ‘low’ retail prices help define the earliest and farthest point of parity at each location, giving a good idea of future prospects for microgrids. The two future electricity price trend lines, or edges defining the parity region are:

- The recent trend of retail prices extrapolated
- Future price estimates done by respective governments

All price figures are in constant 2014 US dollars, so that the region reflects the actual or real change in prices over the years. Grid parity points in this study are defined as the points of intersection between the estimated LCOE figures with these two edges of the parity region. The following sections describe the parity region working for each location with the two edges highlighted in each figure.

The United States. Historical residential retail price figures for the US are obtained from the EIA (EIA, Electricity Data Browser, 2014). Figures from 2006 onwards are considered as the basis for subsequent extrapolation. The extrapolated trend determines the upper bound of the price projections, referred to as the *Recent Trend*. The lower bound in this case is a price forecast completed by the EIA in their Annual Energy Outlook 2014 Reference case (EIA, AEO 2014 Table Browser, 2014). These figures are considered 'as-is' for the *Government Estimate*. The figure below shows the parity region on the graph. The upper edge of the wedge in this case represents the recent trend of prices extrapolated, while the lower edge shows prices forecasted by the government.

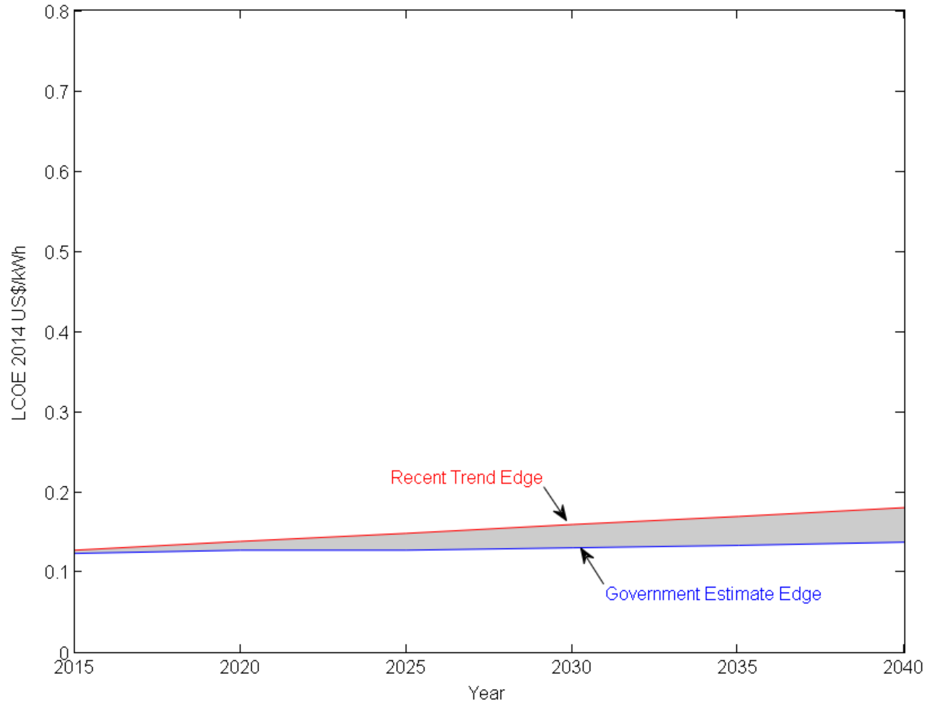

Figure 6. Parity region for the US. The red and blue edges mark the two boundaries used to define grid parity in this study

Table 9

Grid Parity region for the US. Extrapolated recent trend of real grid prices and future government estimates of real electricity prices for the US. Both define the two edges of the parity region

UNITED STATES	2015	2020	2025	2030	2035	2040
Recent Trend $/kWh	0.128	0.139	0.149	0.160	0.170	0.181
Government Estimate $/kWh	0.124	0.128	0.128	0.131	0.134	0.138

Germany. For Germany, (Schlesinger, Dietmar, & Lutz, 2014) provide a forecast for residential retail electricity prices till the year 2050. These are used as the government estimate in this study, with all values converted to 2014 real US dollars. For a recent trend, residential price data available on (Eurostat, 2014) is used to extrapolate a future price trend line. Figures for the period 2003-2014 are used as the basis for this extrapolation.

The German government projects an increase in retail prices up until 2025, which is governed by rising wholesale prices. However, following 2025, they forecast prices to decrease for residential customers considering a falling EEG surcharge – a surcharge to promote renewables in Germany. This explains the discontinuous and conservative government forecast, as shown by the lower edge of the parity region in Figure 7.

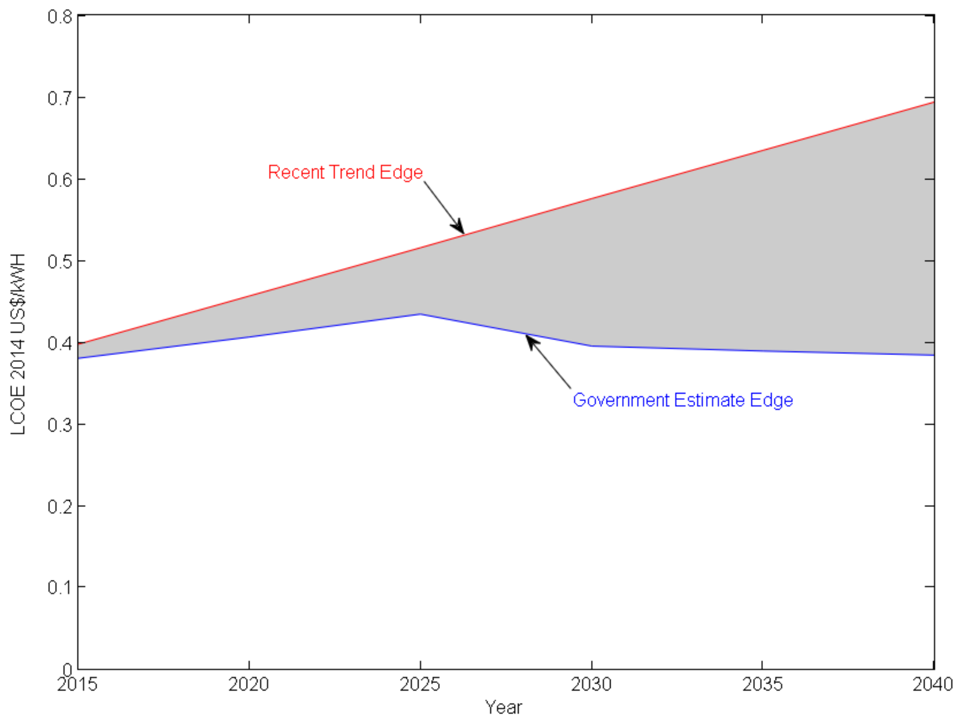

Figure 7. Grid Parity Region for Germany

Table 10

Government and recent trend projections for real electricity prices in Germany. Beginning in 2025, the German government expects the fall in EE (G) surcharge to have a stronger impact than the increasing prices. Due to this, they estimate a net real price decrease following 2025.

GERMANY	2015	2020	2025	2030	2035	2040
Recent Trend $/kWh	0.397	0.456	0.515	0.575	0.634	0.693
Government Estimate $/kWh	0.380	0.406	0.434	0.395	0.389	0.384

Pakistan and South Africa. For the cases of Pakistan and South Africa, price forecasts are not as readily available. Therefore, multiple studies are used to determine future trends for utility prices which are representative of the energy market situation in the two countries. Given that both countries currently face power shortage, frequent power cuts known as *load shedding* are a norm. It is important to account for and monetize any costs associated with this unreliability of the grid when comparing it with a microgrid solution which provides reliable power. This cost of reliability is incorporated within the utility price forecasts for both Pakistan and South Africa.

Utility price forecasts for Pakistan and South Africa. Due to a troubled power sector in Pakistan, the country has recently seen unprecedented hikes in power prices. Residential electricity bills of a typical medium sized household for the years 2007, 2011, 2013 and 2014 reveal that prices have increased in the range of 9-12% real. An annual report by the national power regulator shows a 9% real increase in residential prices (medium scale 301-700 electric units used) for the years 2010-2012 (NEPRA, 2013). The National Transmission and Despatch Company (NTDC) determines an 8.2% real increase in prices for the years 2009-2010 (NTDC, 2011). Given the fact that these electricity price hikes are directly linked to the increasing power crisis, which has gone out of hand since the year 2008, the use of historical figures for 2009 and beyond seems logical. Keeping this in view and data from the electric meter readings, a 9% real increase figure is used as the upper bound for the retail price trend. Future estimates of (NTDC, 2011) are directly used as the government's prediction of retail prices in the future. However, figures are extrapolated beyond the year 2035. The government assumes a highly optimistic scenario in this report, predicting a 2.2% real increase till the year 2020, a 1.1% real increase up until 2030 and none beyond that. Both these trends are shown in the following table.

Table 11

Grid parity region for Pakistan. Extrapolated recent trend and government forecast of real electricity prices in Pakistan without the cost of unreliable power accounted for.

PAKISTAN	2015	2020	2025	2030	2035	2040
Recent Trend $/kWh	0.158	0.242	0.373	0.574	0.883	1.359
Government Estimate $/kWh	0.139	0.154	0.163	0.170	0.170	0.170

It is well known that the price of electricity in South Africa has been too low for years (Rycroft, Botha, & Yelland, 25). Identifying this low price of energy as one of the significant barriers to the investment in energy efficiency in the country, the government has recently taken bold actions to increase the retail price of electricity with a goal to establish cost reflective tariffs (de la Rue du Can, Letschert, Leventis, Covary, & Xia, 2013). Electricity prices have increased 78% in real terms from 2008 to 2011 according to Eskom (de la Rue du Can, Letschert, Leventis, Covary, & Xia, 2013), a public utility and the largest producer of electricity in South Africa

(REEEP, 2013). With a Multi-Year Price Determination (MYPD) process in place, the National Energy Regulator of South Africa (NERSA) finalizes electricity rates based on Eskom's proposal. In the recent MYPD 3 for the years 2013-2018, NERSA approved an 8% nominal increase in prices, opposed to the 16% requested by Eskom. This was however recently changed to an average 12.6% nominal annual increase in prices for standard customers (NERSA, Nersa Media Releases and Statements, 2014). This approved MYPD 3 figure of 12.6% increase is extrapolated to determine the government price projection. The resultant trend closely resembles the maximum price scenario considered in (NERSA, Integrated Resource Plan for Electricity 2010-2030, 2013), up until their peak price in the years 2022-2025. However, the use of a 12.69% annual increase up until 2040 is logical because, it can be argued that in order to keep pace with an increasing demand and the need to upgrade an aging fleet of coal-fired power stations (Rycroft, Botha, & Yelland, 25), Eskom will have to push for price hikes at least similar to those in recent times.

Even though the government seems to be committed to limit these increases to the inflation rate, the recent update to a 12.69% increase from the prior 8% approved shows the contrary. Therefore, the short and long term outlook for electricity in South Africa is for prices to increase as Eskom continues to deal with generation and infrastructure costs (NUS Consulting, 2013). Retail electricity prices from 2008 are extrapolated to determine the other edge of the parity region since these capture the government approved price hikes in recent years. Price data from (de la Rue du Can, Letschert, Leventis, Covary, & Xia, 2013) and (NUS Consulting, 2013) are used as the starting points for this extrapolation.

Table 12

Future electricity price projections for South Africa. The recent trend is an extrapolation of the real electricity price trend from 2008-2014. The government estimate is a 12.5% nominal increase in prices. This is the government approved increase till the year 2018. Figures do not include the cost of unreliable grid power.

SOUTH AFRICA	2015	2020	2025	2030	2035	2040
Recent Trend $/kWh	0.125	0.189	0.254	0.319	0.384	0.449
Government Estimate $/kWh	0.103	0.133	0.174	0.228	0.301	0.397

The cost of reliability. The ESM's 'improver' routine or local optimization is used to simulate the unreliable grid and determine the cost of producing substitute power during outages. This estimate is used as a monetary measure of the cost of reliable power in the analysis. A similar approach is used by (Murphy, Twaha, & Murphy, 2014) to model an unreliable grid for a grid-connected distributed generation system in order to identify optimal systems providing more reliable power. They model the unreliable grid in HOMER, using a diesel generator module with scheduled downtime. A similar approach is used in this study, however the solar PV is used to model the grid. The solar resource time series emulates the load shedding schedule for a particular location, with arbitrary values of 1200 for power and 0 for an outage. This results in an intermittent solar PV energy source, similar to an unreliable grid. Given the hybrid microgrid system, the battery or generator can be used as substitutes to fill in whenever solar PV (the grid) is out. Inputting costs for either the battery or generator alone helps ensure that the LCOE obtained with either substitute can be used to determine the cost of substitute power. Even though the mathematics of these calculations are included in Appendix J, the general relations used to estimate final utility price forecasts (inclusive of the cost of reliability) are presented here for the purpose of explanation.

With a battery substitution case, the diesel generator is completely eliminated from the analysis so that a grid-battery system is modelled. In case of an outage, only the batteries supply power to meet the load. A large enough battery is initially input to the base system configuration for the 'improver routine', to ensure the load is met completely. With only battery costs input to the model, the resulting LCOE for the optimized system gives a cost associated with this substitute power. This $LCOE_{ESM}$ can be represented by the relation:

$$LCOE_{ESM} = \frac{Cost\ of\ battery\ power\ output\ (Cost_{batt})}{kWh_{batt} + kWh_{grid}}$$

where kWh_{batt} are the kilowatt-hours supplied by the battery and kWh_{grid} are those supplied by the grid. To account for the total cost associated with the substitute power from the battery, the cost of energy lost during the charge-discharge cycle (due to the inefficiency of the batteries) also needs to be accounted. Moreover, in order to effectively add this cost of reliability to price trends, it has to be normalized to an LCOE figure which accounts for the energy supplied by the grid and the battery collectively. ESM outputs allow this calculation so that the following general relation is used to determine the final price figures for the battery backup scenario:

$$LCOE_{Batt} = \frac{Cost_{grid} + Cost_{batt} + Cost_{lost}}{kWh_{total}}$$

where $Cost_{grid}$ is the cost associated with the energy used from the grid whenever it is available. This cost is determined from the utility price estimates and the kilowatt-hours of energy used from the grid when available. The $Cost_{batt} + Cost_{lost}$ essentially determines the total cost associated with the use of the battery, considering both the output and any energy lost during charging. kWh_{total} is the total load that is to be met. For mathematical details, refer to Appendix K.

A similar approach is used for the diesel generator back-up system with the battery eliminated from the analysis. Equations similar to those used for batteries are applied here, with the exception of the cost associated with energy lost in the batteries. Mathematical details are included in Appendix K.

Even though this approach and the model help simulate an unreliable grid, there are limitations to the outage schedule used for the analysis. For Pakistan, outage data is not readily available. With mostly unscheduled power outages, populating an hourly load shedding schedule is challenging. The data used in this study is from a leading telecommunications corporation. Cell towers typically use the main grid as the prime source of power with diesel and battery back-ups during power cuts. Actual data for daily and monthly number of ‘hours in outage’ for company operated cell towers due to power cuts is used to prepare an outage schedule. Due to the unavailability of hourly pattern of these power cuts, the average number of daily outage hours are spread over the 24 hour period from personal experience of the author. Based on this cell tower data, a total of around 4500 hours of power outage are used in the analysis for Pakistan. It is also assumed that load shedding will continue to stay at the current levels throughout the study period. This is a reasonable assumption, given the slow pace of mitigation efforts of the government contrary to the ever growing energy demand.

For South Africa, the level of load shedding is currently lower than that experienced in Pakistan. Eskom issues a load shedding schedule to distribute power cuts across the country in order to cope with the supply and demand gap. Based on this gap, they define three stages of load shedding, with Stage 1 being the lowest and Stage 3 the highest (Eskom, 2014). Recently, South Africa is experiencing Stage 1 to Stage 3 load shedding only during some months of the year. In order to have a good estimate of future power shortfalls in light of the discussion from (Trollip, Butler, Burton, Caetano, & Godinho, 2014), a year round Stage 1 load shedding schedule is assumed for this study. This amounts to almost 400 hours of power outage in a year, mostly implemented in 4 hour blocks a week. This gives a very conservative estimate for the reliability cost and given the blossoming power crisis in South Africa, one can certainly expect more outage hours in the future. However, the outage schedule is kept constant over the entire study period. The schedule used is obtained from (Eskom, 2014), and is for the Orange Farm Area, a rural suburb of Johannesburg.

The effective cost of unreliable grid power in Pakistan and South Africa. The following figures summarize the working from the preceding two sections and present future trends of the effective costs of unreliable grid power at both locations. In each case, as discussed earlier, the numbers represent the respective final $LCOE_{Batt}$ and $LCOE_{Gen}$ based off of extrapolated recent trends, government projections and any costs associated with grid reliability calculated for each back-up option separately. Thus, both locations have two grid parity regions defined by the choice of substitute used to power up during outages.

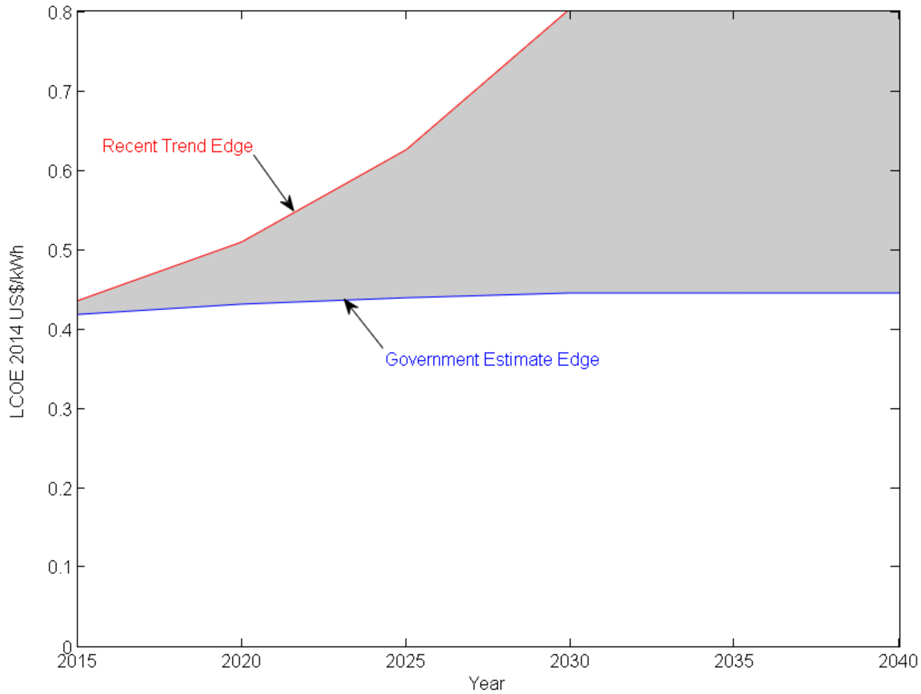

Figure 8. Grid parity region for Pakistan where consumers use a battery back-up system to make up for the unreliable grid. The two edges are the $LCOE_{Batt}$ figures representing the effective real costs of uninterrupted power supply to consumers. These are made up of the actual grid price estimates (Table 11) and the cost to produce back-up power from batteries (Appendix K).

Table 13

$LCOE_{Batt}$ figures for both edges of the parity region for Pakistan in a battery back-up scenario. The $LCOE_{Batt}$ represents the effective real cost of uninterrupted power and is made up of grid price estimates and cost to produce back-up power from batteries during outages.

PAKISTAN	2015	2020	2025	2030	2035	2040
Recent Trend - $LCOE_{Batt}$ \$/kWh	0.435	0.509	0.625	0.803	1.076	1.496
Government Estimate - $LCOE_{Batt}$ \$/kWh	0.418	0.431	0.439	0.445	0.445	0.445

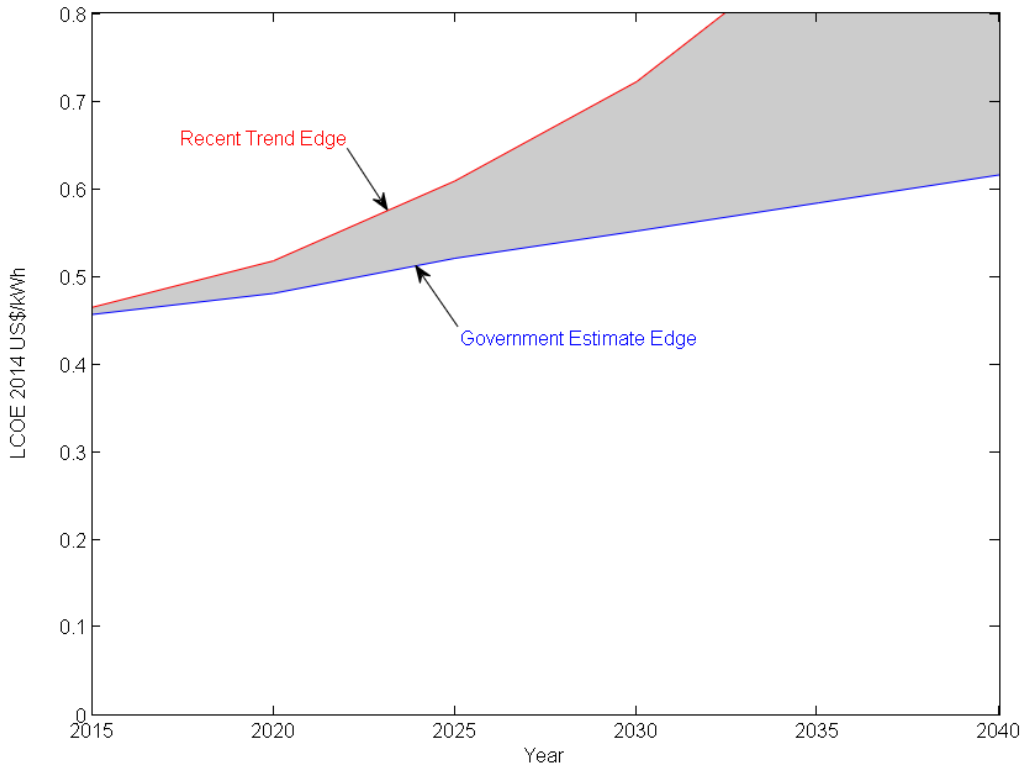

Figure 9. Grid parity region for Pakistan where consumers use a diesel generator back-up system to make up for the unreliable grid. The region is a representation of the estimated future trend of electricity costs to consumers if they stay grid-tied and use a generator back-up system.

Table 14

$LCOE_{Gen}$ figures for both edges of the parity region for a generator back-up scenario in Pakistan .They reflect the total cost of power to the consumer, with an unreliable grid and a substitute generator

PAKISTAN	2015	2020	2025	2030	2035	2040
Recent Trend - $LCOE_{Gen}$ $/kWh	0.464	0.517	0.608	0.721	0.882	1.114
Government Estimate - $LCOE_{Gen}$ $/kWh	0.456	0.480	0.520	0.551	0.583	0.615

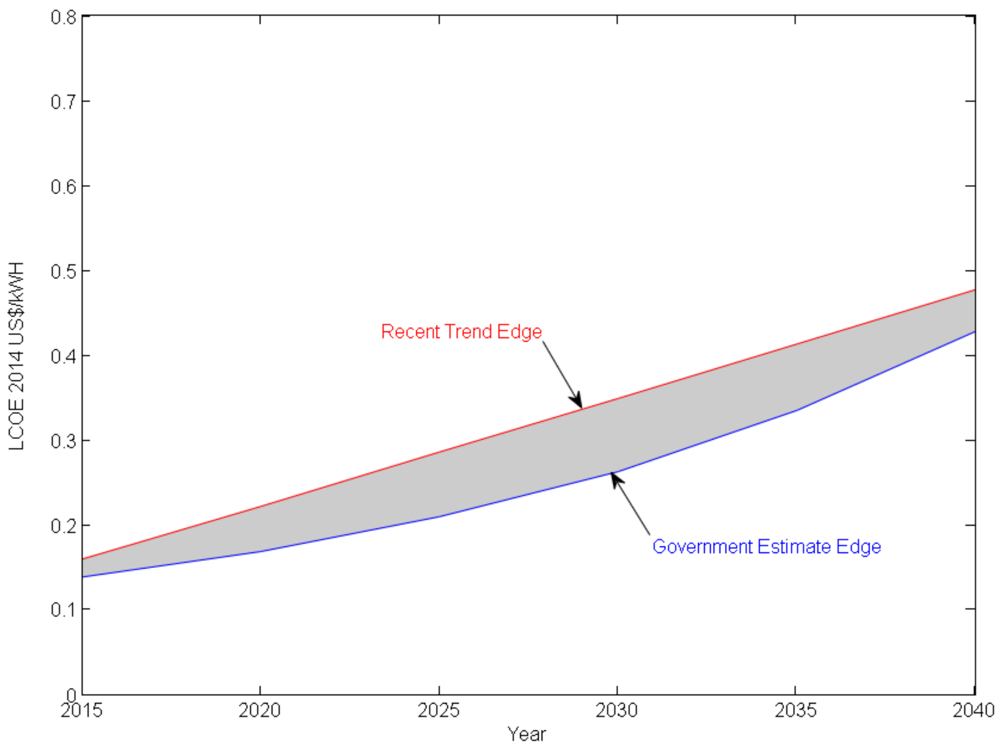

Figure 10. Grid parity region for South Africa where consumers use a battery back-up system to make up for the unreliable grid. The two edges are the $LCOE_{Batt}$ figures representing the effective real costs of uninterrupted power supply to consumers.

Table 15

$LCOE_{Batt}$ figures for both edges of the parity region for South Africa in a battery back-up scenario. The $LCOE_{Batt}$ represents the effective real cost to get uninterrupted power and is made up of future utility estimates and the costs of substitute power from the batteries.

SOUTH AFRICA	2015	2020	2025	2030	2035	2040
Recent Trend - $LCOE_{Batt}$ $/kWh	0.205	0.267	0.330	0.393	0.456	0.519
Government Estimate - $LCOE_{Batt}$ $/kWh	0.184	0.213	0.253	0.305	0.375	0.468

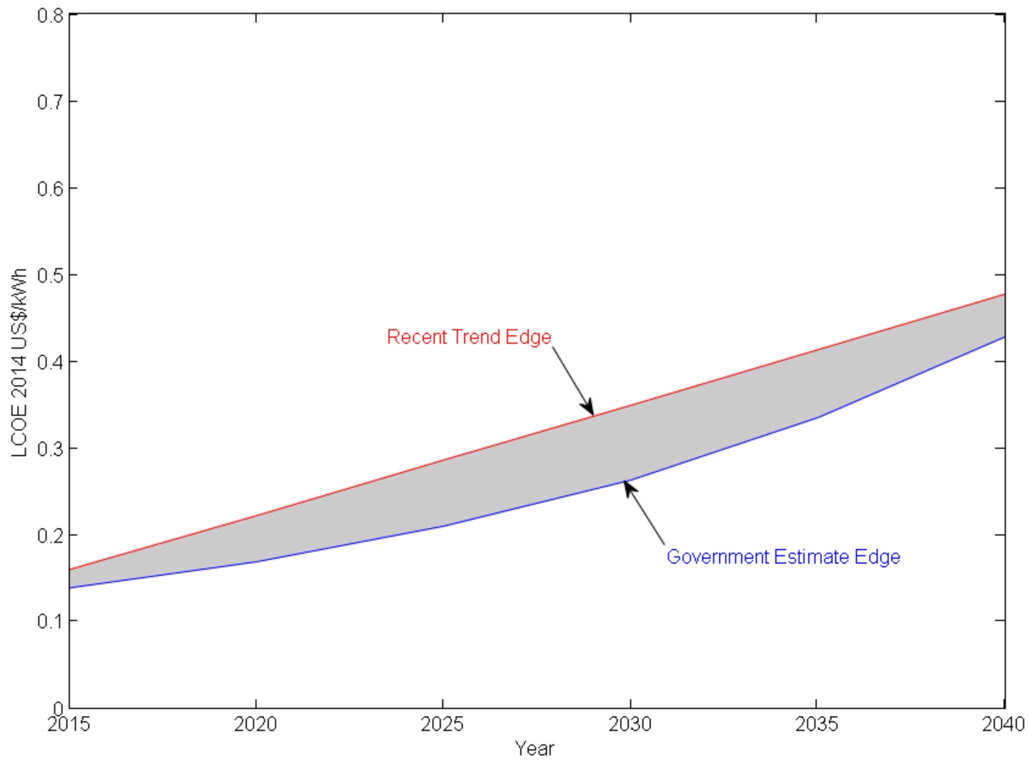

Figure 11. Grid parity region for South Africa where consumers use a back-up diesel generator to make up for the unreliable grid. The region is a representation of the estimated future trend of effective electricity costs to consumers if they stay grid-tied and use a generator

Table 16

$LCOE_{Gen}$ figures for both edges of the parity region for a generator back-up scenario in South Africa. They reflect the total cost of power with an unreliable grid and substitute generator. The use of an LCOE figure helps incorporate costs of power from different sources (unreliable grid and back-up generator)

SOUTH AFRICA	2015	2020	2025	2030	2035	2040
Recent Trend - $LCOE_{Gen}$ $/kWh	0.160	0.222	0.286	0.349	0.413	0.477
Government Estimate - $LCOE_{Gen}$ $/kWh	0.139	0.169	0.210	0.263	0.335	0.428

By comparing these results for South Africa and Pakistan, it is obvious that the choice of a back-up system affects the final cost of power borne by the end users, thus giving two distinct parity regions. In order to select a single parity region for the base case analysis, data from Appendix K can be used to determine the cheapest back-up system on a per kWh basis for each location.

The 2015 costs of substitute power from the two back-up systems are compared at each location. This is done to determine the current cost effective back-up option for each market. For Pakistan, with high levels of load shedding, the difference between the cost/kWh of substitute power from the battery and generator is small. Contrary to this, for South Africa the generator is clearly the cost effective back-up system with almost half the cost/kWh of the battery option (refer to Appendix K). Therefore, the parity region obtained from the generator-backup system is considered for analysis.

However, it is important to note that these results are solely based off of the inputs and all assumptions used in the analysis. Moreover, they reflect the cost-effective option to the consumer and do not account for any social costs associated with environmental emissions of diesel generators.

Results of the base case and sensitivity analysis for the battery back-up option are presented in Appendix A.

The following figures overlay the future utility price estimates on the parity region depicting the effective cost of unreliable power at each location. The effective cost in each case is higher than the price estimate due to the additional costs of generating substitute power during outages. Since the amount of load shedding in Pakistan is much higher than that in South Africa, the effective costs are much higher than the price estimates Pakistan.

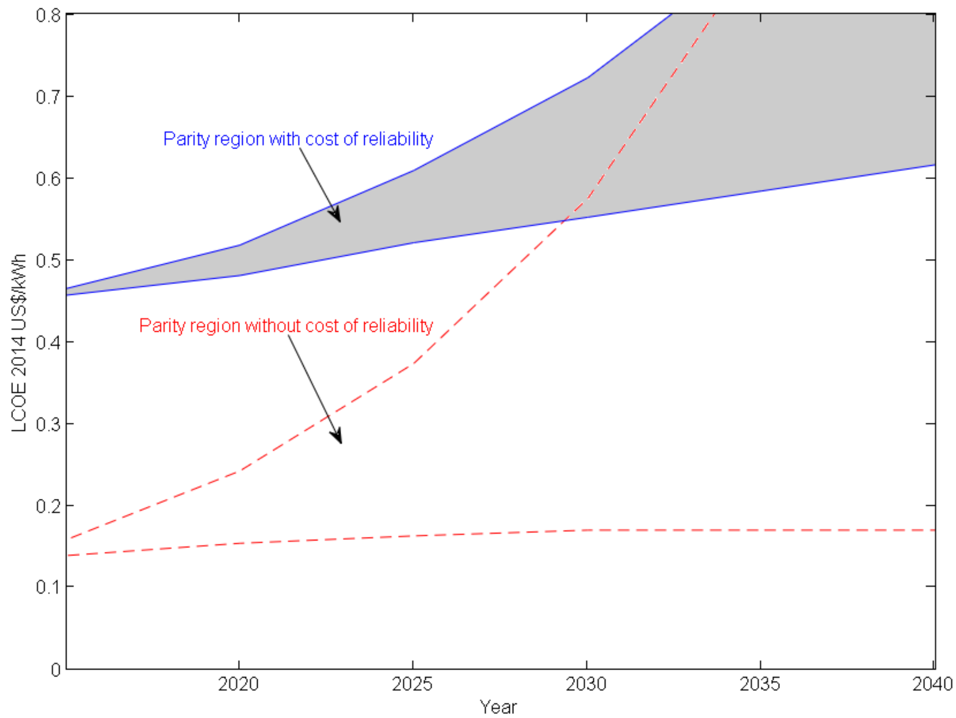

Figure 12. Effective cost estimates vs. future price estimates of electricity in Pakistan. The parity region enclosed by the dotted red line reflects the future trend of electricity prices in Pakistan without the effect of load shedding (Table 11). The shaded region bound by blue solid lines represents the future estimates of the effective cost of unreliable power to consumers, based on a generator back-up system (Table 14). The effective cost of unreliable power is higher than the price, due to the cost of substitute power from the generator

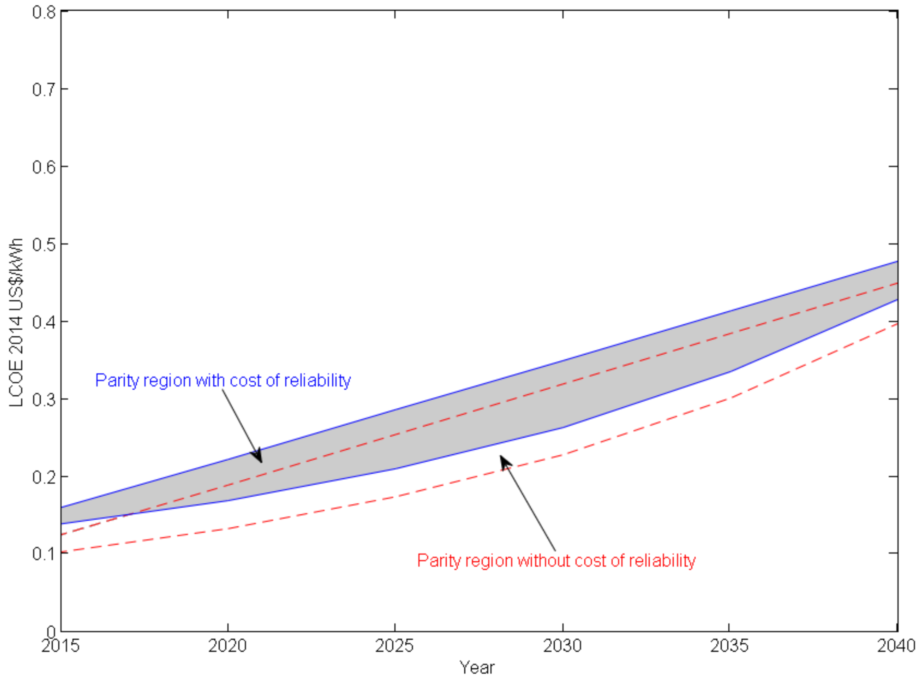

Figure 13. Effective cost estimates vs. future price estimates of electricity in South Africa. The parity region enclosed by the dotted red line reflects the future trend of electricity prices in Pakistan without the effect of load shedding (Table 12). The shaded region bound by blue solid lines represents the future estimates of the effective cost of unreliable power to consumers, based on a generator back-up system (Table 16). The effective cost of unreliable power is higher than the price, due to the cost of substitute power from the generator

Results and Discussion

Base Case Results

Grid parity for an alternative energy source occurs when it can generate electricity at an LCOE that is less than or equal to the price of purchasing power from the electricity grid (GlobalData, 2012) . For this study, as discussed earlier, it is defined by the intersection of the LCOE trend line with the two edges of the parity region. This grid parity region is a representation of a sensitivity analysis for utility prices, bound by the upper and lower edges. It is worth mentioning that the author acknowledges that there is considerable uncertainty in these parity results due to various simplifying assumptions and limitations of the optimization software. However, the best estimates based on these assumptions and the working discussed in the previous sections are reported as the base case results here. These are followed up by a sensitivity analysis to further investigate the effects of variations in important input parameters. The use of two parity edges is also part of this approach to provide a range of expected parity years.

The following figures show HOMER and ESM LCOE results for the four places. System configuration details for HOMER results are presented in Appendix A. Each figure comprises a graph and table with numerical values describing the optimal system along with financial information for each of the system components. Unless mentioned separately, the numerical entries in the tables correspond to those obtained from the optimization runs done using the ESM.

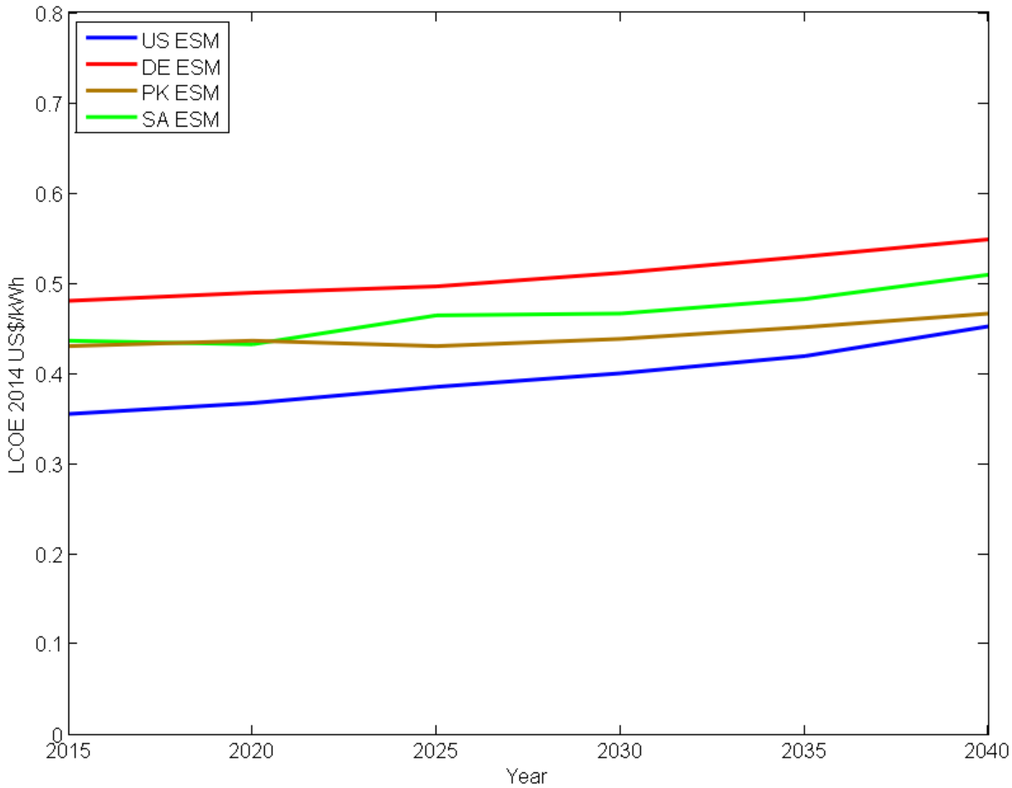

Figure 14. ESM LCOE base case results for all four locations

Table 17

ESM base case LCOE results for all four locations. This is the cost to produce power from the optimal system given the inputs. In all cases, the increase in LCOE is less than 10 cents/kWh real over the span of 25 years.

ESM LCOE 2014 US $/kWh	2015	2020	2025	2030	2035	2040
USA	0.355	0.367	0.385	0.400	0.419	0.452
Germany	0.480	0.489	0.496	0.511	0.529	0.548
Pakistan	0.430	0.436	0.430	0.438	0.451	0.466
South Africa	0.436	0.432	0.464	0.476	0.493	0.509

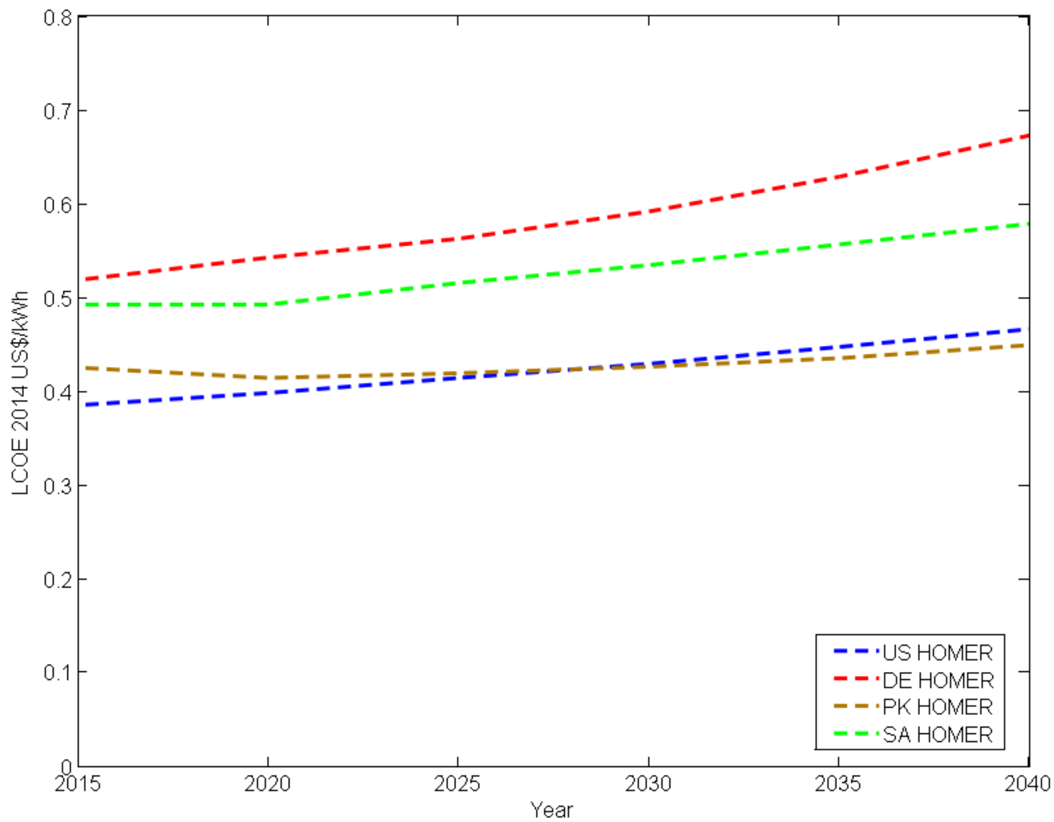

Figure 15. HOMER LCOE base case results for all four locations

Table 18

HOMER base case LCOE results for all four locations. Values are in real 2014 US dollars. Except for Germany, the increase in LCOE over the 25 years is less than 8 cents/kWh real.

HOMER LCOE 2014 US$/kWh	2015	2020	2025	2030	2035	2040
USA	0.385	0.398	0.414	0.429	0.447	0.466
Germany	0.518	0.542	0.562	0.591	0.628	0.672
Pakistan	0.425	0.414	0.419	0.426	0.435	0.449
South Africa	0.492	0.492	0.515	0.534	0.556	0.578

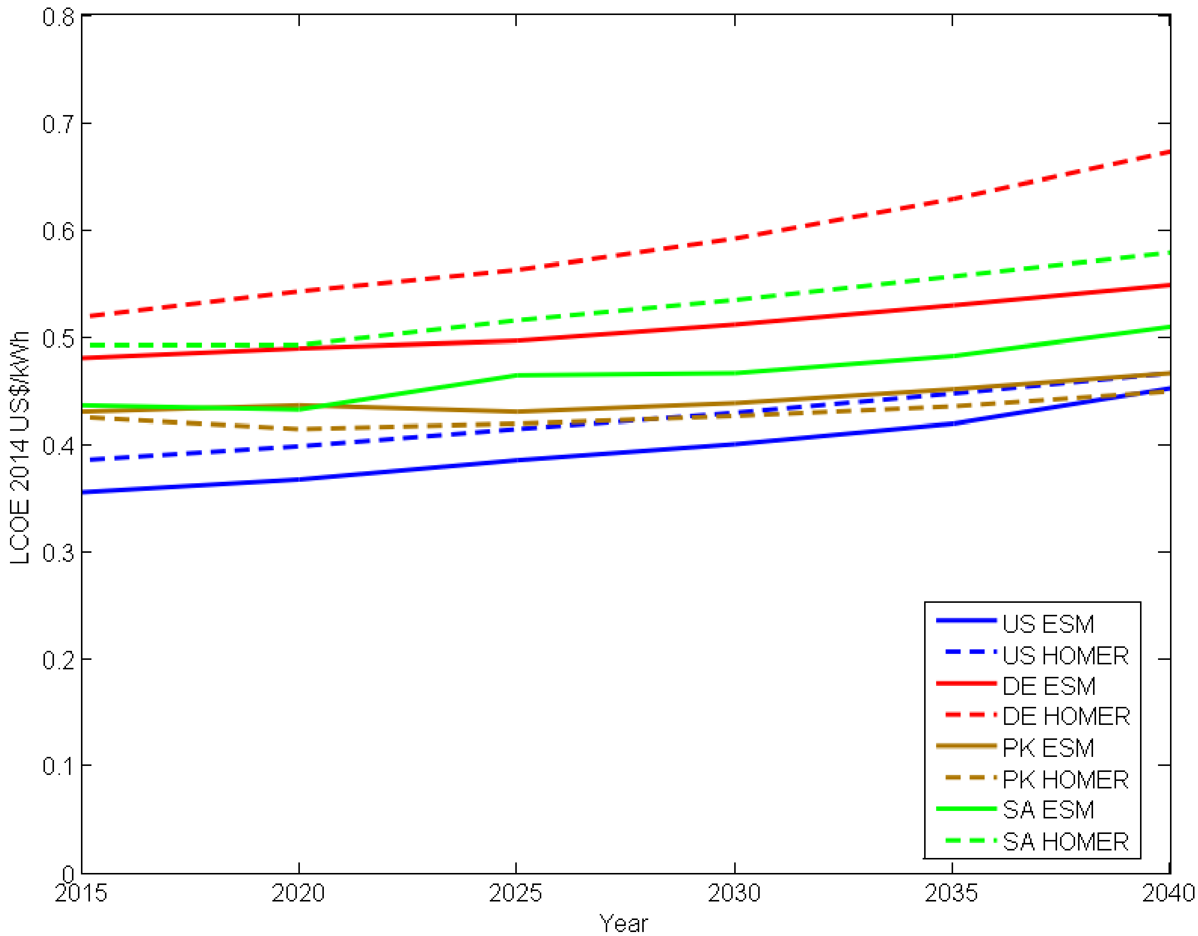

Figure 16. Base case LCOE results obtained from both HOMER and the ESM. HOMER results span over the 0.37-0.66 2014 US$/kWh range while the ESM results vary between the 0.35-0.55 2014 US$/kWh range. In general, HOMER results for each country are higher than the corresponding ESM LCOE values. In both cases, however, Germany has the highest LCOE figures and US the lowest. Results from both tools follow a general trend of a small increase in LCOE for each country

As seen from the results, the complete set of LCOE values obtained from both the ESM and HOMER lie within the 35-55 cents/kWh range. With only a few exceptions, the increase in LCOE values over the study period is less than 10 cents/kWh. Given the level of uncertainty associated with the optimization, simplifying assumptions used in input data conditioning and the considerable length of the study period, the general conclusion about this trend of results is that of a very small increase which may be looked at as constant values over the span of 25 years into the future. Corresponding results for each year from both HOMER and the ESM are mostly within 10 cents/kWh, reinforcing this future trend of LCOE values, given the inputs used in this analysis. The subsequent discussion of results however mostly refers back to the ESM values.

Correlating results with input data reveals that LCOE values in each case follow a trend similar to that of the diesel prices in the respective country. This is because the optimal system in each case has a large share of diesel generator as the lowest-cost way to meet the load (most of the times around and above the 50% mark). However, due to a significant amount of renewables in the optimal systems, the overall increase in LCOE values over the 25 years is smaller compared to the increase in diesel prices everywhere. For every country, the lowest LCOE value corresponds to an optimized system with at least 50% diesel generator share. Germany has the highest diesel fuel prices and therefore the highest LCOE values, while the US has the lowest. In all cases, as solar prices decrease and diesel prices increase, the solar fraction in the optimal systems increases (shown in the following details). Optimal systems for Pakistan, Germany and South Africa have relatively higher solar PV fractions corresponding to conditions favorable to solar i.e. good solar resource or low prices.

United States. The United States has the lowest LCOE figures for the solar hybrid microgrid system. With the lowest diesel fuel prices and significant government incentives for solar PV, LCOE values range within the 30-40 cents/kWh range. However, given the relatively poor solar resource for a place like Columbus Ohio, the optimal systems for each year are predominantly diesel generator systems with small fractions of solar/battery. Both, a gradual decrease in solar prices and an increase in diesel prices is not enough to offset the significant difference between solar and diesel. So over the entire period of the analysis, even though there is a gradual yet small increase in the renewable fraction, the diesel generator remains the dominant system element. This also gets reflected in the high daily fuel costs for diesel in comparison to solar PV and batteries.

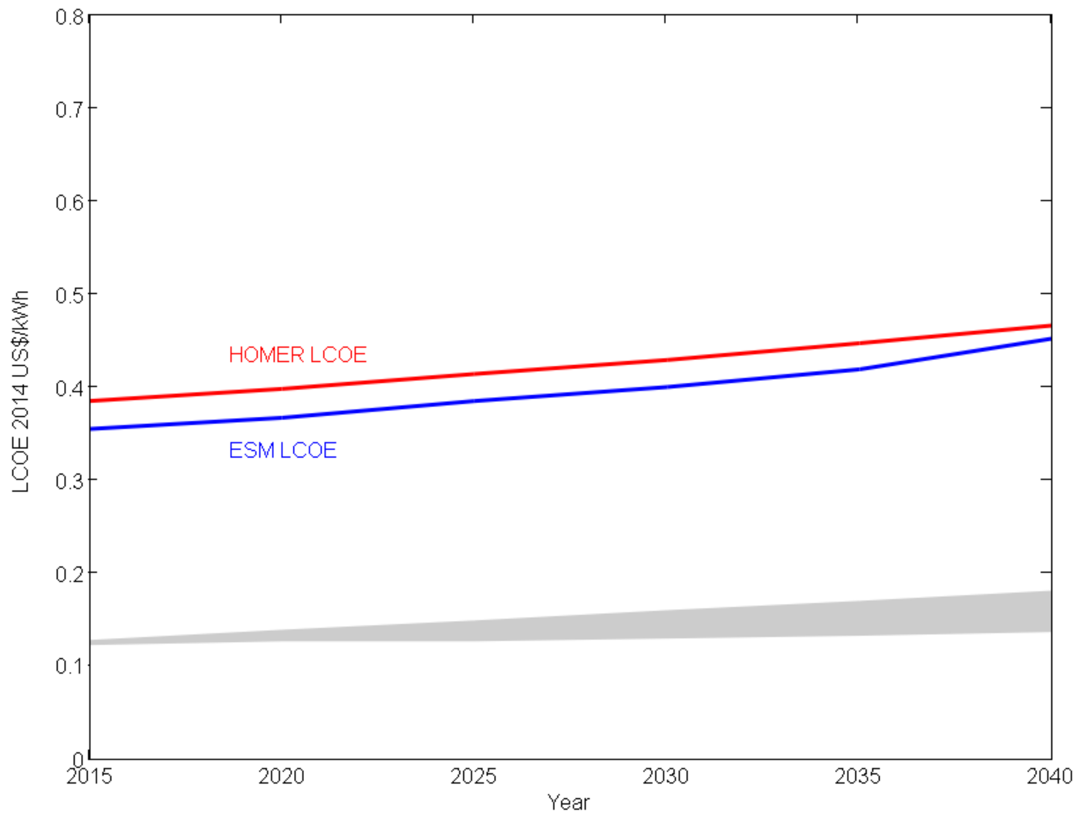

Figure 17. HOMER and ESM LCOE results with future grid electricity price estimates defined by the shaded parity region for the United States in real US 2014 dollars. Grid parity does not occur in the US during the study period due to low electricity prices

Table 19

ESM Results for the US. The optimal system is a diesel generator dominated system. The solar fraction increases somewhat with decreasing solar PV prices. However, the decrease in prices is offset by an increase in diesel fuel prices.

UNITED STATES	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.355	0.367	0.385	0.400	0.419	0.452
Solar Fraction %	30.6	28.5	31.8	32.7	34.5	40.0
PV (kW)	154.3	134.2	160.9	174.2	181.8	217.6
Generator (kW)	111.3	110.9	111.4	110.8	110.7	128.8
Battery (kWh)	134.4	151.4	168.6	146.1	226.7	541.4
Solar PV Cost ($/day)	105.5	99.2	106.2	107.3	107.5	125.9
Generator Cost ($/day)	17.8	17.8	17.8	17.7	17.7	20.6
Battery Cost ($/day)	16.8	25.3	32.4	20.9	60.2	115.6
Diesel Cost ($/day)	412.5	432.3	444.6	479.4	468.2	436.3

HOMER LCOE results follow a similar trend over the study period. Even though HOMER reports slightly higher values, they stay on average within 3 cents/kWh of the ESM results. HOMER optimal system configurations (Appendix A) also closely resemble ESM results with around 30% solar PV fraction throughout the analysis.

Owing to low grid electricity prices in the US in general, and Ohio in particular, microgrids do not hit grid parity during the analysis period. As seen in Figure 14, there is a considerable difference in grid electricity price projections and the LCOE values. This is large enough to make microgrids economically unattractive for places with grid electricity prices similar to those in the US during the study period.

Germany. Germany has relatively high diesel fuel prices. This has much to do with the high levels of taxes levied on the consumption of diesel in order to push for cleaner fuels. On the other hand, solar PV prices in Germany are one of the lowest in the world due to their pro-solar PV policy initiatives, even though they have a relatively poor solar resource. These aspects are reflected in the ESM and HOMER LCOE results, which turn out to be the highest for a hybrid system in this analysis.

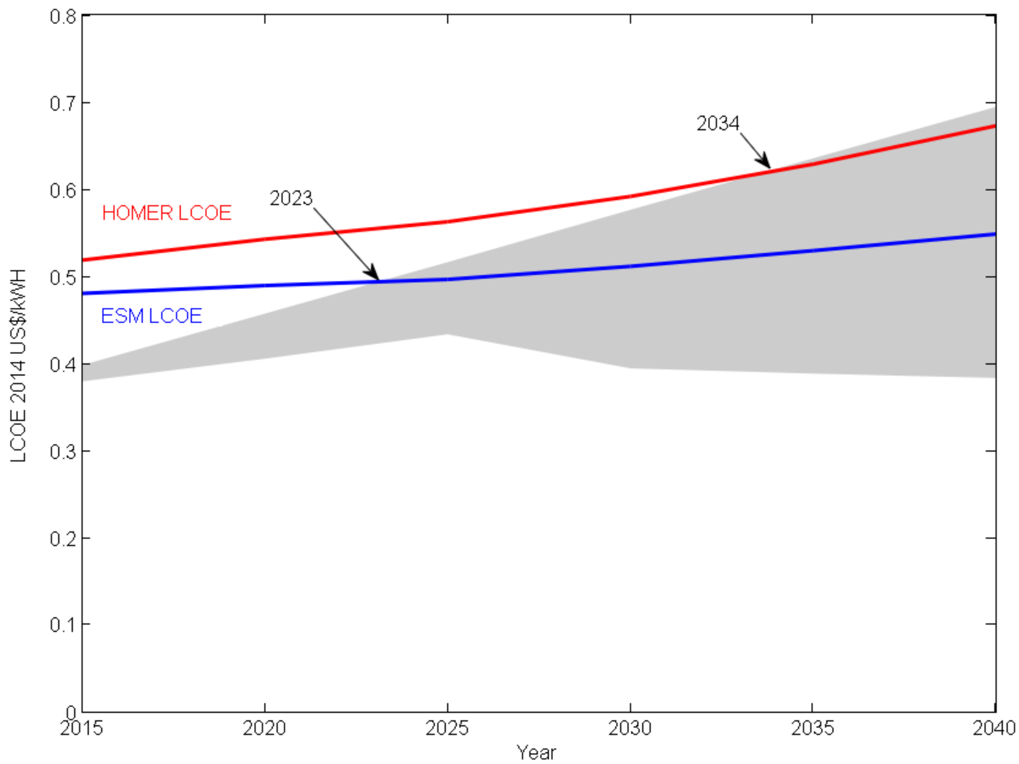

Figure 18. HOMER and ESM LCOE results with future estimates of grid electricity prices for Germany in real 2014 US dollars. Owing to high grid electricity prices, grid parity points occur in the years 2023 and 2034 for ESM and HOMER results respectively. Both these points are on the extrapolated recent trend edge of the parity area, signifying that this occurs in case recent increases in real grid electricity prices continue in the future. With future estimates of prices from the government, grid parity does not occur during the study period.

Table 20

ESM results for Germany. The optimal system has a high enough solar PV fraction so that it is a solar dominated system. However, due to poor solar resource, the system heavily relies on batteries with their daily costs comparable to those of the PV costs. Still, the operational costs of diesel fuel turn out to be the highest because of high diesel prices in Germany

GERMANY	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.480	0.489	0.496	0.511	0.529	0.548
Solar Fraction %	53.7	56.4	60.4	60.7	65.0	66.4
PV (kW)	92.9	104.9	119.7	121.5	141.9	149.9
Generator (kW)	35.0	35.1	34.9	34.9	35.2	35.0
Battery (kWh)	295.4	274.5	294.3	294.3	317.6	317.8
Solar PV Cost ($/day)	44.5	45.7	49.3	48.5	55.6	58.3
Generator Cost ($/day)	4.5	4.5	4.5	4.5	4.5	4.5
Battery Cost ($/day)	42.2	41.4	42.1	42.2	43.1	42.9
Diesel Cost ($/day)	93.5	96.7	93.9	101.1	98.7	103.2

Due to the poor solar resource, the optimal system is always forced to push in enough diesel generator to meet the load. Even though solar PV is cheap, it is unable to make up for the poor solar intensity in Germany, as a result of which the solar PV fraction in the optimal system stays around the 50-60% mark. Due to the expensive diesel fuel consumption in the system, the average LCOE for Germany turns out to be 15% higher than the combined average for the other three countries. As diesel gets more and more expensive over time, the solar PV fraction for the optimal system increases gradually, while the generator size remains the same.

The greatest difference in HOMER and ESM LCOE results in the analysis is observed for the case of Germany, with HOMER figures higher on average by 8 cents/kWh. Comparison of the optimal system configurations reveals that HOMER makes a greater use of the diesel generator, which is reflected in higher daily costs of fuel, lower solar PV fractions and thus higher LCOE figures.

For Germany, even though the system has a high LCOE, it hits grid parity around the year 2023 assuming grid electricity prices follow a recent trend. Since 2011, government taxes, levies and fees have amounted to about 50% of the nominal price per kWh paid by residential customers in Germany (Morey & Kirsch, 2014). The trend means an aggressive price hike, pushing the parity point closer in comparison to the conservative government projections which show a decline in electricity prices following 2025 due to a fall in the EEG surcharge (Schlesinger, Dietmar, & Lutz, 2014). Therefore, based on the assumptions used for the input data, hybrid solar PV/Diesel/Battery microgirds hit grid parity in Germany around the year 2023 at the earliest, as suggested by the ESM. For HOMER, this estimate is around the year 2034 due to higher LCOE numbers. However, it is important to note here that both these parity points occur at the ‘Recent trend’ edge of the parity region. This implies that unless real grid prices in Germany are high, a stand-alone solar PV/diesel/battery hybrid microgrid does not hit cost parity with the grid during the study period.

Pakistan. Given the best solar resource amongst the four locations under consideration, the optimal system for Pakistan maintains a solar PV fraction comparable to systems in Germany. Throughout the analysis, this fraction hovers around the 50-60% mark. This suggests a decent balance between the two sources, reflected in the final LCOE results for Pakistan where the rise in LCOE is only around 3 cents over the entire study period. Values lie within the upper (German LCOE) and lower (US LCOE) bounds of the ESM set of results. This could be explained by diesel prices comparable to those in the US and a good solar profile which pushes in more solar PV in the system. However, it is important to mention here that one significant aspect of the optimal system configuration is the input load that needs to be met. The considerable differences in electric load profiles for all of these places plays an important role in determining the final configurations of the optimal systems. Even though such correlations to input data make for sound arguments, the importance of this diversity in different load profiles needs to be acknowledged at the same time.

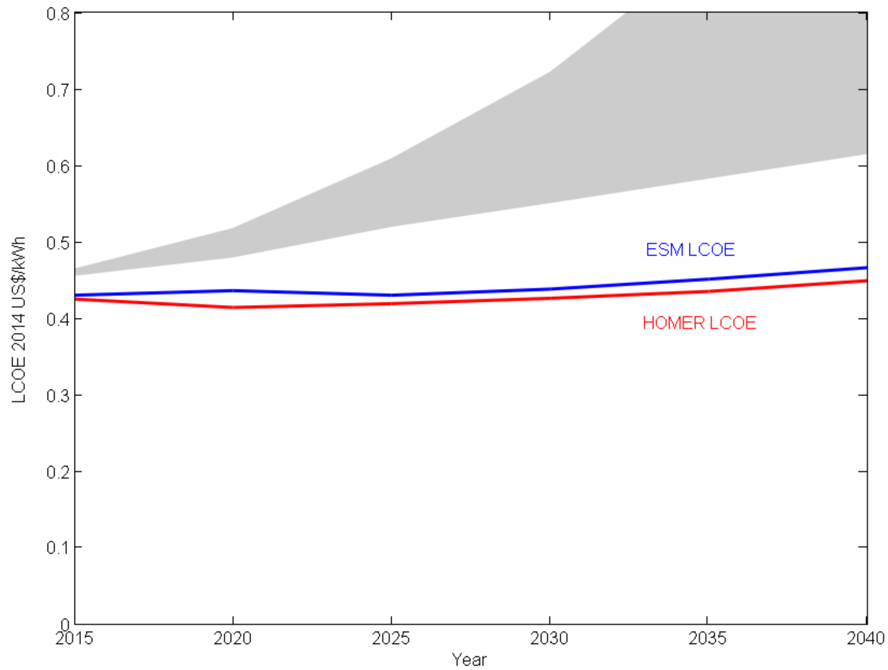

Figure 19. HOMER and ESM LCOE Results with estimates of the effective cost of unreliable power to consumers in Pakistan in 2014 US Dollars. The parity region depicts this effective cost determined by incorporating costs of substitute power from a diesel back-up generator into grid prices. Due to high levels of load shedding (power cuts) and recent increases in grid power prices, this cost comes out around 45 cents/kWh in 2015. Due to these high estimates, both HOMER and ESM LCOE lines are significantly lower than the parity region, showing that grid parity is already here in Pakistan.

As can be seen from Figure 19, both HOMER and ESM results are within 1 cent/kWh on average, representing a high level of agreement in results. However, in terms of the optimal system configurations, HOMER results (Appendix A) show a slightly higher solar PV + battery fraction.

Table 21

ESM results for Pakistan. Due to a good solar resource, the optimal system is a solar PV dominated system with one of the highest solar PV fraction figures in the analysis. However, diesel fuel has the highest share of operational costs. With decreasing solar prices, the solar PV fraction somewhat increases over time. The 3 cents/kWh real increase in LCOE values over time is the lowest for the analysis, reflected by the flattest LCOE lines.

PAKISTAN	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.430	0.436	0.430	0.438	0.451	0.466
Solar Fraction %	55.8	66.3	59.2	58.6	59.2	60.1
PV (kW)	167.9	232.6	196.7	188.9	196.1	206.8
Generator (kW)	107.9	109.9	98.3	98.4	98.2	97.3
Battery (kWh)	107.7	103.5	135.1	137.2	135.9	138.0
Solar PV Cost ($/day)	154.9	185.5	143.7	131.7	132.7	138.2
Generator Cost ($/day)	16.1	16.4	14.7	14.7	14.7	14.5
Battery Cost ($/day)	43.6	34.2	66.8	70.6	68.1	69.3
Diesel Cost ($/day)	261.5	242.6	249.3	268.1	283.7	293.3

The results of the analysis show that grid parity is already here for Pakistan. The parity region in Figure 19 suggests that the parity point lies some time before the year 2015 since LCOE values stay under the highlighted region. With increasing electricity prices and an unreliable grid characterized by 8-10 hours of average power outages (load shedding), microgrids make economic sense in Pakistan at present. The parity region shown in Figure 19 accounts for the retail price of electricity and the cost of unreliable grid to the end consumers. As discussed earlier, this effective cost is determined using the cost of substitute power from a back-up generator to meet load during power cuts.

South Africa. The optimal system configurations in South Africa turn out to be diesel dominated systems with the solar fraction accounting for just above one third the energy supplied. Therefore, the final LCOE results from both HOMER and the ESM follow a gradual increasing trend, similar to that of the diesel prices.

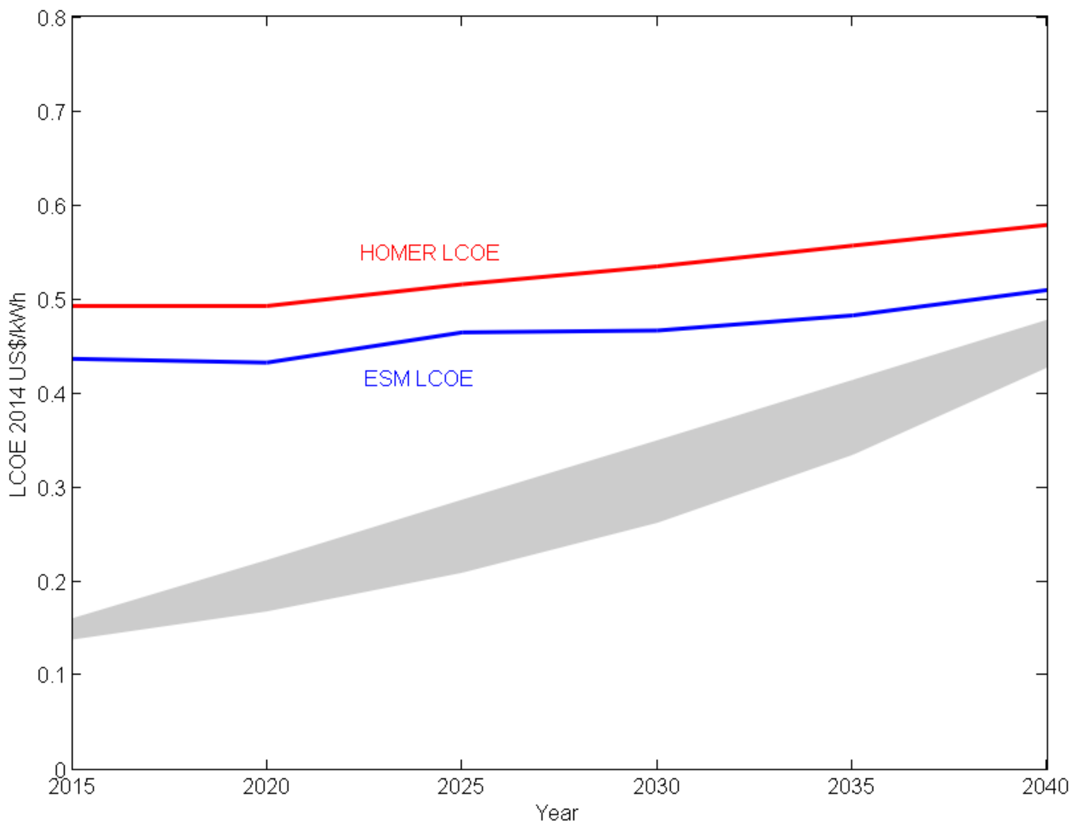

Figure 20. HOMER and ESM LCOE results for South Africa with estimates of the effective costs of unreliable grid power in 2014 US dollars. The parity region corresponds to the effective costs of electricity calculated for the substitute power generated using a diesel back-up generator. With current low grid prices, microgrids do not hit grid parity in South Africa during the study period.

Table 22

ESM results for South Africa. The optimal systems are diesel generator dominated systems, with only one third of the output coming from solar PV. However, with decreasing solar PV prices and increasing diesel fuel prices, this fraction increases. There is a sudden 'jump' in results seen in the year 2025, where the optimal system pushes in a considerable amount of solar PV + battery.

SOUTH AFRICA	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.436	0.432	0.464	0.476	0.493	0.509
Solar Fraction %	34.3	37.1	46.8	47.0	46.3	46.7
PV (kW)	112.3	128.6	197.9	199.0	199.7	202.6
Generator (kW)	114.4	112.4	113.4	113.1	114.2	112.9
Battery (kWh)	161	171.8	243.3	247.2	230.8	233.2
Solar PV Cost ($/day)	107.6	106.4	150.2	144.2	140.6	140.5
Generator Cost ($/day)	19.7	19.4	19.6	19.5	19.7	19.5
Battery Cost ($/day)	60.3	64.5	92.5	94.2	86.5	87.5
Diesel Cost ($/day)	408.8	400.7	364.3	386.5	421.1	443.9

The LCOE values increase by around 7 cents/kWh over the 25 year period, almost as much as for Germany (6.7 cents/kWh). While the results start off similar to values for Pakistan, the gradually increasing difference of solar PV + battery prices in the two countries translates into diverging LCOE results, as seen earlier in Figure 11. Even with a solar resource almost as good as that in Pakistan, the most optimal system remains one with relatively lower amounts of solar PV up until 2025.

HOMER and ESM LCOE results differ by an average 6 cents/kWh, only second to the deviation in results for Germany. Comparison of optimal system configurations reveal somewhat similar solar PV fractions with high diesel fuel daily costs (Table 22 and Appendix A).

As for grid parity, microgrids do not hit parity in South Africa during the study period. Currently South Africa has one of the lowest electricity prices in the world (Trollip, Butler, Burton, Caetano, & Godinho, 2014). Even though historically South Africa has seen years marked with unprecedented increases in the retail prices for electricity, the government in recent times has blocked such proposals. With these present controlled low electricity prices, these grids are an expensive option with parity sometime around the years beyond 2040. However, given the decaying condition of the power sector in the country, the government may not be able to sustain this price control for long since it would only worsen the power outage situation. This, very much like Pakistan, would ultimately raise the effective cost of reliable grid power to consumers. In such a scenario, one can expect grid parity to occur sooner than it is suggested by these results.

To sum up, base case analyses with both HOMER and the ESM show that the grid parity points for microgrids greatly vary across countries considered in this study. While it is already here for Pakistan, the US does not see parity within the 25 year period. For South Africa, unless utility retail prices increase drastically, microgrids do not make economic sense until beyond the end of the study period. For Germany, parity occurs within the next decade. The following table summarizes these results.

Table 23

Base case grid parity point estimates for all four locations. While grid parity is already here for Pakistan, it does not occur for both the US and South Africa during the study period. For Germany, grid parity occurs during the study period in the year 2023 only if recent electricity price hikes continue.

	BASE CASE PARITY ESTIMATES	
	Earliest	Latest
USA	Past 2040	Past 2040
GERMANY	2023	Past 2040
PAKISTAN	Before 2015	Before 2015
SOUTH AFRICA	Past 2040	Past 2040

Uncertainty and Model Limitations

At this stage, it is important to mention the author acknowledges that there is uncertainty associated with these results of the analysis. Since the analysis involves many input parameters and complex optimization models, one can expect multiple sources of uncertainty and systematic errors in these final results. Therefore, even though the results provide a high level estimation of grid parity points for these locations, they are only limited to the considered input conditions and the form of predictive models used in the two tools.

Quantitative errors introduced with simplifying assumptions used for input parameters of the models limit the final results. Errors like rounding errors or the use of average numbers are simple examples. Temporal variations in factors assumed to be constant for this study may have an impact on the results. One such example are the currency exchange rates. Another such factor is the constant electric load profile at each location. The choice of discount rates based on limited empirical sources of information can be another source of error. With a considerable number of extrapolations used in the analysis, there is uncertainty inherent in these estimates due to imperfect fits to past data. More importantly, the underlying assumption of the future being like the past may well be another source of judgmental uncertainty. Historically, renewable energy and technology have had an unpredictability associated with them. Due to this, results of such a prognosis study are only limited to the assumptions and defined scope of work.

Moreover, computational limitations of the software and the optimization models are important limiting agents such that the accuracy of final results is limited by the accuracy and detail of the models themselves. For example, inaccuracies in these models may stem from their inability to correctly and/or completely model the operation of system components (like batteries, generators etc.) under the given conditions. Optimization algorithms such as simulated annealing and the uphill climb may have limitations when determining an optimal solution. For instance, the number of iterations before an optimal system configuration is finalized may not be enough to determine the best optimal system. Since such models are simplifications of reality, not all real-world system behaviors and scenarios can be reproduced by them (Morgan & Henrion).

To account for these limitations in the models to an extent, two different modelling tools are used here to compare and validate parity estimates for each location. However, the use of other optimization tools that employ a methodology different from both the ESM and HOMER may further help improve validity of results. Due to limited time for this study, such an investigation has been left for further research. For uncertainty in empirical input quantities of the models, a one way sensitivity analysis is conducted using the more important input parameters. This helps highlight the impact of variations in these inputs on the final parity points and provides estimates of grid parity under different input scenarios.

Based on these arguments, the results of this study cannot be termed as exact. Moreover, even though the results help draw conclusions that may be generalized for both the developing and developed markets, it is important to acknowledge that parity is a function of many socio-economic, technical and policy parameters and may vary greatly between different markets as suggested by the results of this study. Therefore, even though the results in this study provide a high level view of parity estimates, give important insights into the considered markets and help draw policy implications for developing and developed markets, exact parity point estimates from this study cannot be simply translated to other similar markets. And so, throughout the study, the author stresses on parity point ranges rather than exact figures, which may be representative of similar markets with similar energy situations and policies.

Sensitivity Analysis

A sensitivity analysis is the computation of the effect of changes in input values or assumptions on the outputs (Morgan & Henrion). Since the choice of most input parameters to the model are based on simplifying assumptions and empirical estimates from only a limited number of sources, there is uncertainty inherent in the final results. In order to assess the impact of a change in some of these parameters on the grid parity points, and to draw important policy conclusions, a one way sensitivity analysis is conducted for each location.

Of the many input variables in the model, the following are used to conduct the sensitivity study:

- Cost of Capital (Interest Rate)
- Diesel Fuel Prices
- Temperature

In the first two cases, a ‘high’ and ‘low’ value for the input parameter is used relative to the values from the base case. This helps determine the upper and lower bounds for the LCOE values and thus highlights the sensitivity of grid parity points to these ESM inputs. For temperature, a climate-controlled temperature time series data is used as an alternative to the base case time series. This helps assess the impact of changes in temperature on the lead acid batteries, which in turn could affect the system configuration, the LCOE and the final parity points.

A sensitivity analysis on the utility retail electricity prices is already discussed in the methodology section. It provides a grid parity region, enclosing the area by an upper and lower bound (the two edges) for future prices, characterizing both conservative and aggressive future estimates of electricity prices. Furthermore, additional sensitivity analysis for particular situations are presented in the discussion section.

Cost of Capital rate. The cost of capital (discount or borrowing rate) rate is an important input parameter in both the ESM and HOMER. Considering LCOE results, present worth calculations in the optimization make use of this parameter to determine the optimal and cheapest system configurations. This is because the hybrid system under consideration involves two different sources of energy:

- Solar PV + Battery : Technology with high upfront costs and low operational costs
- Diesel Generator: Technology with low upfront costs and very high operational costs

Considering this, the choice of energy source (renewable and non-renewable fractions) in the optimum and cheapest system greatly depends on this input. This choice of a discount rate also makes for an important policy matter and the impact on the final grid parity helps provide valuable policy insights.

The following table shows the cost of capital rate values used in the sensitivity analysis for each location. As discussed earlier, ‘low’ and ‘high’ values relative to the base case are chosen for each location to determine bounds for the LCOE values and parity points

Table 24

Cost of capital (discount) rate variations for the sensitivity analysis.

Cost of Capital	Low	Base	High
United States	2%	8%	15%
Germany	2%	5%	10%
Pakistan	2%	14%	20%
South Africa	2%	10%	20%

The following figures summarize results for all locations.

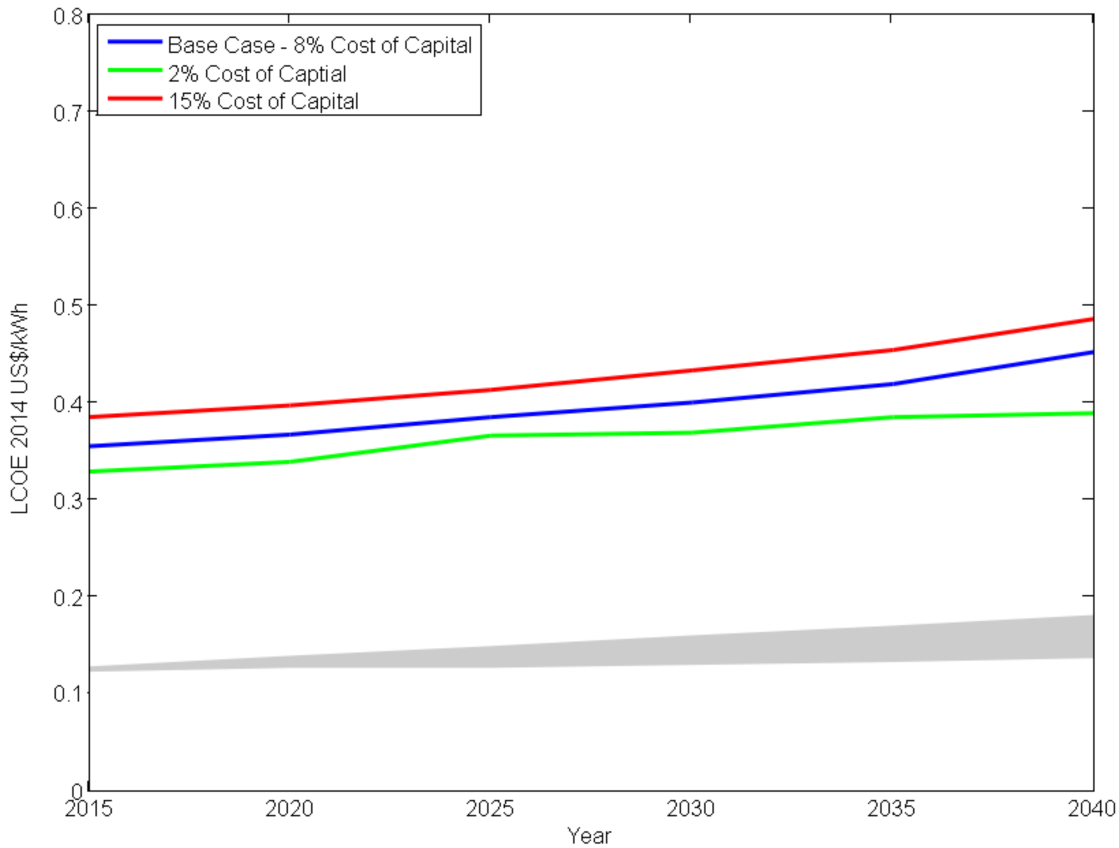

Figure 21. Impact of changes in the cost of capital rate on the ESM LCOE and grid parity points for the United States. A lower discount rate lowers the final LCOE. However, grid power prices are low compared to these, so that microgrids do not hit grid parity even at a 2% rate

Table 25

ESM LCOE results for the cost of capital rate sensitivity analysis in the US. With lower rates, the optimal system has a higher solar fraction and vice versa. With high capital costs and small operational costs, this nature of cash flows for solar PV results in the observed changes in solar PV fractions for the optimal systems

UNITED STATES		2015	2020	2025	2030	2035	2040
2% Cost of Capital	ESM LCOE $/kWh	0.329	0.339	0.366	0.369	0.385	0.389
	Solar Fraction %	*32.0*	*32.6*	*62.6*	*62.6*	*77.1*	*77.1*
Base Case	ESM LCOE $/kWh	0.355	0.367	0.385	0.400	0.419	0.452
	Solar Fraction %	*30.6*	*28.5*	*31.8*	*32.7*	*34.5*	*40.0*
15% Cost of Capital	ESM LCOE $/kWh	0.385	0.397	0.413	0.433	0.454	0.486
	Solar Fraction %	*26.8*	*26.3*	*26.4*	*27.2*	*32.2*	*34.5*

For the US, lowering the interest rate by a factor of 4 almost doubles the solar PV fraction in the optimal systems beyond 2025. The 2% rate also renders one of the lowest LCOE values of the analysis. Almost doubling this rate does not really affect the LCOE figures, raising them on average by just 3 cents/kWh. However, it returns optimal systems with some of the lowest solar PV fractions. Even though a decrease in this cost of capital rate helps bring down LCOE figures, it still does not affect the parity points for the United States given the low electricity prices.

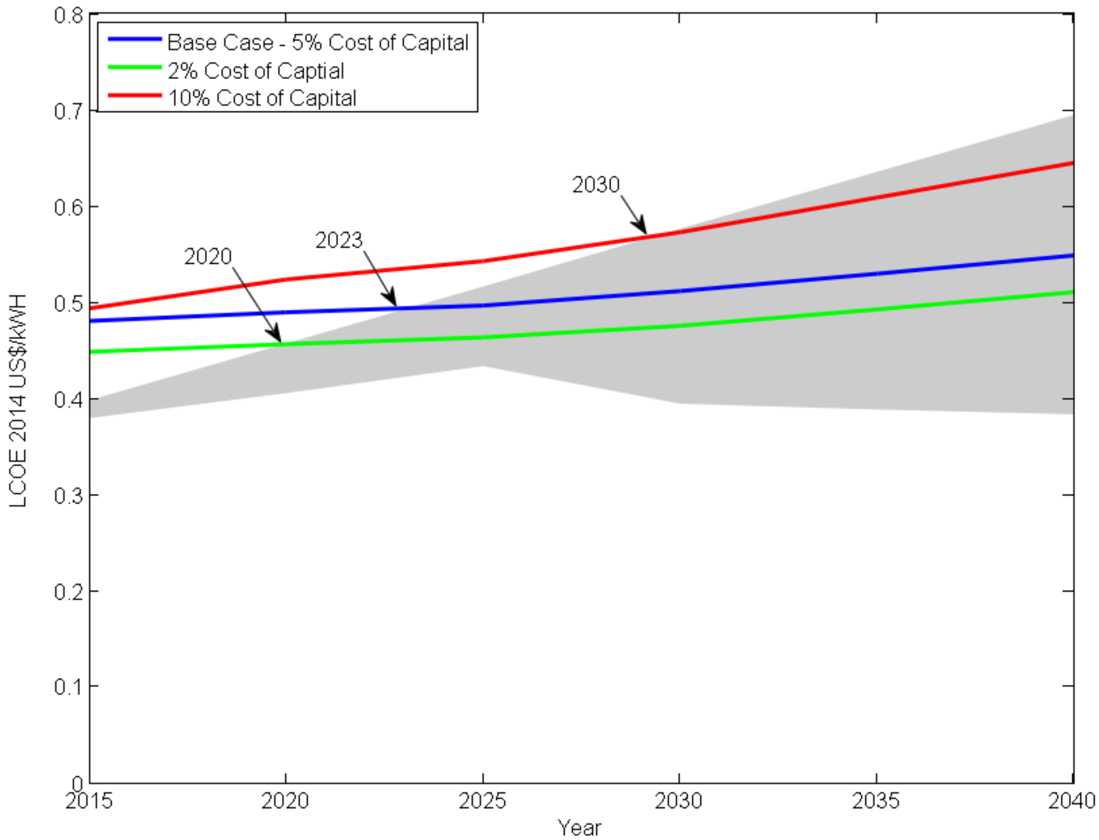

Figure 22. Sensitivity analysis results for the cost of capital rate in Germany. Grid parity occurs in the year 2020 at a 2% cost of capital, provided the recent increase in real electricity prices continues. A 10% cost of capital pushes the estimated earliest parity point to the year 2030. Thus, lowering the discount rate pushes the parity point earlier in time. However, even with a 2% rate, the system does not hit parity with government estimates of future grid power prices.

Table 26

ESM LCOE results for the cost of capital rate sensitivity analysis in Germany. Doubling the discount rate reduces the solar fraction to almost half that of the base case level. Due to the recurring nature of fuel expenses for a diesel generator, at a higher discount rate, the optimal system switches to a diesel dominated system. A low rate however helps maintain a decent amount of solar PV, making up for the generally poor solar resource in Germany.

GERMANY		2015	2020	2025	2030	2035	2040
2% Cost of Capital	ESM LCOE $/kWh	0.448	0.456	0.463	0.475	0.492	0.510
	Solar Fraction %	*58.0*	*60.7*	*63.8*	*66.4*	*68.6*	*69.6*
Base Case	ESM LCOE $/kWh	0.480	0.489	0.496	0.511	0.529	0.548
	Solar Fraction %	*53.7*	*56.4*	*60.4*	*60.7*	*65.0*	*66.4*
10% Cost of Capital	ESM LCOE $/kWh	0.493	0.523	0.542	0.572	0.608	0.644
	Solar Fraction %	*29.2*	*34.0*	*33.9*	*33.9*	*34.3*	*39.9*

A rise in the cost of capital for the case of Germany clearly depicts its impact on the amount of solar PV used in the optimal system. With a rate double that of the base case scenario, the solar fraction falls to roughly half the value. Moreover, the LCOE values are on average higher by about 6 cents/kWh for a given year. Moving further into the future, this high interest rate pushes LCOE figures up by more than 10% of the base case values. This suggests that low interest rates in Germany help counter the poor solar resource and high diesel fuel prices. Even though lowering the rate does not change the renewable fraction by much, the LCOE values are pushed down by 3-4 cents/kWh. These changes have a somewhat limited impact on the final parity point, which gets pushed 7 years farther and 3 years earlier for the two cases.

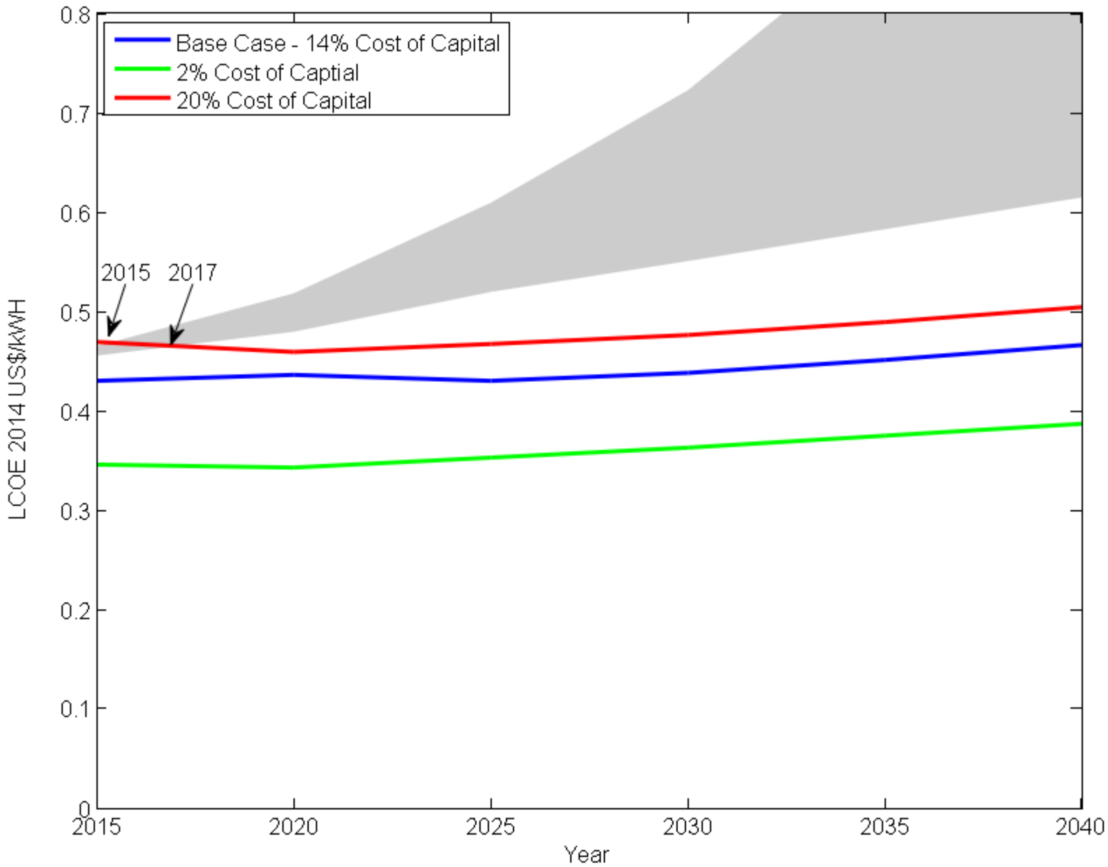

Figure 23. ESM LCOE cost of capital rate sensitivity results with the effective cost of unreliable power calculated from a generator back-up system in Pakistan. With an interest rate as high as 20%, the farthest parity point corresponding to the government estimate edge of the region occurs in the year 2017. Following recent price trends, parity is already here for scenarios with the cost of capital rates ranging from 0% - 20%.

Table 27

Discount rate sensitivity results for Pakistan. Even though the solar PV fraction somewhat changes with the rate, it stays around the 50% mark because of good solar irradiance. Due to a high current discount rate of 14%, LCOE values for a 2% cost of capital fall by an average 8 cents/kWh for a given year. This reflects the importance of financing for such a system in Pakistan.

PAKISTAN		2015	2020	2025	2030	2035	2040
2% Cost of Capital	ESM LCOE $/kWh	0.346	0.343	0.353	0.363	0.375	0.387
	Solar Fraction %	*59.7*	*60.6*	*61.6*	*62.1*	*62.4*	*63.2*
Base Case	ESM LCOE $/kWh	0.430	0.436	0.430	0.438	0.451	0.466
	Solar Fraction %	*55.8*	*66.3*	*59.2*	*58.6*	*59.2*	*60.1*
20% Cost of Capital	ESM LCOE $/kWh	0.469	0.459	0.467	0.476	0.489	0.504
	Solar Fraction %	*53.0*	*56.8*	*56.8*	*57.6*	*57.6*	*57.7*

Unlike the other three places, for Pakistan, changes in the cost of capital do not affect the composition of the optimal system to a great extent as the average solar fraction only goes down by around 5% with an interest rate as high as 20%. Due to good solar resource and relatively cheaper batteries, the optimal system continues to supply almost half of the energy through solar PV. The LCOE values fall to levels comparable to those in the US at a 2% cost of capital. For a given year, the values on average fall by about 8 cents/kWh with this drop in the interest rate to 2%.

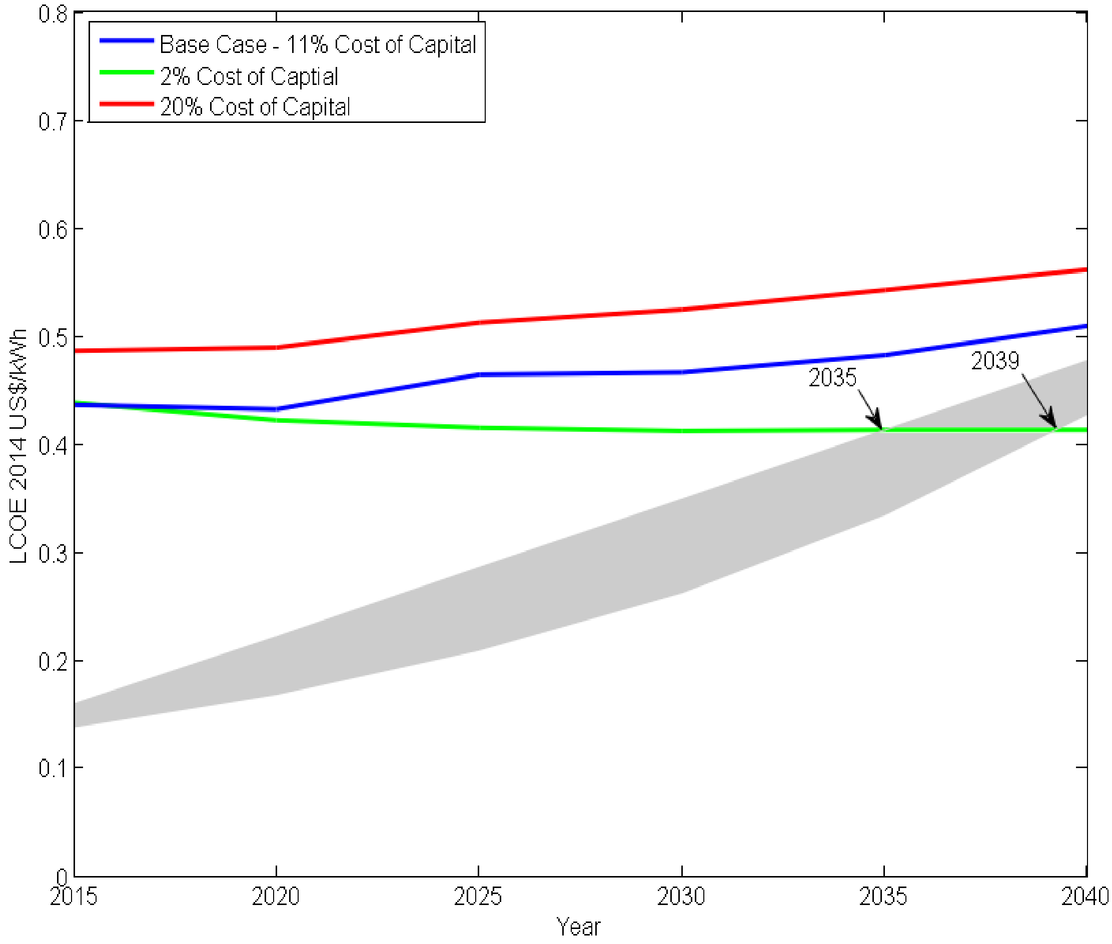

Figure 24. Sensitivity analysis results for the cost of capital rate and the effective cost of unreliable grid power characterized by the parity region for South Africa. Results are ESM LCOE values in constant 2014 US$. Due to low current grid power prices, only a 2% cost of capital results in grid parity over an estimated range of 2035-2039.

Table 28

ESM LCOE sensitivity to the discount rate in South Africa. A higher rate results in high LCOE values and vice versa. With a rate as low as 2%, the solar PV fraction roughly doubles to one of the highest levels in the analysis. This is due to the opposite nature of solar PV and diesel generator cash flows, where the cheapest optimal system favors a high capital cost solar PV option compared to a high operating cost diesel generator option.

SOUTH AFRICA		2015	2020	2025	2030	2035	2040
2% Cost of Capital	ESM LCOE $/kWh	0.438	0.422	0.415	0.412	0.413	0.413
	Solar Fraction %	*82.1*	*88.0*	*88.0*	*89.0*	*90.4*	*91.7*
Base Case	ESM LCOE $/kWh	0.436	0.432	0.464	0.476	0.493	0.509
	Solar Fraction %	*34.3*	*37.1*	*46.8*	*47.0*	*46.3*	*46.7*
20% Cost of Capital	ESM LCOE $/kWh	0.486	0.489	0.512	0.524	0.542	0.561
	Solar Fraction %	*30.3*	*39.2*	*41.5*	*41.6*	*41.6*	*41.5*

Sensitivity results for South Africa show that a fall in the cost of capital to 2% pushes solar PV fractions to very high numbers. For both the high and low cases, the difference in LCOE figures from the base case tend to increase with time, seen by diverging lines. The decent solar resource helps maintain a fair share of solar PV in the optimal system, even for the case where the interest rate doubles. However, given the very low electricity prices in South Africa, the optimal systems only hit parity if there are unprecedented increases in the retail price of electricity.

Overall, the analysis reveals that the cost of capital rate has an impact on the LCOE values of the optimal system. Higher interest rates translate into higher LCOE values. However, the resulting changes in LCOE are limited to less than 10 cents/kWh real for all places.

Moreover, the rate governs the composition of the optimal system, with an increase in the fraction of solar PV and battery for lower costs of capital. As discussed earlier, this is because of the stark difference in the two technologies being used in the hybrid system, where one has greater upfront costs, while the other is more costly to maintain. In all cases, a higher interest rate pushes the parity points farther in time whereas lower rates imply microgrids hit parity sooner. However, in most cases this change in parity point is limited to 5 years. The following table summarizes these results.

Table 29

Grid parity results summarized for the cost of capital (discount) rate sensitivity analysis. A lower discount rate pushes the parity earlier in time by lowering the LCOE of the optimal system. The discount rate also governs the solar PV fraction in the optimal system, with higher PV at lower rates. The impact of lowering the discount rate is most pronounced in Pakistan and South Africa.

	LOW		BASE		HIGH	
	Earliest	Latest	Earliest	Latest	Earliest	Latest
USA	Past 2040	Past 2040	Past 2040	Past 2040	Past 2040	Past 2040
GERMANY	2020	Past 2040	2023	Past 2040	2030	Past 2040
PAKISTAN	Before 2015	Before 2015	Before 2015	Before 2015	2015	2017
SOUTH AFRICA	2035	2039	Past 2040	Past 2040	Past 2040	Past 2040

Diesel fuel prices. Of the two energy sources used in the hybrid microgrid system, diesel fuel assumes great importance indicated by a large fraction of the output power supplied by the generator in all optimized systems. Since with a diesel generator, the main costs associated are the operational costs of the fuel used, varying diesel fuel prices can help assess the sensitivity of the optimal system configuration and the grid parity point to variations in fuel prices. In most cases, with unpredictable world fuel prices and future projections based on historical data, a sensitivity study on this helps determine bounds for the LCOE results accounting for any unprecedented changes. In all cases, the lower and upper bounds used for the fuel prices are relative to the price trend from the base case analysis. For the 'high' end, a price increase twice that of the base case trend is used. For the 'low' end, current prices are extrapolated in real dollars without any change. Mathematical working for the two cases is presented in Appendix L.

Table 30

Diesel fuel price variations.

DIESEL FUEL PRICES	LOW	BASE	HIGH
ALL LOCATIONS	Constant real 2014 US$ prices	Base Trend	2 x Base Trend

Results of the sensitivity analysis are summarized in the following figures.

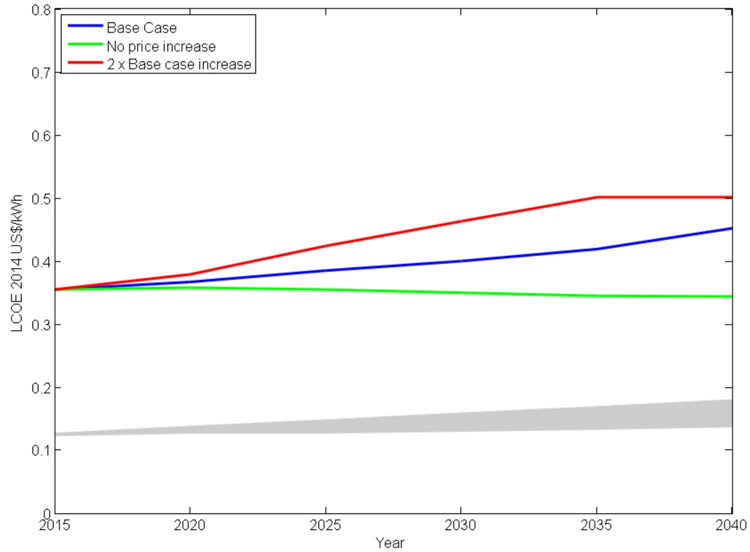

Figure 25. Diesel price sensitivity results for the US and grid power price estimates. Higher fuel prices translate to higher LCOE values and vice versa. Due to low grid electricity prices, the optimal system does not hit parity during the study period

Table 31

Diesel price sensitivity results for the US. Even with high fuel prices, the optimal system continues to be a diesel generator dominated system. Even though the fuel price impacts the LCOE results, its effect on the system configuration is small.

UNITED STATES		2015	2020	2025	2030	2035	2040
No Price Increase	ESM LCOE $/kWh	0.355	0.358	0.355	0.350	0.345	0.344
	Solar Fraction %	*30.6*	*28.5*	*32.0*	*32.0*	*32.1*	*32.1*
Base Case	ESM LCOE $/kWh	0.355	0.367	0.385	0.400	0.419	0.452
	Solar Fraction %	*30.6*	*28.5*	*31.8*	*32.7*	*34.5*	*40.0*
Double Price Increase	ESM LCOE $/kWh	0.355	0.379	0.424	0.463	0.501	0.541
	Solar Fraction %	*30.6*	*29.8*	*33.6*	*40.2*	*42.1*	*41.7*

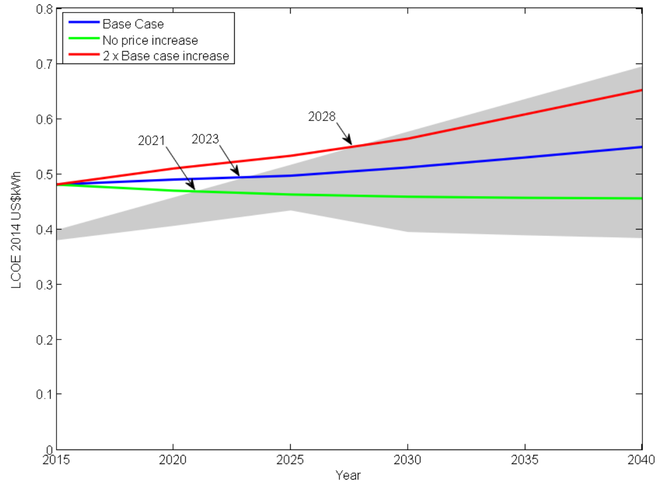

Figure 26. ESM LCOE sensitivity to diesel prices in Germany and grid power price estimates. Higher prices lead to higher LCOE and vice versa. The effect of these changes in fuel prices on the parity points is only limited to the recent trend edge of the parity region. Even with current real fuel prices extrapolated till 2040, the system does not hit grid parity according to government estimates.

Table 32

ESM LCOE sensitivity to diesel prices in Germany. With an increase in prices at a rate twice of that used in the base case, the solar PV fraction increases only somewhat. This may be explained by the poor solar resource in Germany, which inhibits a significant decrease in the use of a generator.

GERMANY		2015	2020	2025	2030	2035	2040
No Price Increase	ESM LCOE $/kWh	0.480	0.469	0.462	0.458	0.456	0.455
	Solar Fraction %	*53.7*	*55.0*	*55.0*	*57.7*	*57.7*	*57.7*
Base Case	ESM LCOE $/kWh	0.480	0.489	0.496	0.511	0.529	0.548
	Solar Fraction %	*53.7*	*56.4*	*60.4*	*60.7*	*65.0*	*66.4*
Double Price Increase	ESM LCOE $/kWh	0.480	0.509	0.532	0.563	0.607	0.651
	Solar Fraction %	*53.7*	*60.4*	*65.1*	*66.4*	*69.8*	*72.7*

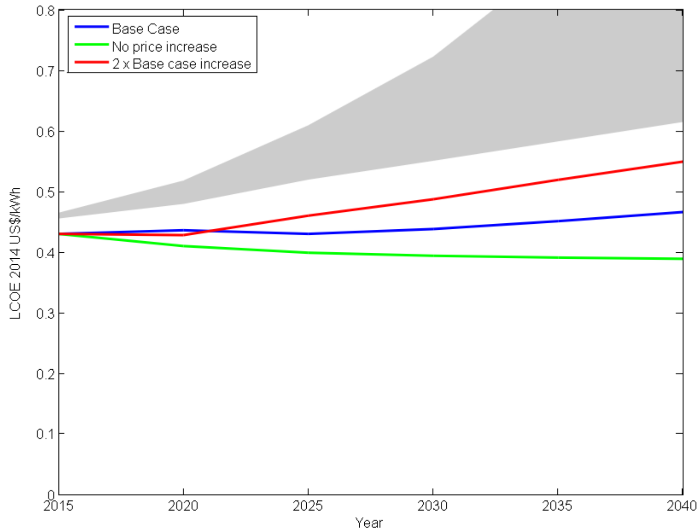

Figure 27. ESM LCOE sensitivity to diesel prices in Pakistan and the effective cost of electricity calculated using the cost of substitute power for a generator back-up system. Due to the high levels of load shedding and increasing grid power prices, diesel prices do not have an impact on the parity point since the LCOE in each case is considerably lower than the expensive grid power.

Table 33

ESM LCOE diesel price sensitivity results for Pakistan. With a good solar resource, fuel prices have a limited impact on the solar PV fraction. Lower fuel prices result in a lower LCOE and vice versa.

PAKISTAN		2015	2020	2025	2030	2035	2040
No Price Increase	ESM LCOE $/kWh	0.430	0.410	0.399	0.394	0.391	0.389
	Solar Fraction %	*55.8*	*56.6*	*56.5*	*57.2*	*57.2*	*57.5*
Base Case	ESM LCOE $/kWh	0.430	0.436	0.430	0.438	0.451	0.466
	Solar Fraction %	*55.8*	*66.3*	*59.2*	*58.6*	*59.2*	*60.1*
Double Price Increase	ESM LCOE $/kWh	0.430	0.428	0.460	0.487	0.519	0.549
	Solar Fraction %	*55.8*	*57.0*	*58.5*	*58.8*	*60.5*	*64.7*

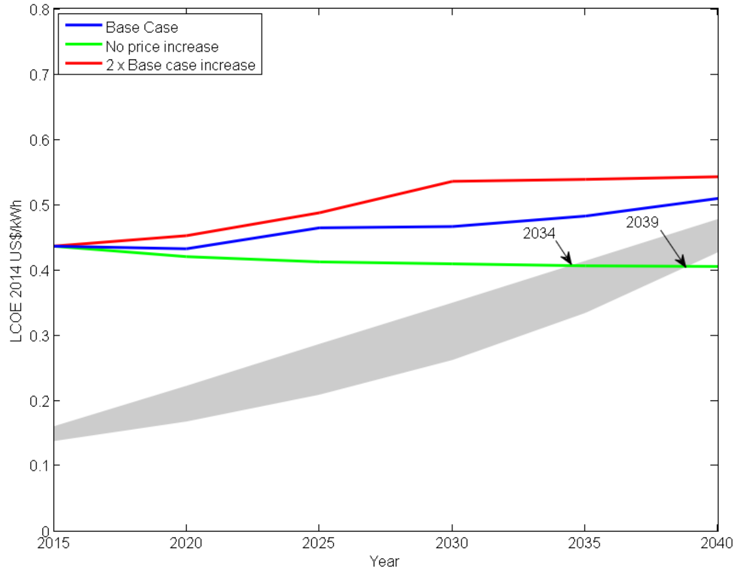

Figure 28. ESM LCOE diesel price sensitivity results for South Africa and grid power price estimates. The parity region represents the effective cost of unreliable grid power to the consumer with a generator back-up. With current real fuel prices extrapolated, grid parity occurs between the years 2034 and 2039.

Table 34

ESM LCOE sensitivity to diesel price for South Africa. At high fuel prices, the solar fraction gradually increases to almost double of the base case result in 2040. Higher fuel prices result in higher LCOE and vice versa

SOUTH AFRICA		2015	2020	2025	2030	2035	2040
No Price Increase	ESM LCOE $/kWh	0.436	0.420	0.412	0.409	0.406	0.405
	Solar Fraction %	*34.3*	*39.5*	*39.3*	*39.2*	*39.2*	*39.6*
Base Case	ESM LCOE $/kWh	0.436	0.432	0.464	0.476	0.493	0.509
	Solar Fraction %	*34.3*	*37.1*	*46.8*	*47.0*	*46.3*	*46.7*
Double Price Increase	ESM LCOE $/kWh	0.436	0.452	0.487	0.535	0.538	0.542
	Solar Fraction %	*34.3*	*39.9*	*42.7*	*50.5*	*89.1*	*92.5*

As seen from the above results, the effect of a change in diesel prices translates to similar changes in the LCOE. For each location, higher diesel prices result in higher LCOE values and vice versa. The difference between these sensitivity values and the corresponding base case results gradually increases up to around 20% in the year 2040 for all locations. A similar yet opposite trend is observed with lower prices. Therefore, the graphs depict LCOE lines 'fanning' out from the year 2015. The final optimized system configurations for both the 'high' and 'low' diesel price cases are not significantly different from the base case with a few exceptions. This indicates that the optimal system configuration, given the assumptions considered in the analysis, is not very sensitive to changes in fuel prices. However, daily cost figures (refer to Appendix A) reveal that the ultimate utilization of the three energy sources is definitely governed by the price of diesel. Grid parity point sensitivity to diesel prices are summarized below.

Table 35

Variations in grid parity points with diesel fuel price variations. For the US and Pakistan, diesel prices do not affect the base case parity points, with grid parity already here for Pakistan and parity past 2040 for the US. For Germany and South Africa, lower prices push parity points earlier in time

	LOW		BASE		HIGH	
	Earliest	Latest	Earliest	Latest	Earliest	Latest
USA	Past 2040	Past 2040	Past 2040	Past 2040	Past 2040	Past 2040
GERMANY	2021	Past 2040	2023	Past 2040	2028	Past 2040
PAKISTAN	Before 2015	Before 2015	Before 2015	Before 2015	Before 2015	Past 2040
SOUTH AFRICA	2034	2039	Past 2040	Past 2040	Past 2040	Past 2040

Temperature. Unlike HOMER, the ESM helps model temperature effects. Lead acid batteries experience faster degradation at higher temperatures while their ability to deliver energy is reduced considerably at low temperatures (Hittinger, Wiley, Kluza, & Whitacre, 2015). The base case analysis in this study uses the actual air temperature for each respective location in an attempt to capture variations in these effects at different locations in the final LCOEs. In some microgrids, batteries can be stored in a climate controlled area at little or no cost. At other places, this might not be true. Since calculation of such costs is beyond the scope of this study, rather than assuming a constant temperature time series in the base case analysis, the actual series is used to account for variations. A sensitivity analysis is used here to further investigate the effect of this choice on the final LCOE and parity point results. A fixed 23ºC time series is used to model a climate controlled area at each location. The LCOE and parity points are compared to those obtained from the base case. The figures below show these results.

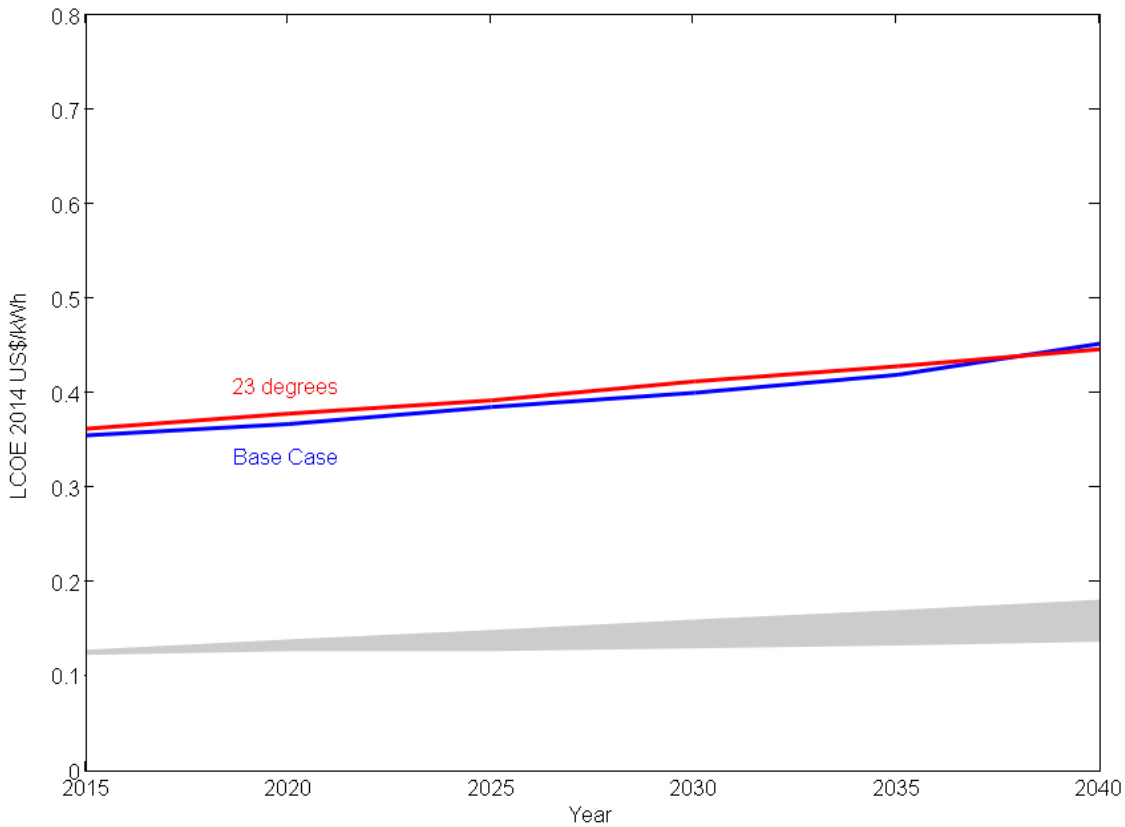

Figure 29. ESM LCOE sensitivity to temperature for the US and grid power price estimates. At average temperatures lower than 23 ºC in the base case, the optimal system has to push in more batteries to meet the same load due to the reduced energy delivering capability of lead acid batteries at lower temperatures. At 23 ºC controlled temperature, the system uses fewer batteries. However, with a mediocre solar resource, this has no real impact on the solar PV fraction in the optimal system. As a result, there is a very small change in the LCOE and no impact on grid parity during the study period.

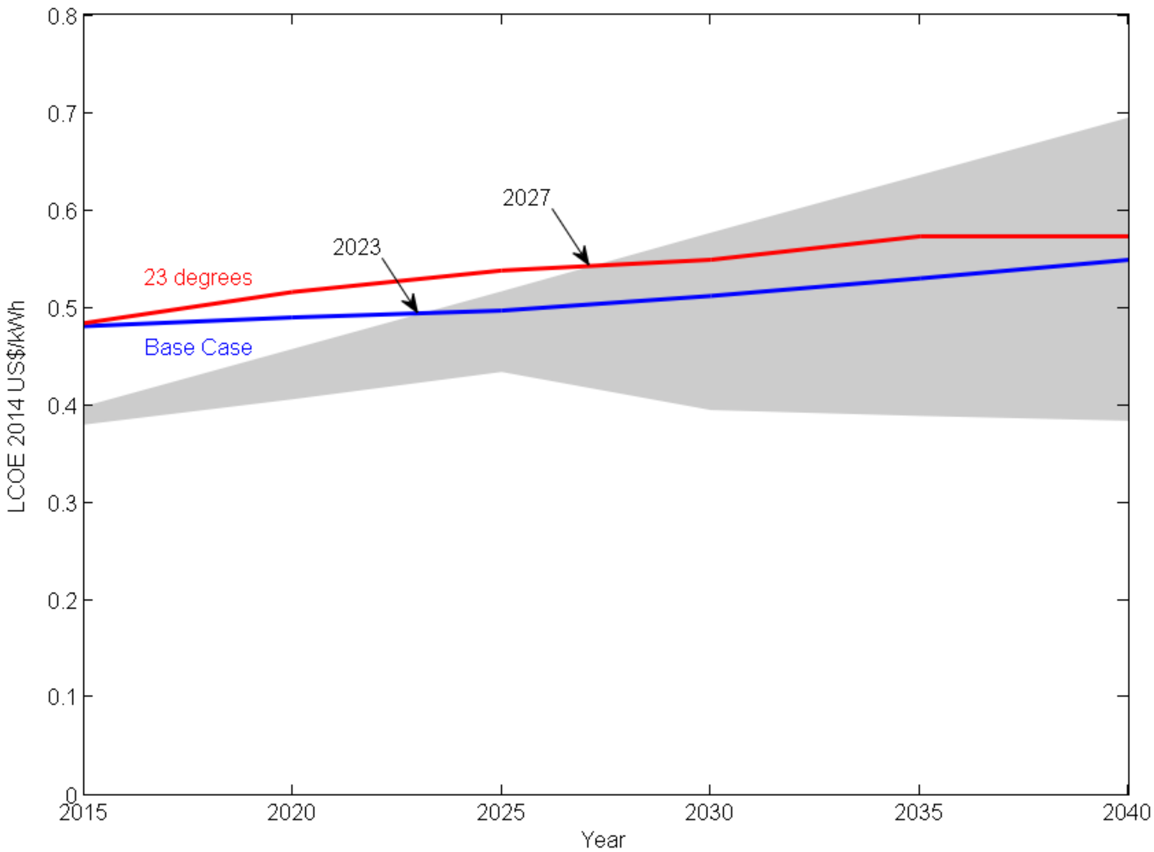

Figure 30. . ESM LCOE sensitivity to temperature for Germany and grid power price estimates. Impact of temperature control on the LCOE is somewhat considerable, raising it by around 4 cents/kWh. At low temperatures like those in Germany, lead acid batteries experience reduced energy delivering capacity. At a much higher temperature of 23 ºC, the optimal system meets the same load with fewer batteries. However, with a poor solar resource, this leads to a reduction in the solar PV fraction of the optimal configuration, with expensive diesel assuming a greater share of daily costs. This results in a slightly higher LCOE optimal system, which shifts the earliest parity point estimate by 4 years to 2027.

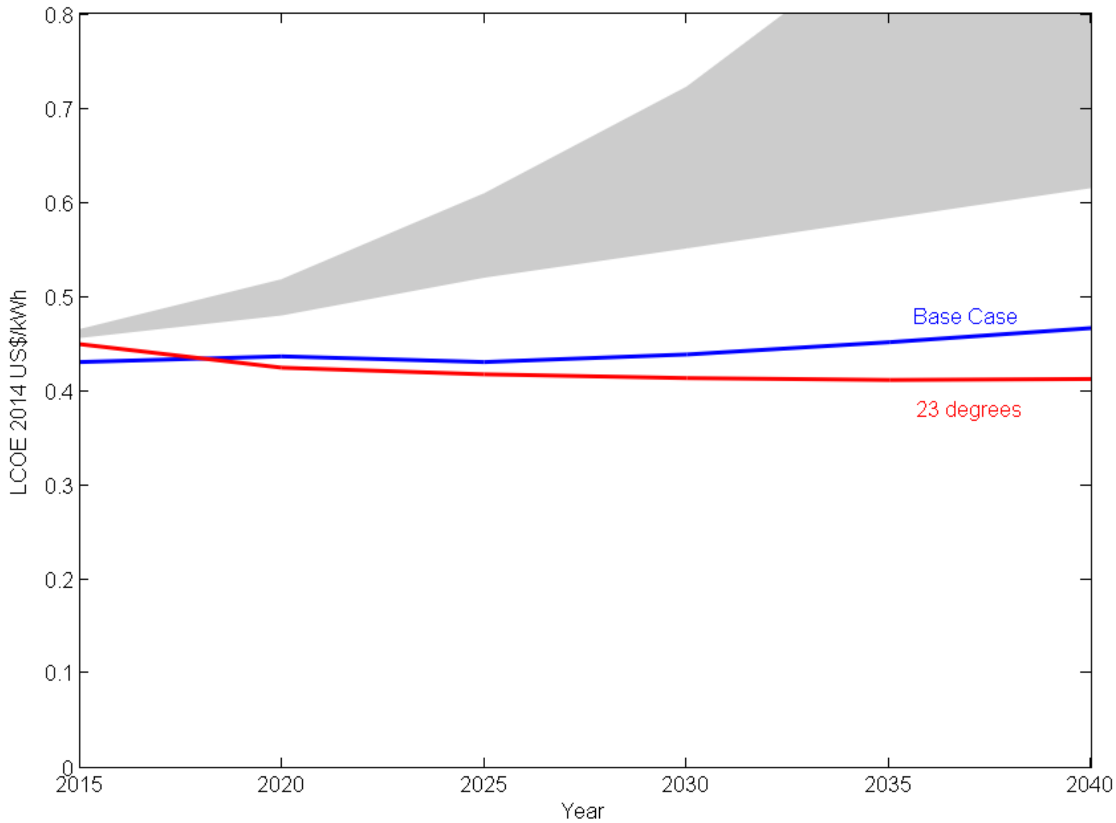

Figure 31. ESM LCOE sensitivity to temperature in Pakistan with the effective cost of unreliable grid power using a generator back-up. At 23 ºC, which is lower than the average temperature in the base case, the LCOE is somewhat lower due to better storage capabilities of batteries at this lower temperature. With a good solar resource, this has a significant impact on the optimal system configuration, which switches to a solar PV dominated system. However, this has no impact on grid parity during the period studied.

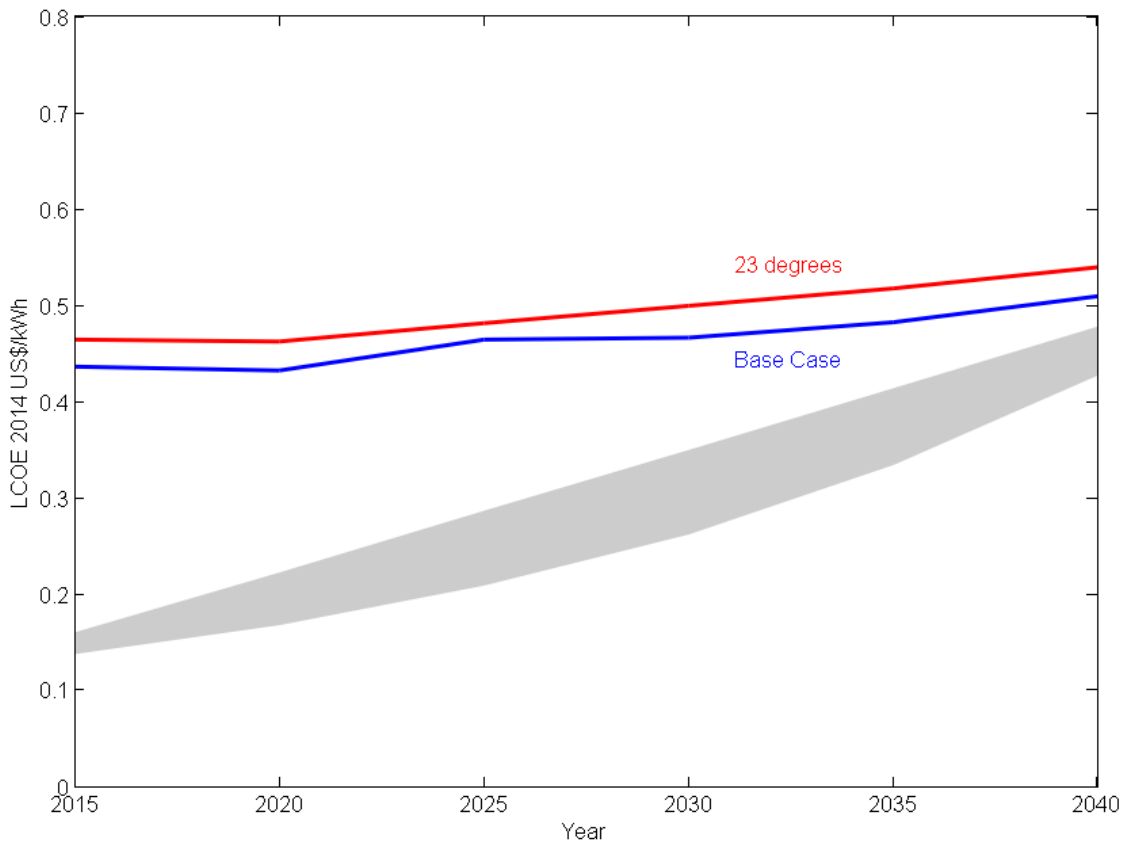

Figure 32. ESM LCOE sensitivity to temperature for South Africa with the effective cost of grid power calculated using a generator back-up. With a temperature higher than the average of time series data used in the base case, at 23 ºC the optimal system uses fewer batteries to meet the load. This is due to the improved energy delivering capability of lead acid batteries at a higher temperature. The final LCOE is on average higher by 3 cents/kWh. However, this has no impact on the grid parity points during the studied period.

As seen from the results, changes in temperature have minimal effect on the final LCOE and parity points. However, the final optimal system configurations show important variations. The complete data tables are presented in Appendix A. For places with actual average temperatures lower than 23ºC (in this case US, Germany and South Africa), sensitivity results show system configurations with fewer batteries than the base case. For Pakistan, where the average temperature in the original time series is higher than 23ºC, the optimal system obtained with the 23ºC time series has a higher solar + battery fraction than the base case.

This is in line with the behavior of lead acid batteries which experience reduced energy delivering capacity at lower temperatures and faster degradation at higher ones. The relatively low or moderate average temperatures at the considered locations in the US, Germany and South Africa reduce the energy delivering capacity of batteries because of which the optimal system has to push in more of them to meet the same load. However, at a higher temperature of 23ºC, the system meets the same load with fewer batteries. Since the locations considered in the US and Germany have a relatively poor solar resource, this lowers the solar PV fraction in the optimal system. For South Africa, even though the system meets the load with fewer batteries at 23ºC, due to a relatively good solar resource it makes a greater use of these fewer batteries which is reflected in higher daily battery costs (Appendix A). Thus the final impact on the solar PV fraction is small. Contrary to this, at a much warmer place like Hyderabad Pakistan, faster degradation of lead acid batteries at higher average temperatures limits their use in the base case. At a lower temperature of 23ºC, the system pushes in more solar PV and storage. With a good solar resource, this has a significant impact on the final solar PV fraction, which stays above 80% in this case.

However, the interesting point here is that in either case, the change in LCOE is limited to less than 10% of the base case values for each location, which only means a change less than 3-5 cents/kWh. This is an important insight and can form the basis for further research into the evaluation of the costs of climate control against optimal system configurations and the share of renewable fraction. This can be important, not only for warmer places like Pakistan which experience a greater change in the configuration as a result of this, but also at large because many of the applications of off-grid systems are in warmer areas without easy access to climate control (Hittinger, Wiley, Kluza, & Whitacre, 2015). Since the change in temperature does not greatly impact the final results in this study (LCOE and parity points), further investigation into this is left open for research due to limitations of scope.

Discussion and Policy Implications

Results from the previous section highlight some important findings of the analysis. This section aims to discuss these to draw important conclusions and policy implications.

The complete set of LCOE base case values for the four locations lie within a range of 35-50 cents/kWh, with the lowest results in the US and the highest values for Germany. The results reflect the considerable variation in geographic and economic conditions across these places because the input parameters to the LCOE are mainly dependent on circumstances regarding geography, time, energy and financial markets (Breyer & Gerlach, 2013). With significantly different electric load/usage patterns, solar resource profiles and the costs associated with the relevant technologies, the LCOE helps capture this diversity. However, the results follow a similar trend in time for all locations, with a rough increase of 10 cents/kWh real in LCOE values over the 25 year study period. Based on this, it can be concluded that this levelized cost does not significantly change over time, even though the costs associated with the inputs to this hybrid system change considerably. This suggests that, given the used assumptions, the levelized cost of producing electricity from a stand-alone solar PV/diesel/battery hybrid microgrid are expected to follow similar trends in time for different energy markets. However, this expectation is strongly dependent on regional and local policies which have a pivotal role in defining the course taken by this technology.

This somewhat constant trend of estimated LCOE results also points at the strong influence of retail electricity prices on the timing of grid parity. A similar optimization for Hawaii (ESM output results in Appendix A), clearly shows this dependence of grid parity on electricity prices, as seen in Figure 33. Even with a better solar resource coupled with solar PV subsidies, the final LCOE results for Hawaii are quite similar to those obtained for Columbus Ohio. However, due to higher electricity prices in Hawaii, grid parity is already here for such a stand-alone hybrid microgrid.

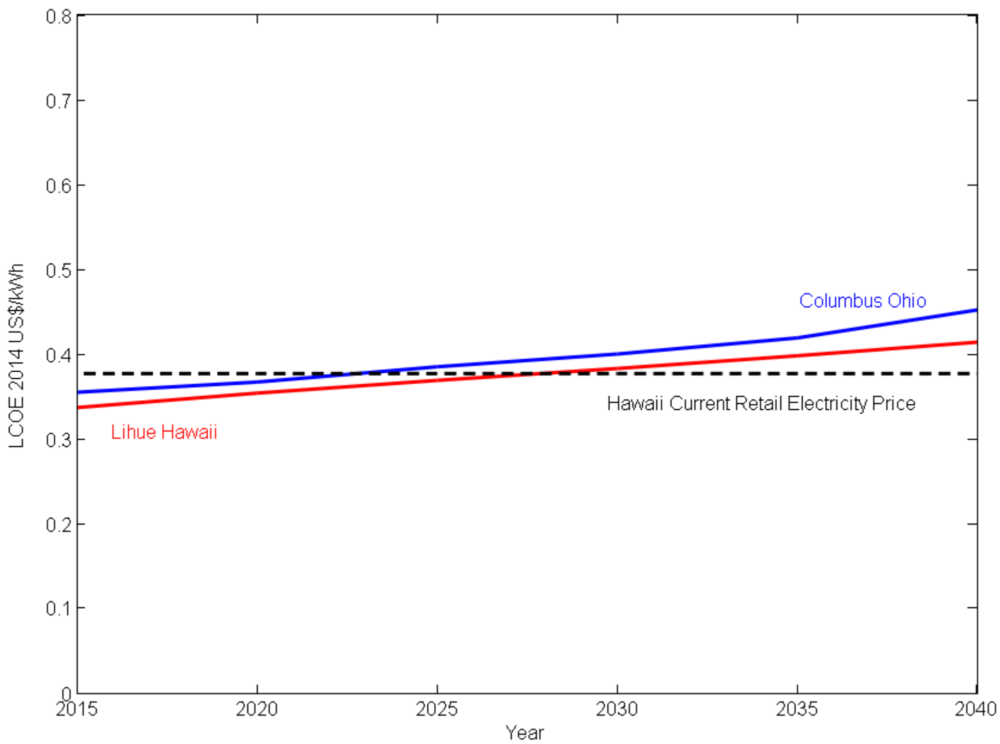

Figure 33. ESM LCOE output for Lihue Hawaii and Columbus Ohio. A better solar PV resource in Hawaii does not significantly affect the final LCOE results. The dotted line represents the current real average electricity prices for Hawaii. Due to high grid power prices, grid parity is already here for such a stand-alone off-grid system in Hawaii.

It is important to point out here that this relatively constant LCOE trend is contrary to that reported by (Bronski, et al., 2014) for different geographies within the US, where solar PV-diesel hybrid systems hit parity with a downward sloping LCOE trend. Even though this is what one may suspect of a new technology, a comparison with their working and results shows that their use of optimistic assumptions for interest rates and cost forecasts for system components, an inaccurate HOMER model, a definition of parity which skews the final results and a constrained use of the diesel generator to meet a small proportion of the demand, all result in the fairly optimistic results. This study however does not constrain the system operation and in most cases resorts to the use of conservative assumptions and future estimates. Moreover, it uses both HOMER and the ESM to reinforce the working.

The important observation from this Hawaii-Columbus comparison, as well as from other parity results is that grid parity for microgrids strongly depends on the retail price or the effective cost (in case of unreliable grids) of grid electricity at a given location. For places like Pakistan, Germany, and Hawaii, electricity prices are high enough for microgrids to hit parity earlier. On the other hand, prices in Columbus Ohio and South Africa are low because of which microgrids either hit parity sometime around 2040 or do not hit parity during the study period.

Following this investigation, it can be concluded that microgrids make more economic sense in places where grid electricity is either already expensive or is unreliable due to which the effective cost of this grid power is very high. This is of course for cases where utility electricity is already available. For rural remote places, especially in developing countries which do not have access to grid power, microgrids may still be the only economical solution. This, however requires further investigation into the feasibility of setting up these grids versus extending the main grid to such locations. A recent study published by the United Nations Foundation uses microgrid case studies from such areas around the world to assess the progress and success of these in underprivileged villages without access to electricity. They recognize the technical and financial inefficiencies associated with connecting the remote areas to the main grids and present benefits of microgrid use (Schnitzer, et al., 2014). However, such an investigation into the economic feasibility of microgrids for rural remote areas is not within the scope of this study

In addition to places where grid power is expensive and unreliable, locations with congested transmission and grid infrastructure can also use microgrids to their advantage. Germany is a good example of this where the transmission grid carrying power from northern Germany to the south is increasingly congested (REEEP, 2013). With variations in the wind and solar PV power supply, situations arise which require long distance transport of huge amounts of power for which this grid capacity is insufficient (Bach, 2012). The geographic concentration of planned wind power plants in the north where demand is low will further strain the network because most of it will be transported to the industrial south where much of the power is consumed (REEEP, 2013). In such a situation, and given the parity results of this study for Germany, government and policy makers can consider the option of hybrid microgrids to localize the supply of power. With an accelerated phase out of nuclear power plants in Germany, wind and/or solar PV hybrid microgrids can be an important option to consider during this energy transition. They not only offer a solution to the grid congestion problems, but can also help in achieving the aggressive GHG reduction targets of the German government.

It is important to point out that the analysis is limited in scope to a comparison of LCOE obtained from cost figures with subsidies and taxes accounted for, rather than the true social costs associated. The retail electricity prices used are also the final prices that the users face. The inclusion of these market distortions helps internalize some of the externality costs associated with the use of fossil fuels, and allows it to be from the perspective of the end consumer. A similar analysis using the true social costs would certainly render different results that reflect grid parity at the socially optimal point. Since the goal of this study is to determine grid parity with the retail electricity prices, the perspective of the end consumer is considered.

Considering retail electricity prices, in order to prevent final parity point estimates from being skewed, both the lower and upper bounds of electricity price forecasts are used to define grid parity in this study. This is contrary to the approach adopted by (Bronski, et al., 2014) where they define parity as the point of intersection between the LCOE and the upper bound of the utility price projections (Bronski, et al., 2014). Additionally, monetization of power cuts to account for unreliable grids in two of the four locations helps reflect the true costs of unreliable grid power to the end consumers. These results, using both the generator and battery back-up options, also show that the effective cost to the end consumers depends on the choice of a back-up system.

This consideration of back-up options not only provides a much more comprehensive insight to parity points for such developing countries with unreliable grids, it also highlights the impact of public choice on the gird parity point for microgrids. It reveals how the choice of a back-up system affects the true cost of unreliable power, which may be the basis for a decision to switch to a new technology option such as a microgrid. As discusses earlier in this study, the willingness to pay for reliable power in such developing countries is expected to be high. These higher effective costs of unreliable power implicitly point at this greater willingness. So for places with unreliable grid power, the cost of back-up solutions (and in turn the effective cost of power to the end users) is an important factor for microgrids to make their way into the market. With higher back-up costs, a microgrid solution is a more attractive option given its reliability.

Another important observation from the LCOE results and the respective renewable fraction figures is that the final optimized system configurations are quite 'flexible'. Multiple optimization runs in the ESM reveal that the model tends to go back and forth between two optimal system configurations for its final choice of the best system. Even though this is not observed for every location, enough runs for most locations show this *bi-stability* of the chosen system configuration, significantly different in their renewable fractions used to meet the load. The following table illustrates this with LCOE results obtained from multiple runs for the year 2030 in South Africa

Table 36

ESM LCOE and solar fraction results from multiple runs for South Africa in 2030. For runs 2 and 4, the solar fraction is twice that for the other runs. However, the resultant change in LCOE is small.

SOUTH AFRICA 2030	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 8	Run 9
ESM LCOE $/kWh	0.466	0.512	0.466	0.513	0.464	0.466	0.465	0.465
Solar Fraction %	*42.4*	*84.1*	*39.4*	*84.0*	*41.7*	*42.0*	*41.9*	*41.9*

As seen above, the solar fraction switches back and forth a few times, almost doubling to around 84% twice. However, in each case the difference in LCOE is on average around 4.5 cents/kWh. Similar multiple runs for places and years with this *bi-stability* reveal that even though the renewable fraction changes significantly, the LCOE does not. Table 36 and Figure. 32 on the following page show the two LCOE trajectories with system configurations for South Africa. Similar results are obtained for other places.

Table 37

Comparison of LCOE and solar fraction between generator dominant and solar PV dominant optimal system configurations for South Africa. ESM's bi-stable nature of results is evident from the diverging solar PV fractions for the two runs. Even though the renewable fraction almost doubles beyond 2025, the increase in LCOE stays less than 4 cents/kWh.

SOUTH AFRICA	2015	2020	2025	2030	2035	2040
LCOE $/kWh *Generator Dominant System*	0.436	0.432	0.464	0.466	0.482	0.509
Solar Fraction %	*34.3*	*37.1*	*46.8*	*43.2*	*43.2*	*46.7*
LCOE $/kWh *Solar PV Dominant System*	0.436	0.432	0.451	0.514	0.515	0.517
Solar Fraction %	*34.3*	*37.1*	*42.3*	*81.5*	*85.1*	*84.0*

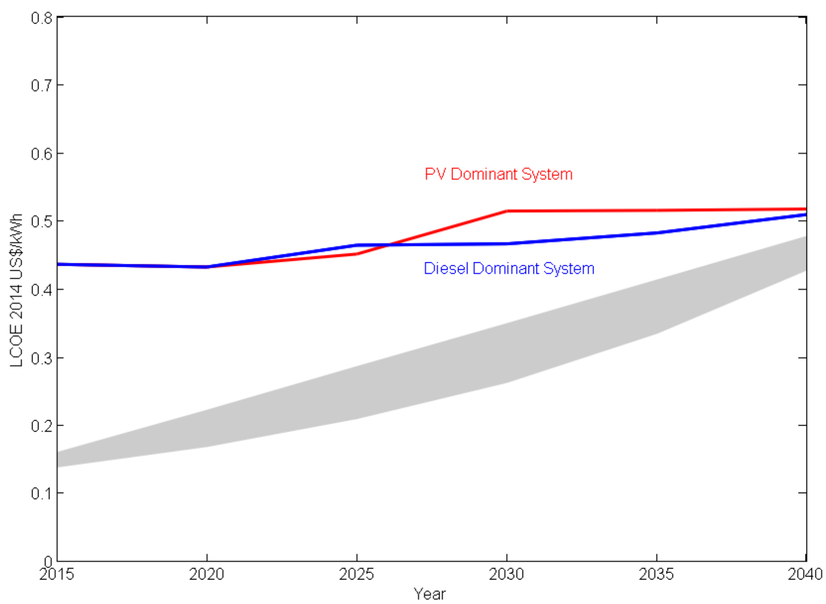

Figure 34. ESM LCOE *bi-stable* results for the two system configurations in South Africa. The difference in LCOE values for the PV dominant and Diesel dominant systems is around 4 cents/kWh. Due to this small difference, the ESM semi-randomly chooses either one of the optimal system configurations.

It is important to highlight that even though the renewable fraction almost doubles during some optimization runs, the change in LCOE remains within the 2-5 cents/kWh. In order to meet the load, the model tries to push in a large generator and limit solar PV or settles for a higher renewable fraction with batteries. However, in each case it fails to find a cheaper system with a configuration between these two extremes. Due to fairly close final LCOE values, it tends to semi-randomly choose either one of them. The limited time used to complete the optimization runs may also explain this uncertainty as a greater time limit set for the runs (which is defined before each run), reduces the frequency of this switch. Moreover, this switch is more frequently observed in LCOE values for later years of the analysis. This is due to the gradually diminishing difference in input costs for solar PV and diesel prices because of their opposing future trends. With increasing fuel prices and decreasing solar PV costs, the model finds it increasingly difficult to settle for a particular system configuration since the corresponding LCOE values are fairly close.

This *bi-stability* of system configurations has important implications. Results from this and the sensitivity analysis with temperature reveal that the cost differential between *PV-dominant* and *generator-dominant* optimal system configurations is small. This observation implies that such a hybrid microgrid with little additional costs can be turned from a heavy diesel generator system to a cleaner and environment friendly solar PV system. Depending on the willingness to pay for greener energy solutions, this presents governments with an important policy option if they do choose to adopt these microgrids.

In their recent work, (Schnitzer, et al., 2014) identify the environmental impacts of microgrids as one of the key microgrid performance indicators. They consider a microgrid that utilizes renewable energy sources to mitigate emissions and environmental damage as more successful than the one that does not. To get a fair idea of these impacts in this study, the discussed *bi-stable* results obtained from the ESM can be used to investigate the effects of the choice of a high renewable fraction system. For instance, using above discussed results for South Africa, spending an additional 4.5 cents/kWh on top of the base case LCOE values (which is approximately 10% of the LCOE) gives an optimal system with an 80% renewable fraction for the year 2030. As compared to the base case results, this means a lower consumption of diesel fuel and an almost double renewable fraction, leading to a reduction in CO_2 emissions. With around 85290 liters of diesel saved annually, and a 2.66 kg/liter CO_2 emissions figure for diesel (Valsecchi, et al., 2009), this turns out to an annual 227 tons of CO_2 emissions reduced by displacing the diesel generator with solar PV in the optimal system. This is a 70% decrease in CO_2 emissions compared to the diesel dominated system with ~45% solar PV fraction. In other words, the higher PV fraction system is about 70% 'cleaner' than the diesel dominated system.

The calculated emissions are also equivalent to 0.000439 tons/kWh, which at the additional cost of 4.5 cents/kWh returns a CO_2 abatement cost of 102.4 $/tons . Even though this seems relatively high, it is well within future carbon price estimates used in previous literature, ranging from US$8 to more than US$300 over the long run (National Treasury Republic of South Africa, 2010). Current carbon abatement cost figures for the US show much higher costs for off-shore wind and solar thermal technologies at around 190 $/ton and 230 $/ton respectively (CATF, 2013). The important point to be made here is that this short working reveals the optimal system configuration's flexibility to allow for a much greener option, depending on the willingness to pay. This provides for an interesting policy debate, especially for a place like South Africa where almost 90% of power generation is done from coal-fired power stations (REEEP, 2013). Or Germany where the government has historically pushed for cleaner renewable sources of energy. Analysis results show that the additional cost of switching to a higher renewable fraction system ranges within 2-5 cents/kWh for all locations.

One of the determinants of the final renewable fraction and the LCOE is the cost of system storage or in this case, the lead acid batteries. As seen from the *bi-stable* ESM results, a high renewable fraction system configuration has a battery size 5 to 6 times that of the low fraction system. Based on this, it can be argued that one of the limiting factors for solar PV in the microgrid is storage and the costs associated with it. Drawing from the recent German government's subsidies on battery storage for solar PV residential systems, the effect of such a policy intervention on the final LCOE and configuration of the hybrid microgrid makes for an interesting investigation. This is because for places like Germany, where the solar PV component of the system has historically seen aggressive price declines with not enough room for further reduction, subsidizing storage seems to be the next logical step.

The following table shows results for two optimization runs with a 30% subsidy on lead acid batteries for Germany against the base case results. Even though the German policy is deemed successful by many due to the healthy number of additional residential grid connected solar + battery units installed after the subsidy (Ayre, 2014), the LCOE results for the hybrid microgrid tell a different story.

Table 38

ESM LCOE sensitivity to battery prices in Germany. A 30% subsidy on battery prices has a small impact on the LCOE results, bringing it down by just 5%. Its impact on the optimal system configuration is also limited.

GERMANY		2015	2040
Base Case	LCOE 2014 $/kWh	0.480	0.548
	Solar Fraction %	*53.7*	*66.4*
30% Battery Subsidy	LCOE 2014 $/kWh	0.449	0.516
	Solar Fraction %	*56.4*	*66.4*

The results show that a 30% subsidy only brings down the LCOE by roughly 5% in each case. This suggests that subsidizing storage may not be an effective policy intervention for such stand-alone hybrid microgrids. Moreover, a comparison of the renewable fraction with base case results revels that the subsidy has very little or no impact on the amount of solar PV used in the hybrid system. This indicates that even a subsidy as high as 30% is not enough to reduce prices to the extent where enough battery is pushed in to meet the necessary load in the optimal system. This is an important observation regarding future policies for such microgrids, especially for places like Germany where governments may attempt to bring down the effective cost of power generation from these grids once they do hit grid parity.

Sensitivity investigation reveals that the LCOE for these grids is fairly sensitive to diesel prices at all locations with lower LCOE values for lower fuel prices. These results suggest that places with good solar resource and cheap diesel make for an attractive location to set up a microgrid. Countries like Saudi Arabia are a good example, as demonstrated by (Shahid &

Elhadidy, 2007) in their analysis of a stand-alone hybrid PV-diesel-battery power system, where they conclude that a portion of Saudi Arabia's demand may be harnessed from such a system.

The cost of capital rate (or discount rate) is also an important factor, as shown by sensitivity results in particular for developing places like Pakistan and South Africa. With currently higher costs of capital, these countries have a greater opportunity to capture the advantages of these microgrids. This is reflected by a significant decrease in the LCOE figures with a fall in discount rates. The poor energy situation in both countries with relatively high (Pakistan) or steadily increasing (South Africa) effective costs of electricity to consumers, rising electricity demands and a fair amount of uncovered rural population centers make them even more attractive. Results for Pakistan show grid parity is already here considering the true cost of grid power to the end consumers. This takes into account the cost of substitute power that needs to be generated to make up for the roughly 4000 hours of power outage annually. For South Africa, even though the parity point is farther into the future, the possibility of it occurring earlier than the results of this analysis cannot be completely ignored. Given the recent power shortage situation, and the South African government's failed attempts to have cost reflective tariffs, the country may end up in a situation similar to that of Pakistan where the government has to ultimately push for rapid increases in real prices to prevent a complete collapse. Moreover, considering the historical trend of real prices in South Africa following a power shortage situation (Trollip, Butler, Burton, Caetano, & Godinho, 2014), a sudden increase in prices cannot be written off.

Following from this and the sensitivity results, it is also fair to conclude that microgrids, like many renewable technologies, are highly dependent on public policies. A short sensitivity analysis for Pakistan with the following two scenarios helps depict this:

- a 20% learning rate applied to solar PV
- a 0% cost of capital used on top of the 20% learning

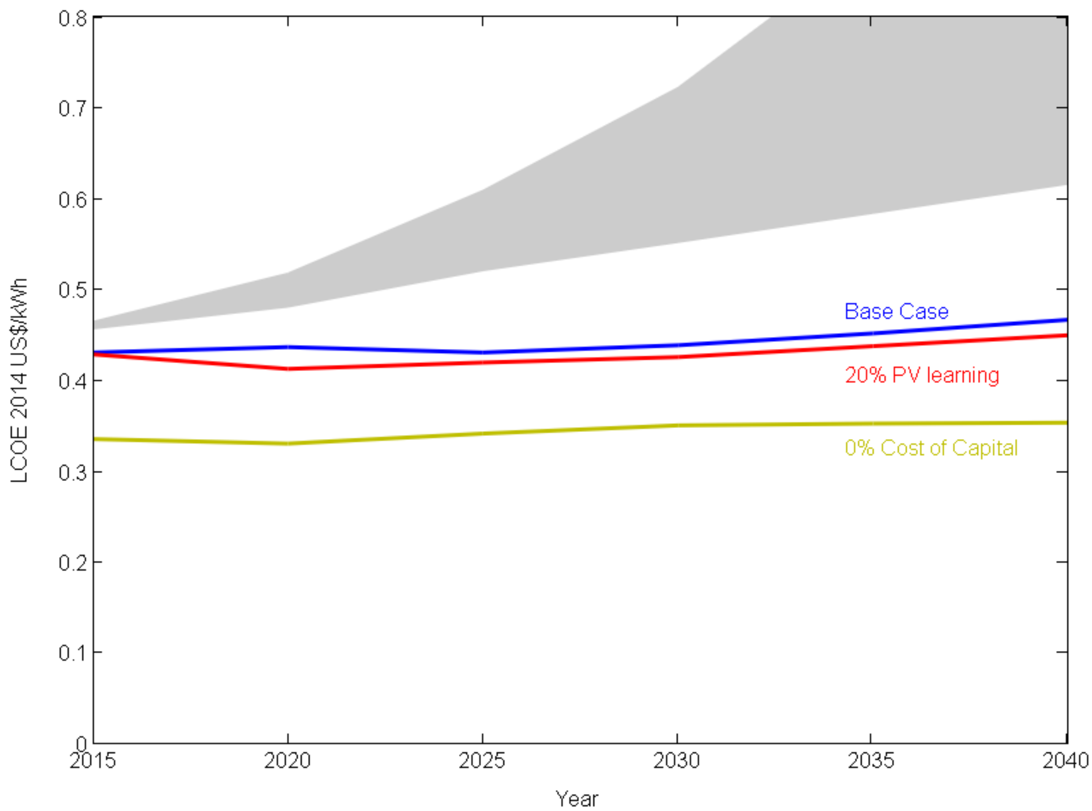

Figure 35. The effect of a high PV learning rate vs. 0% cost of capital rate on the final LCOE for a system in Pakistan. The grid parity region depicts the effective cost of unreliable power to consumers calculated using a generator back-up system. A 20% learning rate for solar PV systems, in comparison to the 14% rate from the base case only lowers the LCOE by an average 5%. The discount rate however has a greater impact on the LCOE, indicating the effectiveness of policies focused on system financing.

A 20% learning rate is a rational choice for the upper limit of solar PV learning. Over the last three decades, the learning rate of PV is reported on a stable 20% level (Breyer & Gerlach, 2013), with this figure used widely in literature for solar PV learning. A 0% cost of capital can be looked as interest free loans, which are possible for Pakistan with options like Islamic Banking.

Results show that the increased learning only reduces the LCOE values on average by less than 5%. However, applying an interest rate as low as 0% to the same improved learning scenario pushes down the value to 35 cents/kWh in 2040. This is almost 25% lower than the 2040 result for the original base case analysis.

The same conclusion can be drawn from the sensitivity results for the cost of capital in all locations. Even though technological progress and experience are characterized and captured in the solar PV learning applied to determine capital cost forecasts, it does not drive the trend of LCOE values, not even for places with favorable conditions to solar PV. However, a decrease in the interest rate pushes down the LCOE trend line for each location, indicating that the cost of capital, and in turn public policies associated with the energy sector are a significant factor. In his work, (Yang, 2010) agrees with this, maintaining that the rapid growth in PV in recent years is limited to a small number of countries, and is largely policy driven. In order to have a sustainable growth, governments will continue to expand financial incentives and policy mandates. The results are also in agreement with the findings of (Ondraczek, Komendantova, & Patt, 2015), which suggest that efforts to expand PV installation in better sunshine regions of the world may benefit greatly from policies designed to make low cost finance more widely available. This importance of financing for renewable energy technologies has also been acknowledged by (Wiser & Pickle, 1998), where they conclude that project financing plays a key role in the overall costs of the renewable energy projects. Therefore, to have better renewable energy policies which may ultimately help microgrids, policy makers need to consider the costs of financing as an important variable. Any efforts to reduce uncertainty in financing can help provide long-term stability and improve policy effectiveness as well as push down the levelized costs of producing energy from these stand-alone grids, as seen in the analysis results.

Given the above discussion, it can be concluded that grid parity for microgrids is not just a matter of technology advancements. The results discussed in this section reveal that grid parity is a function of policies at the respective locations as well. And considering a place like Pakistan where the power sector is heavily regulated with no licensing schemes for small scale private power producers (both grid-tied and stand-alone), such systems can only make headway following important policy reforms. Numerous other studies on stand-alone systems have made a similar point, placing emphasis on policy formulation as a means for effective dissemination and operation of such stand-alone systems (Kaundinya, Balachandra, & Ravindranath, 2009). In their recent case study research on multiple existing microgrids in different locations of the world, (Schnitzer, et al., 2014) also highlight this point. Similar to the conclusions drawn from sensitivity results, their research confirms the dependence of microgrid developers on government policies as well as how the cost of capital is an essential parameter to improve financial outlook and equity requirements for such projects. ESM results validate this, showing that the cost of capital clearly has a great impact on the LCOE and the timing of grid parity.

It is important to realize though, that given the current energy situations in developed and underdeveloped countries like those discussed in this analysis, the results reinforce the general argument that such stand-alone hybrid microgrids may be a niche technology with much better applications in the developing world where they have problems of energy shortage and limited access to grid power without good government policies to solve these issues. Since most of these countries absorb and follow energy policies adopted in the developed world, this leaves them at a disadvantage of not utilizing any benefits that may come from embracing these microgrids before the industrialized world. As seen from sensitivity results for the cost of capital or the comparison between Hawaii and Columbus for the US, even though policy does play an important role in grid parity for such microgrids in the developed world, its effects are only limited. Moreover, with no real energy woes developed countries lack the need to formulate policies for such microgrids. Therefore, the developing countries need to take on the role of policy innovators to effectively make use of these hybrid microgrids to solve problems of their troubled energy sectors.

Given the poor energy situations in places like Pakistan and South Africa, there already appears to be a growing need for policy reforms. With relatively high effective costs of electricity in these places due to unreliable power grids, and lots of sunny days in the year, they have a greater opportunity to make the most out of these hybrid microgrids through such reforms. For a start, these places can prepare clearly spelt out policies and sound implementation mechanisms for such grids to create a supportive environment. Properly defining the scope of regulation and the microgrid policy itself are essential to ensure certainty. Focusing on financing for such projects makes them even more attractive by eliminating or at least reducing the element of risk involved. Providing capital subsidies to cover the initial costs or giving legal cover to third party service providers through efficient licensing frameworks can help bring investment. The 2003 Electricity Act in India is a good example of such a government initiative which deregulated tariffs and allowed third party service providers to set up microgrids in specific areas (Schnitzer, et al., 2014). Enabling private and third party financing through government guarantees, ensuring low-interest loans, standardized power sales contracts and production incentives can all help bring down the cost of capital. At the same time, educating people and institutionalizing to ensure the implementation mechanism is robust is also important. The standard rural electrification scheme (F.A.C.E) encouraged by the French government for hybrid PV systems is one such example (Vallve, Gafas, Mendoza, & Torra, 2001). Additionally, commissioning studies and research to determine the most suited business models for such grids can be useful. Apart from just solar, investigating the use of other alternative sources like wind or biomass would be important. Making use of such local resources other than solar might render completely different results. All such steps can create a conducive environment for these grids in places where it is going to hit parity soon or is already economically viable.

Thus the analysis and results not only help answer the research question regarding grid parity for these microgrids, but also lay the foundation for a more rigorous research into the potential of microgrids in these and other energy markets. It helps draw general conclusions about the use of stand-alone distributed systems, especially in developing markets where they may help solve some of their existing energy sector problems. It can be generalized that moving forward such systems may make more economic sense in places with unreliable grids and/or those with high grid power prices. However, existing policy frameworks play a key role in determining the ultimate fate of such a technology. This is seen by the parity results for Pakistan where, with existing government regulations and policies, these stand-alone systems haven't made their way to the market. Therefore, it is important for such developing nations with similar energy problems (especially problems of energy shortage) to consider these systems as valuable policy alternatives to the conventional measures of load shedding and central grid capacity expansions. For the developed world, parity results suggest that unless grid prices are high, grid defection in such markets is primarily going to be a choice rather than a necessity. And so moving forward, policies will have a key role to play similar to their historic role for renewables.

Conclusion

This study is an attempt to answer the question of grid parity for microgrids in different energy markets of the world. Four different locations, the US, Germany, Pakistan and South Africa are studied to determine grid parity points in the future. The analysis is done for an off-grid solar PV/diesel/battery hybrid microgrid using the Energy System Model and NREL's HOMER Energy software model to determine the least cost systems at each location, at 5 year intervals up until the year 2040. This levelized cost of electricity is compared to retail electricity price trends to determine parity points. Analysis results reveal that even though microgrids are a relatively expensive option, they do hit grid parity in Pakistan and Germany. Germany hits parity around the year 2023 while microgrids have already hit parity for Pakistan. For South Africa, results suggest grid parity sometime around the years 2040-2045. For the US, due to low electricity prices, it does not hit parity any time soon. Even though the variation between these four energy markets is reflected in the LCOE results, they do show that the real levelized cost to produce energy from these grids remains fairly constant over the 25 year period. Moreover, it shows that grid parity for these microgrids greatly depends on the retail electricity price trends at a particular location. For places where either the retail electricity prices (e.g. Hawaii, Germany) or the effective cost of electricity to the end consumer (Pakistan and South Africa) are high, they hit parity sooner. This also indicates that microgrids offer a solution to countries where grid power is unreliable. Even for places where reliability is not an issue, they offer an important policy option to address challenges of a congested transmission infrastructure, like the case of Germany. The investigation also revels the importance of policies for this technology and how government interventions can play an important role in the development and integration of these microgrids within their respective energy sectors. For developing economies with unreliable grid power or high electricity prices, the cost of financing should be one of the more important considerations for policy makers. Any efforts to lower this cost and reduce risk to attract investment can play a pivotal role in the adoption of these microgrids. Other policy measures like defining a clear microgrid policy to eliminate uncertainty, providing legal cover to third party producers, institutionalizing and educating people can all set up an environment conducive to such microgrids. Thus, this study helps conclude that variations in energy markets may determine the fate of emerging energy technologies like microgrids. However policy interventions have a significant impact on the final outcome, such as the grid parity in this case.

Future Research

The analysis approach adopted in this study provides a guide to future research. Such use of micro-power optimization tools like ESM and HOMER can help investigate grid parity for hybrid microgrid systems with other renewables like wind and biomass. Studies comparing parity estimates for different variants of hybrid systems can serve as important inputs to policy formulation for such microgrids. The scope can be broadened to conduct it at a greater scale by studying more markets and using more than two optimization tools. The analysis technique can also be employed to conduct a much more detailed local level analysis within particular energy markets (like those considered here) to identify variations in grid parity estimates within that market. Such an analysis can be coupled with experimental validation to determine the accuracy of system modelling under real-life conditions.

Since this study determines grid parity from the view point of the end consumer, it can be done from the social perspective by accounting the true social costs involved. The optimization tools can also be used to model and look into costs associated with unreliable grids in different developing markets. This may help researchers monetize the costs associated with back-up power which can then be compared with figures obtained from various other approaches.

For developing markets like Pakistan, future research can build on results and conclusions of this thesis to study the potential of such stand-alone grids, especially in locations with access to grid power. This can take the shape of a market research attempting to identify the public’s willingness-to-pay for reliable grid power from such stand-alone grids. A similar study for developed markets like the US can highlight the willingness to pay for reliable, cleaner sources of energy and feed into any research investigating the potential of such stand-alone systems in markets where their adoption will be ‘by-choice’ rather than ‘by-necessity’.

Moreover, for places like Pakistan where such a stand-alone system has hit grid parity (as suggested by this study), future research can investigate in great detail, the effects of various policy interventions on the final LCOE from such systems. This may help highlight the economic merits and de-merits of various policy options and help identify those that may further lower the levelized costs associated with such systems.

For other markets like Germany where transmission grid congestion issues are expected in the near future, further research can study the costs and benefits associated with setting up stand-alone grids close to the target load versus expanding the current grid capacity.

Since such stand-alone systems have the potential to help solve energy problems of reliability and access-to-power in remote locations for developing countries like Pakistan, comparison studies investigating their impact on load shedding against current policy measures of building generation centrally may help highlight the importance of a microgrid policy for such locations.

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Appendix A

HOMER Optimal System Configuration Details

Table 1A

HOMER optimal system configuration details from the base case analysis for the US

UNITED STATES	2015	2020	2025	2030	2035	2040
HOMER LCOE $/kWh	0.385	0.398	0.414	0.429	0.447	0.466
Solar Fraction %	29	29	32	35	35	40
PV (kW)	140	140	160	180	180	210
Generator (kW)	90	90	90	90	90	90
Battery Strings	180	180	180	150	150	150
Solar PV Cost ($/day)	101.9	109.1	112.9	119.8	115.8	132.7
Generator Cost ($/day)	481.5	492.5	516.6	536.6	567.6	581.4
Battery Cost ($/day)	31.8	33.4	32.98	31.3	32.7	33.5

Table 2A

HOMER optimal system configuration details from the base case analysis for Germany

GERMANY	2015	2020	2025	2030	2035	2040
HOMER LCOE $/kWh	0.518	0.542	0.562	0.591	0.628	0.672
Solar Fraction %	45	45	45	45	51	48
PV (kW)	80	80	80	80	100	90
Generator (kW)	20	20	20	20	20	20
Battery Strings	120	120	120	120	120	150
Solar PV Cost ($/day)	38	35.0	33.4	32.5	39.9	35.7
Generator Cost ($/day)	147.9	160.7	170.4	183.3	191.1	209.8
Battery Cost ($/day)	23.9	24.2	24.3	24.6	24.6	28.3

Table 3A

HOMER optimal system configuration details from the base case analysis for Pakistan

PAKISTAN	2015	2020	2025	2030	2035	2040
HOMER LCOE $/kWh	0.425	0.414	0.419	0.426	0.435	0.449
Solar Fraction %	60	60	66	66	69	69
PV (kW)	180	180	210	210	230	230
Generator (kW)	60	60	50	50	50	50
Battery Strings	180	180	270	270	240	270
Solar PV Cost ($/day)	176.9	154.5	166.2	159.2	169.6	167.7
Generator Cost ($/day)	257.3	267.8	247.4	260.4	265.5	277.1
Battery Cost ($/day)	45.1	45.5	59.6	61.1	56.7	63.2

Table 4A

HOMER optimal system configuration details from the base case analysis for South Africa

SOUTH AFRICA	2015	2020	2025	2030	2035	2040
HOMER LCOE $/kWh	0.492	0.492	0.515	0.534	0.556	0.578
Solar Fraction %	33	38	40	42	44	44
PV (kW)	110	130	140	150	160	160
Generator (kW)	80	80	80	80	80	80
Battery Strings	150	150	150	150	150	150
Solar PV Cost ($/day)	109.6	113.5	113.1	116.3	120.9	119.3
Generator Cost ($/day)	500.5	494.2	527	548.9	573.3	603.5
Battery Cost ($/day)	74.7	75.1	77	78.2	80.6	84.3

ESM LCOE Results for Pakistan and South Africa with the Parity Region Determined Using a Battery Back-Up Option

Pakistan

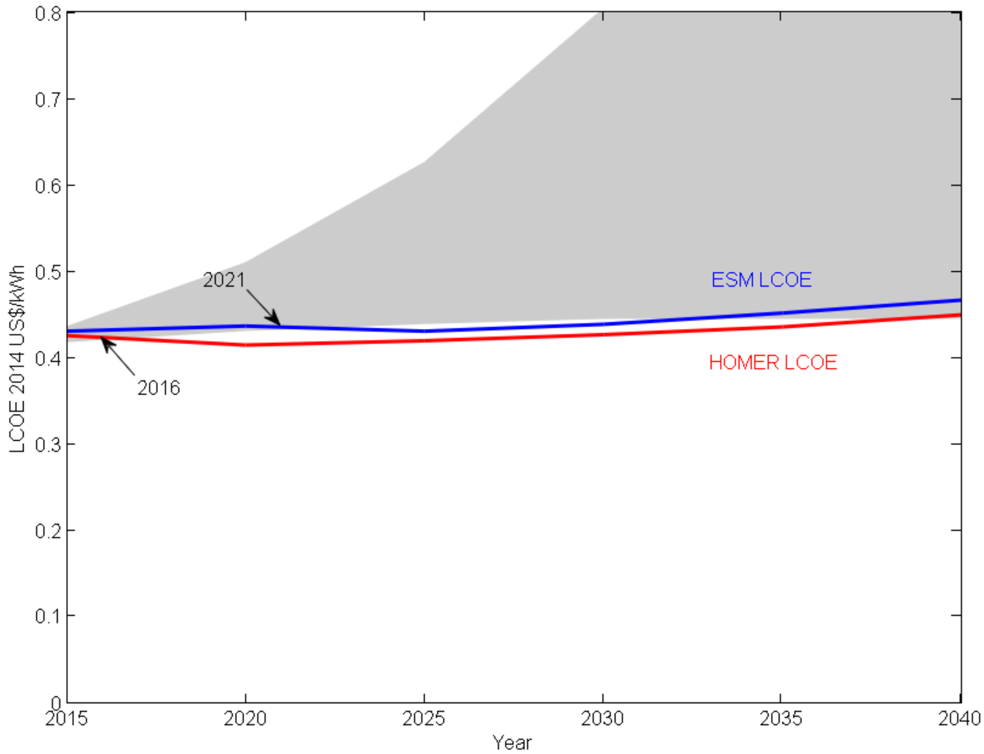


Figure 1A. HOMER and ESM LCOE results for Pakistan show intersection of LCOE lines with an edge of the shaded area, first in the years 2016 and 2021. These points occur on the government forecast edge of the parity region. The region itself depicts the effective cost of unreliable grid power calculated using a battery back-up system

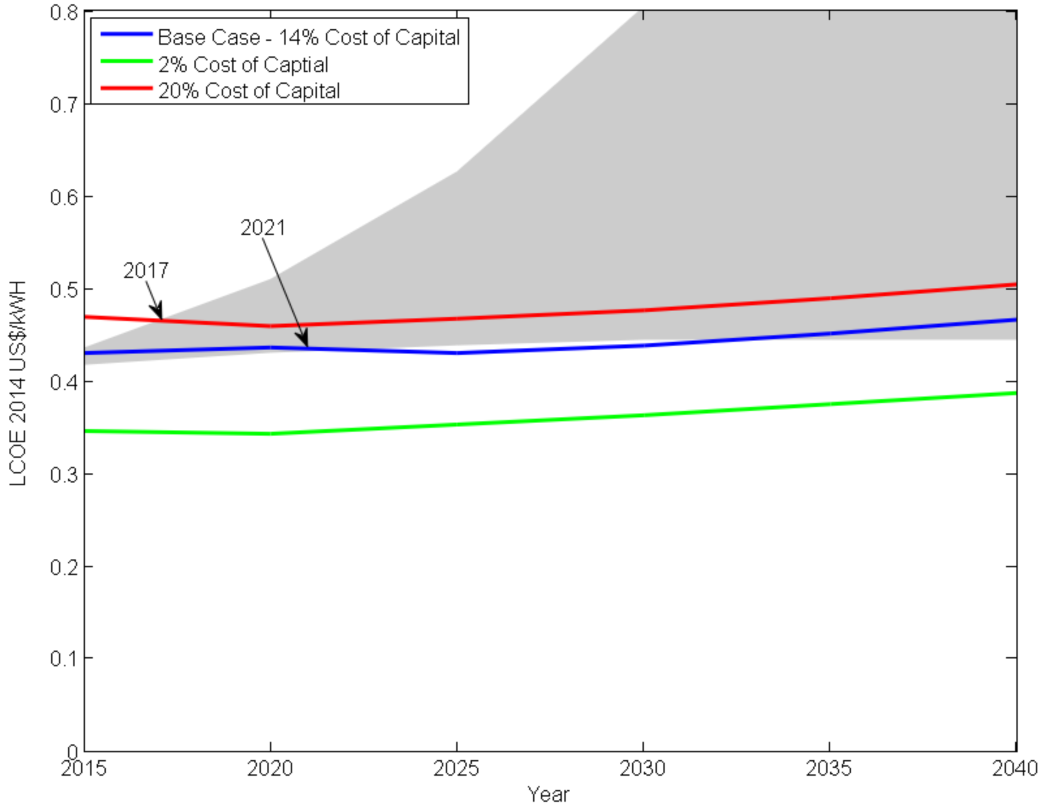


Figure 2A. Interest rate sensitivity analysis results for Pakistan. The grid parity region corresponds to the effective cost of unreliable grid power calculated using a battery-backup system

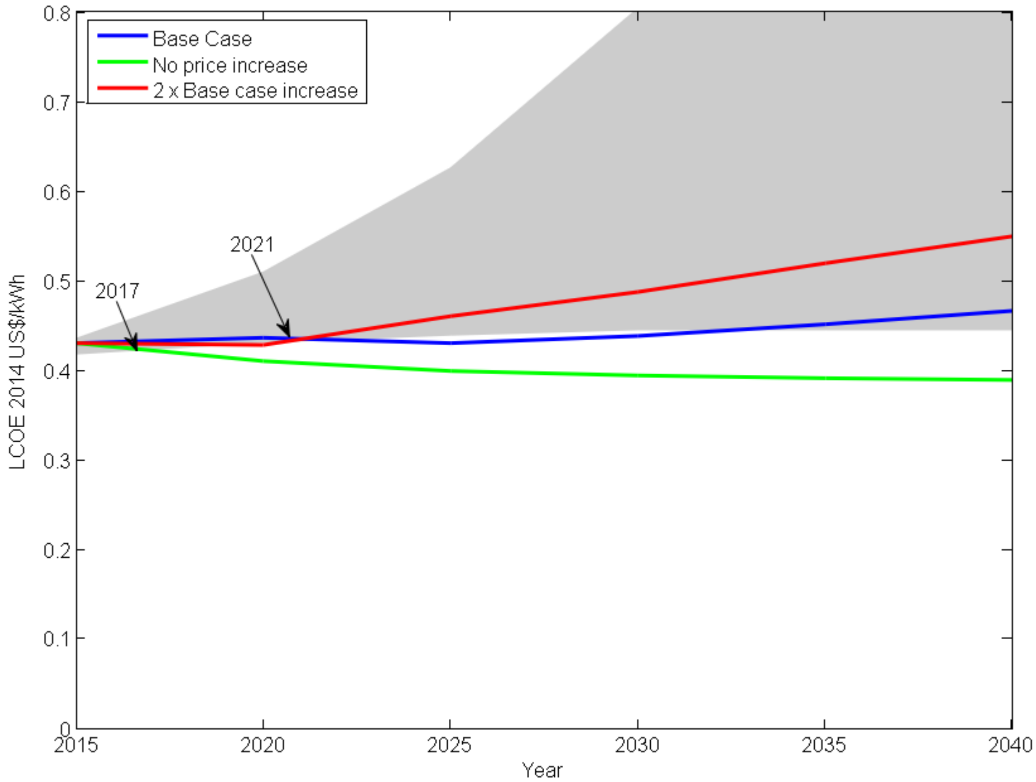


Figure 3A. Diesel price sensitivity analysis results for Pakistan. The grid parity region corresponds to the effective cost of unreliable grid power calculated using a battery-backup system

South Africa

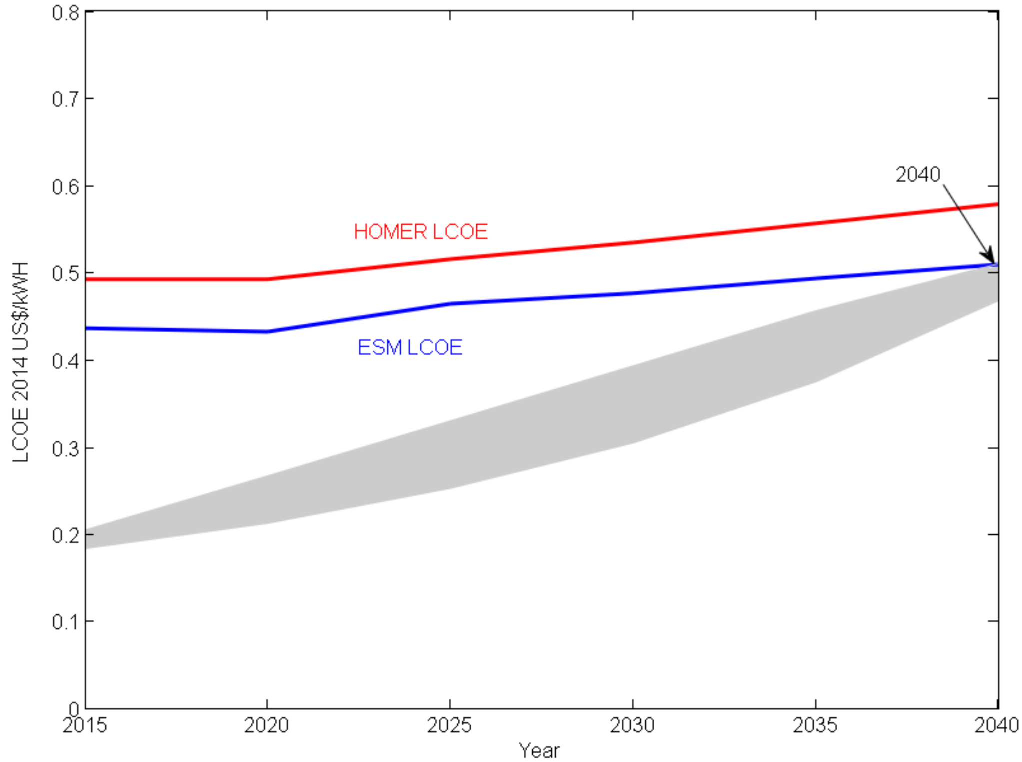


Figure 4A. HOMER and ESM LCOE results for South Africa in 2014 US dollars against the parity region projected using a battery back-up system. The point of intersection between the ESM LCOE and recent price edge of the shaded area shows grid parity in the year 2040

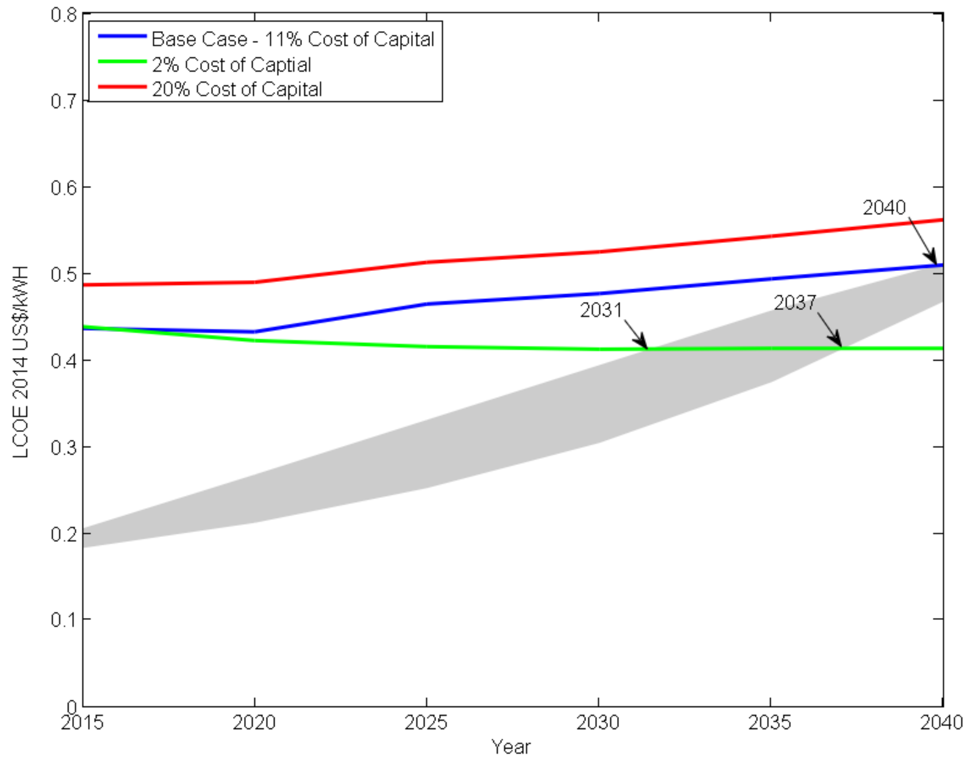


Figure 5A. Interest rate sensitivity results for South Africa with a battery-backup system used to determine the parity region. With a 2% cost of capital, the estimated range for grid parity is 2031-2037

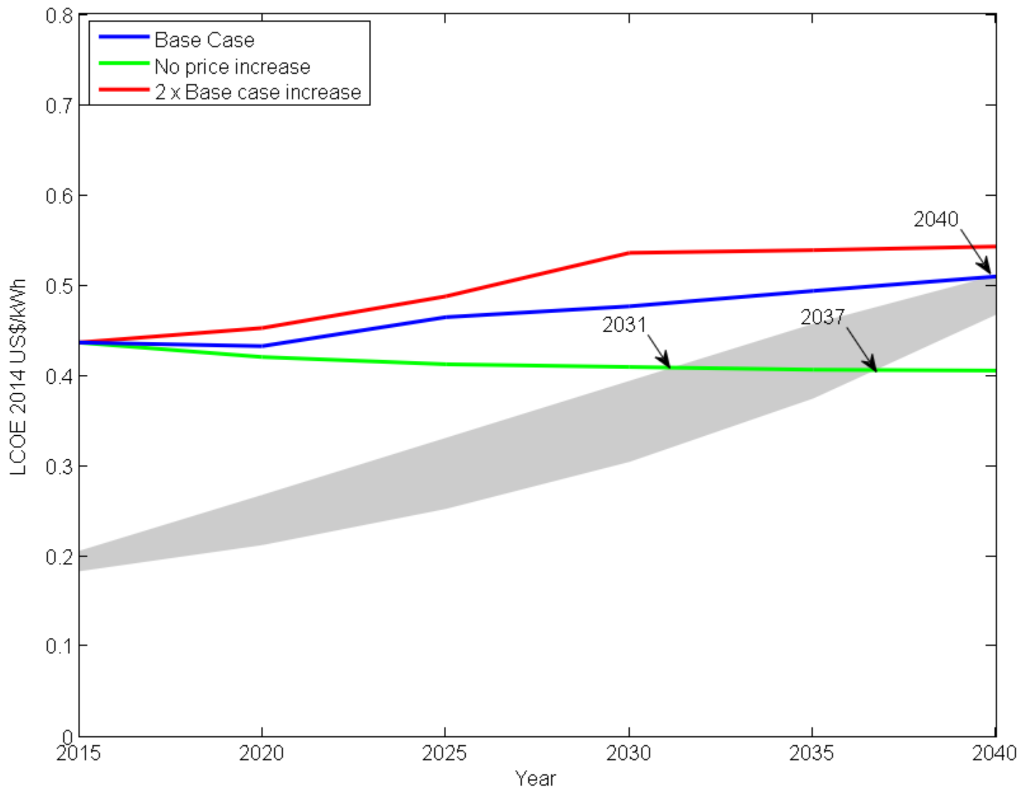


Figure 6A. Diesel price sensitivity results for South Africa with effective cost of power calculated using a battery-backup system. For such a scenario, with current real diesel prices, grid parity estimate first occurs in the year 2031

Sensitivity Analysis – ESM Output Details

Discount rate sensitivity

Table 5A

ESM result details for the Cost of capital rate sensitivity for the US at a 2% interest rate

UNITED STATES 2%	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.329	0.339	0.366	0.369	0.385	0.389
Solar Fraction %	32	32.6	62.6	62.6	77.1	77.1
PV (kW)	164.5	167.6	350.3	350.4	550.6	550.6
Generator (kW)	110.8	109.0	126.4	126.4	113.4	113.4
Battery (kWh)	178	169.9	1118.3	1118.3	1458.1	1458.1
Solar PV Cost ($/day)	77.1		158.3	147.9	223.2	218.5
Generator Cost ($/day)	12.2		13.8	13.9	12.4	12.4
Battery Cost ($/day)	34.8		133.7	133.7	141.6	141.6
Diesel Cost ($/day)	386.6		230.9	248.0	165.8	176.5

Table 6A

ESM result details for the cost of capital rate sensitivity for the US at a 15% interest rate

UNITED STATES 15%	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.385	0.397	0.413	0.433	0.454	0.486
Solar Fraction %	26.8	26.3	26.4	27.2	32.2	34.5
PV (kW)	122.9	118.3	118.9	124.5	161.1	176.6
Generator (kW)	112.7	110.8	109.8	111.1	112.7	118.4
Battery (kWh)	137.2	156.9	164.2	176.5	211.3	352.3
Solar PV Cost ($/day)	119.2	124.1	111.2	108.7	135.1	144.9
Generator Cost ($/day)	25.6	25.2	24.9	25.2	25.6	26.9
Battery Cost ($/day)	22	31.9	35.4	41.3	57.3	100.7
Diesel Cost ($/day)	436.4	443.6	478.9	506.2	492.7	485.7

Table 7A

ESM result details for the cost of capital rate sensitivity for Germany at a 2% interest rate

GERMANY 2%	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.448	0.456	0.463	0.475	0.492	0.510
Solar Fraction %	58.0	60.7	63.8	66.4	68.6	69.6
PV (kW)	108.2	121.5	135.5	149.9	166	172.3
Generator (kW)	34.9	34.9	35	35	35.1	35.1
Battery (kWh)	310.8	294.3	317.1	317.8	315.2	317.9
Solar PV Cost ($/day)	42.5	43.3	45.8	49.1	53.3	54.9
Generator Cost ($/day)	3.6	3.66	3.67	3.67	3.68	3.67
Battery Cost ($/day)	39.8	39.5	39.97	40.1	40.1	40.1
Diesel Cost ($/day)	84.9	87.5	86.3	87.1	88.7	93.7

Table 8A

ESM result details for the cost of capital rate sensitivity for Germany at a 10% interest rate

GERMANY 10%	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.493	0.523	0.542	0.572	0.608	0.644
Solar Fraction %	29.2	34.0	33.9	33.9	34.3	39.9
PV (kW)	49.3	64.4	65.6	65.5	67	98.3
Generator (kW)	28.6	30.3	29.7	29.8	29.9	30.1
Battery (kWh)	40.8	56.5	50.2	49.5	49.8	54.1
Solar PV Cost ($/day)	31.5	37.4	36	34.8	34.9	50.9
Generator Cost ($/day)	4.86	5.16	5.1	5.1	5.1	5.1
Battery Cost ($/day)	12	18.8	16.3	16	16.1	16.4
Diesel Cost ($/day)	149	147.2	158.8	172.7	187.3	183.3

Table 9A

ESM result details for the cost of capital rate sensitivity for Pakistan at a 2% interest rate

PAKISTAN 2%	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.346	0.343	0.353	0.363	0.375	0.387
Solar Fraction %	59.7	60.6	61.6	62.1	62.4	63.2
PV (kW)	211.1	224.6	241.8	250.4	256	267.2
Generator (kW)	104.2	102.6	100.8	98.6	97.1	94
Battery (kWh)	109.7	111.5	116.8	126.5	128	137.4
Solar PV Cost ($/day)	98.5	90.6	89.3	88.3	87.6	90.2
Generator Cost ($/day)	7.87	7.8	7.6	7.5	7.3	7.1
Battery Cost ($/day)	37.9	38.6	41.4	48.3	49.2	58.2
Diesel Cost ($/day)	233.7	236.5	246.4	251.6	264.4	266.3

Table 10A

ESM result details for the cost of capital sensitivity for Pakistan at a 20% interest rate

PAKISTAN 20%	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.469	0.459	0.467	0.476	0.489	0.504
Solar Fraction %	53.0	56.8	56.8	57.6	57.6	57.7
PV (kW)	147.3	175.8	175.8	180	180	179.9
Generator (kW)	108.1	105.2	105.2	102.8	102.8	100.9
Battery (kWh)	110.2	112.9	112.9	125.5	125.5	132.4
Solar PV Cost ($/day)	173.9	179.4	164.4	160.6	155.8	153.8
Generator Cost ($/day)	20.7	20.1	20.1	19.7	19.6	19.3
Battery Cost ($/day)	52.6	48.5	48.5	60.7	60.6	67.5
Diesel Cost ($/day)	275.2	261.6	285.4	287.7	307.9	319.9

Table 11A

ESM result details for the cost of capital sensitivity for South Africa at a 2% interest rate

SOUTH AFRICA 2%	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.438	0.422	0.415	0.412	0.413	0.413
Solar Fraction %	82.1	88.0	88.0	89.0	90.4	91.7
PV (kW)	300.3	350	350.1	364.6	382.5	389.1
Generator (kW)	135.4	132.7	132.6	130.8	128.9	128.9
Battery (kWh)	1192.6	1270.4	1273.9	1248.5	1278.4	1352.9
Solar PV Cost ($/day)	176.9	178.1	163.4	162.4	165.5	165.9
Generator Cost ($/day)	14.35	14.1	14.1	13.9	13.7	13.65
Battery Cost ($/day)	249.3	257.2	257.5	256.3	257.8	262.9
Diesel Cost ($/day)	114.05	80.6	88.4	86.5	81.3	75.1

Table 12A

ESM result details for the cost of capital sensitivity for South Africa at a 20% interest rate

SOUTH AFRICA 20%	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.486	0.489	0.512	0.524	0.542	0.561
Solar Fraction %	30.3	39.2	41.5	41.6	41.6	41.5
PV (kW)	90.7	140.2	149.8	150	150	149.5
Generator (kW)	114	108.7	111.1	111.1	111.1	111.1
Battery (kWh)	156.4	185.7	213.9	213.8	213.8	214.3
Solar PV Cost ($/day)	135.3	180.6	176.9	169.1	164.3	161.4
Generator Cost ($/day)	30.6	29.2	29.8	29.8	29.8	29.8
Battery Cost ($/day)	67.5	76.8	90.9	90.8	90.8	90.9
Diesel Cost ($/day)	433.99	379	399.3	425.6	455.3	485.2

Diesel Price Sensitivity

Table 13A

ESM diesel price sensitivity result details for the US with no real increase in fuel prices

US NO INCREASE	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.355	0.358	0.355	0.350	0.345	0.344
Solar Fraction %	31.0	28.5	32.0	32.0	32.1	32.1
PV (kW)	154.3	133.3	160.4	160.4	164.1	164.1
Generator (kW)	111.3	111.0	112.0	112.0	111.5	111.5
Battery (kWh)	134.4	151.9	181.2	181.2	159.8	159.9
Solar PV Cost ($/day)	105.5	98.5	105.7	98.8	97.1	95.0
Generator Cost ($/day)	17.8	17.8	17.9	17.9	17.9	17.9
Battery Cost ($/day)	16.8	25.6	38.9	38.9	27.5	27.5
Diesel Cost ($/day)	412.5	417.9	389.2	389.2	395.1	395.1

Table 14A

ESM diesel price sensitivity result details for the US with double increase in real fuel prices

US 2 x INCREASE	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.355	0.379	0.424	0.463	0.501	0.541
Solar Fraction %	30.6	29.8	33.6	40.2	42.1	41.7
PV (kW)	154.3	143.4	174.1	231.8	249.6	263.8
Generator (kW)	111.3	111.0	112.1	113.9	114.9	113.9
Battery (kWh)	134.4	150.4	197.6	353.4	374.2	313.5
Solar PV Cost ($/day)	17.8	17.8	17.9	18.2	18.4	18.2
Generator Cost ($/day)	105.5	105.9	114.8	142.8	147.6	152.7
Battery Cost ($/day)	16.8	24.4	46.5	91.6	94.2	84.6
Diesel Cost ($/day)	412.5	445.0	483.3	463.9	516.1	585.0

Table 15A

ESM diesel price sensitivity result details for Germany with no real increase in fuel prices

GERMANY NO INCREASE	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.480	0.469	0.462	0.458	0.456	0.455
Solar Fraction %	53.7	55.0	55.0	57.7	57.7	57.7
PV (kW)	92.9	101.6	101.6	112.2	112.2	112.2
Generator (kW)	35.0	35	35.1	34.96	34.9	34.9
Battery (kWh)	295.4	259.6	259.7	266.1	266.1	266.1
Solar PV Cost ($/day)	44.5	44.2	41.8	44.8	43.9	43.6
Generator Cost ($/day)	4.5	4.48	4.48	4.46	4.46	4.46
Battery Cost ($/day)	42.2	40.8	40.8	41.1	41.1	41.1
Diesel Cost ($/day)	93.5	90.8	90.8	85.4	85.4	85.4

Table 16A

ESM diesel price sensitivity result details for Germany with double increase in real fuel prices compared to the base case

GERMANY 2 x INCREASE	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.480	0.509	0.532	0.563	0.607	0.651
Solar Fraction %	53.7	60.4	65.1	66.4	69.8	72.7
PV (kW)	92.9	120.6	143	150.1	174.2	198.3
Generator (kW)	35.0	35.1	35.1	35.1	35.3	35.4
Battery (kWh)	295.4	290.2	313.3	316.1	322.7	321.4
Solar PV Cost ($/day)	44.5	52.5	58.9	59.9	68.2	77.1
Generator Cost ($/day)	4.5	4.5	4.5	4.48	4.51	4.5
Battery Cost ($/day)	42.2	42.1	42.9	42.9	43.6	43.5
Diesel Cost ($/day)	93.5	95.9	96.6	107.8	115.1	122.8

Table 17A

ESM diesel price sensitivity result details for Pakistan with no real increase in fuel prices

PAKISTAN NO INCREASE	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.430	0.410	0.399	0.394	0.391	0.389
Solar Fraction %	55.8	56.6	56.5	57.2	57.2	57.5
PV (kW)	167.9	174.1	173.4	180.5	180.5	183.3
Generator (kW)	107.9	107.6	107.5	107.5	107.5	105.9
Battery (kWh)	107.7	103.7	104.8	102.7	102.7	108.4
Solar PV Cost ($/day)	154.98	138.8	126.7	125.9	122.1	122.4
Generator Cost ($/day)	16.1	16.1	16.1	16.1	16.1	15.8
Battery Cost ($/day)	43.59	39.1	39.97	37.2	37.2	41.8
Diesel Cost ($/day)	261.5	259.5	259.1	256.4	256.4	249.2

Table 18A

ESM diesel price sensitivity result details for Pakistan with double increase in real fuel prices compared to the base case

PAKISTAN 2 x INCREASE	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.430	0.428	0.460	0.487	0.519	0.549
Solar Fraction %	55.8	57.0	58.5	58.8	60.5	64.7
PV (kW)	167.9	177.8	189.9	192.6	212.5	237.5
Generator (kW)	107.9	105.3	101.9	100.5	96.8	87.9
Battery (kWh)	107.7	112.2	126.9	129.1	139.6	176.9
Solar PV Cost ($/day)	154.98	141.8	138.8	134.3	143.7	158.7
Generator Cost ($/day)	16.1	15.7	15.2	15	14.5	13.1
Battery Cost ($/day)	43.59	45.8	58.4	60	70	117.8
Diesel Cost ($/day)	261.5	270.6	297.3	331	348.2	318.2

Table 19A

ESM diesel price sensitivity result details for South Africa with no real increase in fuel prices

SOUTH AFRICA NO INCREASE	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.436	0.420	0.412	0.409	0.406	0.405
Solar Fraction %	34.3	39.5	39.3	39.2	39.2	39.6
PV (kW)	112.3	143.2	143.8	143.8	143.8	144.7
Generator (kW)	114.4	108.7	108.2	108.1	108.1	107.6
Battery (kWh)	161	184.1	179.2	178.9	178.8	181.9
Solar PV Cost ($/day)	107.6	118.5	109.1	104.2	101.2	100.3
Generator Cost ($/day)	19.7	18.7	18.6	18.6	18.6	18.6
Battery Cost ($/day)	60.3	70.3	67.7	67.4	67.4	69.3
Diesel Cost ($/day)	408.8	364.3	365.9	366.3	366.3	363.5

Table 20A

ESM diesel price sensitivity result details for South Africa with double increase in real fuel prices compared to the base case

SOUTH AFRICA 2 x INCREASE	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.436	0.452	0.487	0.535	0.538	0.542
Solar Fraction %	34.3	39.9	42.7	50.5	89.1	92.5
PV (kW)	112.3	140.6	154.2	227.5	364.1	400
Generator (kW)	114.4	118.2	107.7	112.5	131.2	117.1
Battery (kWh)	161	198.4	226.1	291.7	1257	1354.8
Solar PV Cost ($/day)	107.6	116.4	117	164.8	256.3	277.4
Generator Cost ($/day)	19.7	20.4	18.6	19.4	22.6	20.2
Battery Cost ($/day)	60.3	78.2	90.4	108.6	286.8	294.7
Diesel Cost ($/day)	408.8	401.5	438.9	429.6	118.5	92.7

Temperature Sensitivity

Table 21A

ESM LCOE Results for the US at 23 degrees controlled temperature

UNITED STATES 23 DEGREES CELSIUS	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.362	0.378	0.392	0.412	0.428	0.446
Solar Fraction %	28.5	26.4	29.6	32.3	32.5	32.3
PV (kW)	136.3	119.8	145.7	174.6	172.6	171.4
Generator (kW)	114.6	113.3	112.9	114.7	112.7	112.1
Battery (kWh)	123.2	147.4	130.9	124.5	148.3	141.9
Solar PV Cost ($/day)	18.4	18.2	18.1	18.4	18.0	17.9
Generator Cost ($/day)	93.2	88.6	96.0	107.5	102.1	99.3
Battery Cost ($/day)	20.4	35.7	23.4	18.5	33.4	28.6
Diesel Cost ($/day)	434.6	451.7	477.7	499.5	517.3	554.0

Table 22A

ESM LCOE Results for Germany at 23 degrees controlled temperature

GERMANY 23 DEGREES CELSUIS	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.483	0.515	0.537	0.548	0.572	0.652
Solar Fraction %	30.7	33.9	32.6	34.5	39.9	64.7
PV (kW)	55.9	69.2	64.3	75.7	97.6	142.2
Generator (kW)	28.7	29.1	28.9	29.3	30.2	35.0
Battery (kWh)	31.6	34.2	31.2	26.7	54.6	312.7
Solar PV Cost ($/day)	3.7	3.7	3.7	3.8	3.9	4.5
Generator Cost ($/day)	26.8	30.1	26.5	30.2	38.2	55.3
Battery Cost ($/day)	7.8	11.7	6.9	4.7	15.8	84.6
Diesel Cost ($/day)	155.1	159.9	177.5	189.6	168.6	108.1

Table 23A

ESM LCOE Results for Pakistan at 23 degrees controlled temperature

PAKISTAN 23 DEGEES CELSUIS	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.449	0.424	0.417	0.413	0.411	0.412
Solar Fraction %	83.0	85.3	87.9	88.8	90.1	89.9
PV (kW)	228.2	232.2	244.4	250.4	260.5	259.0
Generator (kW)	126.6	122.6	125.9	125.8	119.7	119.8
Battery (kWh)	638.4	716.1	778.4	785.3	792.0	791.2
Solar PV Cost ($/day)	18.9	18.3	18.8	18.8	17.9	17.9
Generator Cost ($/day)	210.6	185.1	178.6	174.6	176.2	173.0
Battery Cost ($/day)	173.5	179.1	183.0	183.5	182.7	182.2
Diesel Cost ($/day)	82.2	74.7	67.4	66.4	63.3	68.6

Table 24A

ESM LCOE Results for South Africa at 23 degrees controlled temperature

SOUTH AFRICA 23 DEGREES CELSUIS	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.464	0.462	0.481	0.499	0.517	0.539
Solar Fraction %	34.8	34.4	38.9	38.4	39.7	41.5
PV (kW)	121.3	118.0	154.9	148.3	161.7	175.1
Generator (kW)	119	117.5	111.5	112.5	109.5	109.7
Battery (kWh)	133.8	131.9	156.1	159.5	168.5	178.5
Solar PV Cost ($/day)	20.5	20.3	19.2	19.4	18.9	18.9
Generator Cost ($/day)	116.2	97.7	117.5	107.5	113.8	121.4
Battery Cost ($/day)	74.4	74.4	88.1	90.8	96.9	103.7
Diesel Cost ($/day)	425.6	442.4	433.2	466.3	479.3	493.2

Pakistan 20% solar learning vs. 0% cost of capital rate ESM output system details

Table 25A

ESM LCOE results for Pakistan with a solar PV learning rate of 20%

PAKISTAN 20% SOLAR LEARNING	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.428	0.412	0.419	0.425	0.437	0.449
Solar Fraction %	56.9	57.8	58.4	59.0	60.3	60.3
PV (kW)	176.3	185.2	188.3	197.2	214.3	212.6
Generator (kW)	105.1	104.5	103.0	102.2	100.6	98.9
Battery (kWh)	116.2	115.1	130.2	123.5	127.1	132.3
Solar PV Cost ($/day)	160.5	137.7	124.3	121.9	127.1	123.4
Generator Cost ($/day)	15.7	15.6	15.4	15.3	15.0	14.8
Battery Cost ($/day)	50.5	48.6	61.8	54.1	55.7	61.5
Diesel Cost ($/day)	246.8	253.3	262.7	278.8	284.7	297.4

Table 26A

ESM LCOE results for Pakistan with a 0% cost of capital rate

PAKISTAN 0% COST OF CAPITAL	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.335	0.330	0.341	0.350	0.352	0.353
Solar Fraction %	59.7	61.8	62.0	63.0	95.8	96.6
PV (kW)	208.2	247.5	251.6	272.4	380.4	382.2
Generator (kW)	108.7	100.8	100.5	97.0	113.4	121.4
Battery (kWh)	93.1	114.7	114.9	122.6	749.0	848.8
Solar PV Cost ($/day)	84.1	86.3	80.4	83.1	112.5	111.7
Generator Cost ($/day)	7.1	6.6	6.6	6.3	7.4	7.9
Battery Cost ($/day)	24.9	38.6	34.5	43.3	221.3	226.2
Diesel Cost ($/day)	250	225.5	244.5	245.6	27.2	23.5

Lihue Hawaii ESM output system details

Table 27A

ESM output for Lihue, Hawaii

LIHUE, HAWAII	2015	2020	2025	2030	2035	2040
ESM LCOE $/kWh	0.337	0.354	0.369	0.383	0.398	0.414
Solar Fraction %	35.8	36.4	37.7	38.2	40.5	40.5
PV (kW)	226.6	218.5	242.3	250.4	297.6	293.2
Generator (kW)	142.7	143.5	140.3	139.1	134.7	134.1
Battery (kWh)	141.6	140.9	151.2	158.6	181.7	188.8
Solar PV Cost ($/day)	93.5	99.6	98.5	94.9	108.2	104.7
Generator Cost ($/day)	22.8	22.9	22.5	22.3	21.6	21.5
Battery Cost ($/day)	33.0	32.7	39.6	47.0	65.4	72.6
Diesel Cost ($/day)	467.4	494.7	515.6	539.6	532.1	559.9

Appendix B

ESM Input Parameters

The following list summarizes the primary inputs considered during data collection and conditioning. ESM parameter names with short descriptions are also provided.

Table 28B

ESM financial input parameters

Input Parameter	ESM Variable
Generator Capital Costs	in.gencapcost
Generator Replacement Costs	in.genreplacecost
Diesel Fuel Prices	in.fuelprice
Solar PV Capital Costs	in.pvcapcost
Solar PV Replacement Costs	in.pvreplacecost
Lead Acid Battery Capital Costs	in.pbabattcapcost
Battery Replacement Costs	in.pbabattreplacecost
Inverter Capital Costs	in.uncommon.invcapcost
Inverter Replacement Costs	in.uncommon.invreplacecost
Generator Operational Costs	in.uncommon.genopcost
PV Operational Costs	in.uncommon.pvopcost
Installation Costs	in.uncommon.installcost

in.gencapcost – Capital cost of diesel generator in $/W.

in.genreplacecost – Capital cost of replacement diesel generator in $/W. This variable only applies for runs long enough that the generator needs to be replaced (rare) or in the payback period calculations. By default, this should probably be the same number as the initial generator capital cost unless you have a good reason to use another value.

in.fuelprice – Price of diesel in $/L.

in.pvcapcost – Capital cost of PV system ($/Watt). The Watts in these units are "nameplate" Watts, the stated output of the panels.

in.pvreplacecost – Capital cost of replacement PV ($/Watt). The Watts in these units are "nameplate" Watts, the stated output of the panels.

in.pbabattcapcost – Capital cost of PbA batteries ($/Wh). Ignored for AHI battery runs.

in.pbabattreplacecost – Capital cost of replacement PbA batteries ($/Wh). Ignored for AHI battery runs.

in.uncommon.invcapcost - Capital cost of the inverter in $/W.

in.uncommon.invreplacecost - Capital cost of inverter replacement in $/W (only used for extremely long runs or payback period calculations).

in.uncommon.genopcost - Fixed operating cost of the generator in annual dollars per Watt of capacity ($/W-yr).

in.uncommon.pvopcost - The fixed operating cost of the PV array. Units are annual dollars per Watt of capacity ($/W-yr).

in.uncommon.installcost - Installation cost of the system, expressed as a fraction of the capital costs. This is to cover things like clearing land, laying concrete pads, etc. For example, a value of 0.1 indicates that the installation costs are 10% of the capital costs of the system.

Appendix C

Exchange Rates

The following table contains the exchange rates used to convert different currencies to US dollars. The rates used are kept constant throughout the analysis.

Table 29C

US dollar exchange rates

Currency	$ US dollars
1.0 Euro	1.31
1.0 South Africa Rand	0.091
1.0 Pakistan Rupee	0.0097

Source: www.google.com

The values used are those at the time of the analysis. Current values may be different.

Appendix D

Generator Capital Cost Working

For the US, the generator capital cost figures used are from (RMI Study). In order to determine the share of installation costs for the generators, generator prices from multiple vendors are used to determine the average $/W price figure for diesel generators. The following tables show this working along with the sources

Table 30D

Generator costs - $/W working for the US

Generator Size KW	Price $	$/kW	$/W
100	22999.0	229.99	0.230
20	4496.0	224.80	0.225
6.5	1520.3	233.89	0.234
16	4199.0	262.44	0.262
		Average	0.238

Source: http://www.amazon.com/100-Triton-Diesel-Generator-Certified/dp/B00EUIE7MK

Table 31D

Generator costs - $/W working for the US

Generator Size KW	Price $	$/kW	$/W
15	10799	719.93	0.720
22	8909	404.95	0.405
100	24129	241.29	0.241
130	27289	209.92	0.210
150	29529	196.86	0.197
		Average	0.355

Source: http://www.generac.com/all-products/generators/business-standby-generators#?cat=46&cat=-248

Table 32D

Generator costs - $/W working for the US

Generator Size KW	Price $	Installation Costs $	Capital Costs $	Total Cost per KW $/kW	$/W
7	2500	500	3000	428.6	0.429
10	4500	1000	5500	550.0	0.550
12	4000	1000	5000	416.7	0.417
20	10000	1000	11000	550.0	0.550
22	9000	3000	12000	545.5	0.545
45	15000	3000	18000	400.0	0.400
				Average	0.482

Source: http://www.fixr.com/costs/install-backup-generator

Using the above averages, the average generator price for the US comes out to be $0.358/W. Using the capital cost figure from (Bronski, et al., 2014), this gives and installation cost of $0.52 - $.0358 = 0.162 $/W, or 31% of the total generator capital costs. This number is used as a basis for calculations at other locations. Since in most cases installation cost shares for solar PV systems are available, variations in these are proportionately applied to the 31.1% share of generator installation costs in the US.

The final generator capital costs are calculated using generator prices from sellers and installation costs such that:

$$Generator\ Capital\ Costs = Generator\ Price + Installation\ Cost$$

For Germany, cost figures used are based on those reported by (Seel, Barbose, & Wiser, 2014) for solar PV residential systems. The installation costs for these systems are calculated as follows and the % share is used to calculate generator installation costs.

$$Other\ Hardware\ Costs = 0.23\ \$/W \quad Labor\ Costs = 0.23\ \$/W$$

$$Total\ PV\ System\ Costs = 3.00\ \$/W$$

$$Installation\ Share\ (\%) = \frac{(0.23 + 0.23)}{3.00} = 15.3\%$$

A similar working for the US based on numbers from the same study returns a 17.1% share for PV installation costs. Based on these numbers, it is shown that the installation costs in Germany (for solar PV) are lower than those in the US by a factor of $\frac{15.3\%}{17.1\%} = 0.895$. The same factor is assumed to hold for generator installations and is used to determine the share of generator installation costs from the previously calculated US share of 31.1%. This comes out to be: $31.1\% \times 0.895 = 27.9\%$

This number is then used to determine the generator capital costs for Germany. Based on data from multiple vendors, the average generator price in Germany is almost the same as that in the US, in 2014 US dollars so that the final capital cost turns out to be:

$$Generator\ Capital\ Cost\ in\ Germany = \frac{0.358}{(1 - 0.279)} = 0.496\ \$/W$$

For Pakistan, T.S.K Engineering's quote is used to determine the share of installation costs for solar PV. These come out to be 7%. Similar to the working in Germany, the variation in PV installation costs between the US and Pakistan is proportionately applied to generator installation share (31%) in the US. This returns a generator installation share of $\frac{7.0\%}{17.1\%} \times 31.1\% = 12\%$. This share is then applied to average diesel generator prices obtained from multiple vendors listed below. In all cases, the power factor used is 0.80

Table 33D

Generator Costs - $/W working for Pakistan

Generator Size kVA	Generator Size KW	Price PKR (2014)	PKR/W	US$/W
110	88	1,460,000	16.59	0.161
50	40	980,000	24.50	0.238
150	120	1,935,000	16.13	0.156
150	120	2,150,000	17.92	0.174
15	12	490,000	40.83	0.396
			Average $/W	0.225

Source: http://www.ajss-group.com/imported_generators.htm

Table 34D

Generator costs - $/W working for Pakistan

Generator Size kVA	Generator Size KW	Price Rupees	Rupees/W	US$/W
7	5.6	110,000	19.64	0.191
10	8	160,000	20.00	0.194
20	16	220,000	13.75	0.133
50	40	950,000	23.75	0.230
100	80	1,400,000	17.50	0.170
			Average $/W	0.184

Source: T.S.K Engineering

Based on correspondence with engineering staff of T.S.K Engineering, the price of imported diesel generators in Pakistan was taken to be on average three times that of the local ones which results in an average price figure of 0.55$/W. The total capital costs are the average price for both local and imported generators plus 12% for installation costs. This gives a final figure of 0.360 $/W

For South Africa, the following average prices from multiple vendors are used to determine an average $/W generator price figure of 0.214 $/W.

Table 35D

Generator Costs - $/W working for South Africa

Generator Size KW	Price Rand (ZAR)	Price US$ 2014	$/W
20	69,940	6364.54	0.318
80	189,000	17199	0.215
100	145,000	13195	0.132
		Average $/W	0.222

Source: http://www.pricecheck.co.za/search/?search=generator+++generators&search_category_id=442

Table 36D

Generator Costs - $/W working for South Africa

Generator Size KVA	Generator Size KW	Price Rand (ZAR)	Rand/W	$/W
125	100	145,000	1.45	0.132
160	128	195,000	1.52	0.139
			Average $/W	0.135

Source: http://www.icmsa.co.za/10-30%20KVA%20DIESEL%20Generators.htm

Table 37D

Generator Costs - $/W working for South Africa

Generator Size KVA	Generator Size KW	Price Rand (ZAR)	Rand/W	$/W
100	80	250,000	3.125	0.284

Source: Quote from KIPOR

From (EScience Associates, Urban-Econ Development Economists, 2013), the installation share for commercial off grid solar PV systems is 20%. Similar to other locations, the

US PV installation share is used to determine generator installation figure: $\frac{20\%}{17.1\%} \times 31.1\% = 35\%$. This gives a final capital cost figure of 0.502 $/W for South Africa.

Appendix E

Diesel Fuel Price Projections

For the US, figures used are from EIA's AEO 2014. Figures are adjusted to US$2014. Motor taxes have been deducted to reflect the cost of diesel for energy production. Gallon to liter conversion factor used is 1 gallon = 3.785 liters

Table 38E

Diesel fuel price projection working for the US

	2015	2020	2025	2030	2035	2040
Diesel price 2012 $/gal	3.54	3.67	3.97	4.20	4.47	4.73
Diesel price 2014 $/gal	3.69	3.82	4.14	4.37	4.65	4.92
Minus motor tax	3.16	3.30	3.61	3.85	4.12	4.40
2014 $/liter	0.84	0.87	0.95	1.02	1.09	1.16

For Germany, heating oil prices are used to determine the final diesel price trend. TESCON's average figure for 2011 is used as the starting point for the trend. This figure is determined by taking the average of heating oil prices in the 12 months of 2011, as shown in Table 39.

The cumulative % increase in heat oil prices is obtained from (Schlesinger, Dietmar, & Lutz, 2014). This is used to determine prices for subsequent years. For the years 2015 and 2035, due to absence of data points in the projections done by (Schlesinger, Dietmar, & Lutz, 2014), values are obtained using liner interpolation

Table 39E

TESCON Heating oil prices in Germany during the year 2011

2011 Heating Oil Prices	Average Euro per 100 liter
Jan	74
Feb	76
Mar	82
Apr	83
May	80
Jun	80
Jul	82.5
Aug	81
Sep	82.5
Oct	85
Nov	88.5
Dec	86
Total Average 2011	81.7

Source: http://www.tecson.de/pheizoel.html

Table 40E

Heating oil fuel price projection working for Germany

Year	Increase on top of 2011 price	2011 Euros/liter	2014 Euro/liter	2014 US $/liter
2011		0.82	0.867	1.14
2015	8%	0.88	0.939	1.23
2020	19%	0.97	1.029	1.35
2025	27%	1.04	1.101	1.44
2030	37%	1.12	1.188	1.56
2035	50%	1.22	1.298	1.70
2040	63%	1.33	1.409	1.85

For both Pakistan and South Africa, the diesel price trend from the US is applied to current prices for future projections. % increase in US prices is obtained from the AEO 2014 data. The following tables show results for Pakistan and South Africa. The current diesel price used for Pakistan is $1.05/liter obtained from Pakistan State Oil's website.

Table 41E

Diesel fuel price projection working for Pakistan using US price trend

	2015	2020	2025	2030	2035	2040
US Prices - $2014	0.83	0.87	0.95	1.01	1.08	1.16
US % Increase trend		4.24%	9.69%	6.57%	7.15%	6.70%
Pak Prices - $2014	1.05	1.10	1.20	1.28	1.37	1.46

For South Africa, the Road Accident Fund levy is subtracted from the actual current price before applying the US trend.

Table 42E

Net current diesel fuel price in South Africa

	2014 South Africa cents/liter	2014 Rand/liter
Current diesel price	1259.4	12.6
Road Accident Fund (RAF) levy	100.0	1.0
Net Price	1159.4	11.6
Net Price $/liter	1.06	

Table 43E

Diesel fuel price projection working for South Africa using US price trend

	2015	2020	2025	2030	2035	2040
US Prices - $2014	0.83	0.87	0.95	1.01	1.08	1.16
US % Increase trend		4.24%	9.69%	6.57%	7.15%	6.70%
South Africa Prices - $2014	1.06	1.10	1.21	1.29	1.38	1.47

Appendix F

Solar PV Learning Curve Analysis

EPIA's conservative estimates of future global PV cumulative installations along with historical figures reported in (Masson, Orlandi, & Rekinger, 2014) are extrapolated in MATLAB to determine solar PV growth rate projections.

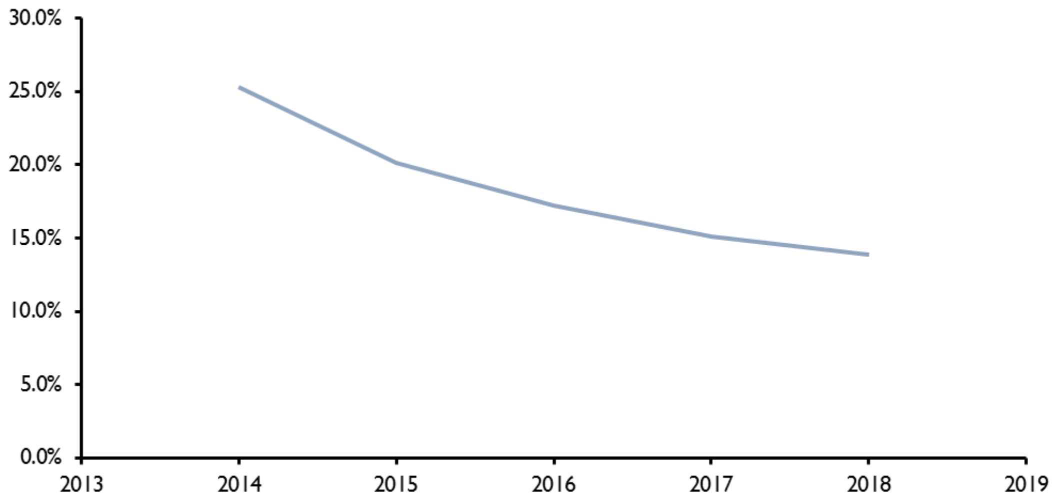


Figure 7F. EPIA projected 'Low Scenario' annual growth rate for global solar PV installations

Table 44F

EPIA 'Low Scenario' global solar PV growth rate projection for 2014-2018

Year	Cumulative Installations GW	Annual Increase %
2013	138.9	
2014	174	25.3%
2015	209	20.1%
2016	245	17.2%
2017	282	15.1%
2018	321	13.8%

The following snapshot shows this growth rate extrapolated as an exponentially decaying curve. Data points are de-normalized using δ = 1.291 and μ = 2017 obtained from the curve fitting tool. They help determine the yearly growth factors for global PV installations. The table below the snapshot shows this working. This helps determine global cumulative installations up until the year 2040, as shown. These global figures are used in the learning curve analysis for each location.

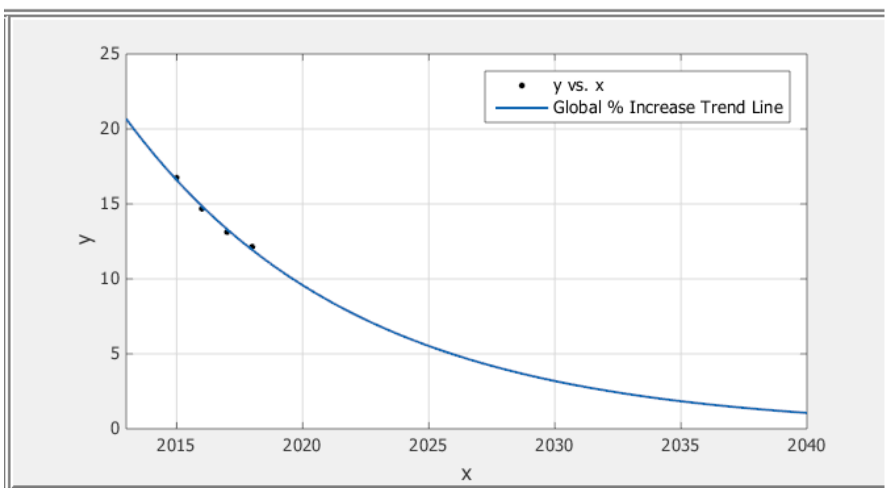
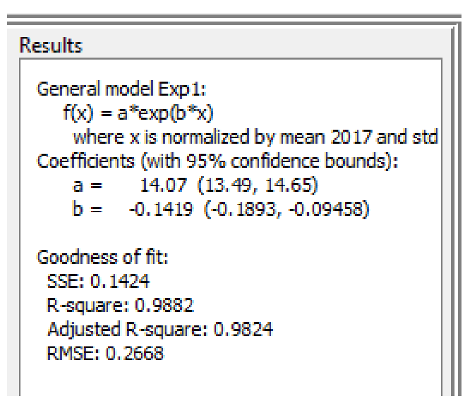


Figure 8F. Extrapolated EPIA 'Low Scenario' annual growth rate for global solar PV installations


Results

General model Exp1:
f(x) = a*exp(b*x)
where x is normalized by mean 2017 and std
Coefficients (with 95% confidence bounds):
a = 14.07 (13.49, 14.65)
b = -0.1419 (-0.1893, -0.09458)

Goodness of fit:
SSE: 0.1424
R-square: 0.9882
Adjusted R-square: 0.9824
RMSE: 0.2668

Figure 9F. Extrapolation results in MATLAB curve fitting tool

Table 45F

Annual growth rate figures for global solar PV installations obtained from MATLAB curve fitting. These are used in the learning curve analysis

Year	Z	Annual % Growth
2019	1.5	11.3%
2020	2.3	10.1%
2021	3.1	9.1%
2022	3.9	8.1%
2023	4.6	7.3%
2024	5.4	6.5%
2025	6.2	5.8%
2026	7.0	5.2%
2027	7.7	4.7%
2028	8.5	4.2%
2029	9.3	3.8%
2030	10.1	3.4%
2031	10.8	3.0%
2032	11.6	2.7%
2033	12.4	2.4%
2034	13.2	2.2%
2035	13.9	1.9%
2036	14.7	1.7%
2037	15.5	1.6%
2038	16.3	1.4%
2039	17.0	1.3%
2040	17.8	1.1%

Table 46F

Final global cumulative solar PV capacity projection figures based off of the estimated growth rates.

Year	Annual Installed MW	Cumulative Capacity MW	Annual Growth Rate %
2014	35144	174000	25.3%
2015	35000	209000	20.1%
2016	36000	245000	17.2%
2017	37000	282000	15.1%
2018	39000	321000	13.8%
2019	36252	357252	11.3%
2020	36146	393398	10.1%
2021	35660	429058	9.1%
2022	34844	463903	8.1%
2023	33753	497655	7.3%
2024	32440	530095	6.5%
2025	30957	561052	5.8%
2026	29355	590407	5.2%
2027	27675	618082	4.7%
2028	25957	644039	4.2%
2029	24232	668271	3.8%
2030	22526	690797	3.4%
2031	20862	711658	3.0%
2032	19255	730913	2.7%
2033	17717	748630	2.4%
2034	16258	764888	2.2%
2035	14882	779770	1.9%
2036	13592	793362	1.7%
2037	12390	805751	1.6%
2038	11273	817025	1.4%
2039	10241	827266	1.3%
2040	9290	836556	1.1%

Different solar learning rates along with different solar PV costs help determine future solar PV system cost forecasts for each location. The following tables show these results for all locations individually.

Learning Curve Analysis – Columbus Ohio, United States

Table 47F

Current solar PV system cost for the US

2014 System Cost US$/W	3.8

Table 48F

Learning curve parameters used for the US

PR	80%
LR	20%
Learning Parameter b	-0.321928095
Inflation	2%

Table 49F

Solar PV learning curve analysis working for Columbus, Ohio

Year	System Cost $/W	Minus Federal ITC 30% till 2016 10% beyond 2016	System cost minus 8% Inverter cost $/W	Inverter $/W	Maintenance Cost 1% of 2015 system cost
2014	3.8				
2015	3.582	2.508	2.22	0.287	0.0358
2016	3.404	2.383	2.11	0.272	0.0358
2017	3.253	2.928	2.67	0.260	0.0358
2018	3.120	2.808	2.56	0.250	0.0358
2019	3.014	2.713	2.47	0.241	0.0358
2020	2.922	2.630	2.40	0.234	0.0358
2021	2.842	2.558	2.33	0.227	0.0358
2022	2.771	2.494	2.27	0.222	0.0358
2023	2.709	2.438	2.22	0.217	0.0358
2024	2.655	2.389	2.18	0.212	0.0358
2025	2.607	2.346	2.14	0.209	0.0358
2026	2.564	2.308	2.10	0.205	0.0358
2027	2.527	2.274	2.07	0.202	0.0358
2028	2.494	2.244	2.04	0.199	0.0358
2029	2.464	2.218	2.02	0.197	0.0358
2030	2.438	2.194	2.00	0.195	0.0358
2031	2.415	2.173	1.98	0.193	0.0358
2032	2.394	2.155	1.96	0.192	0.0358
2033	2.376	2.138	1.95	0.190	0.0358
2034	2.359	2.123	1.93	0.189	0.0358
2035	2.345	2.110	1.92	0.188	0.0358
2036	2.332	2.098	1.91	0.187	0.0358
2037	2.320	2.088	1.90	0.186	0.0358
2038	2.310	2.079	1.89	0.185	0.0358
2039	2.300	2.070	1.89	0.184	0.0358
2040	2.292	2.063	1.88	0.183	0.0358

LearningCurve Analysis – Lihue Hawaii, United States

Table 50F

Current solar PV system cost for the US

2014 System Cost US$/W	3.8

Table 51F

Learning curve parameters used for the US

PR	80%
LR	20%
Learning Parameter b	-0.321928095
Inflation	2%

Table 52F

Solar PV learning curve analysis working for Lihue, Hawaii

Year	System Cost $/W	Minus Federal ITC 30% till 2016 10% beyond 2016	Minus 35% State Tax Credit	System cost minus 8% Inverter cost $/W	Inverter $/W	Maintenance Cost 1% of 2015 system cost
2014	3.8					
2015	3.582	2.508	1.6299	1.34	0.287	0.0358
2016	3.404	2.383	1.5486	1.28	0.272	0.0358
2017	3.253	2.928	1.9030	1.64	0.260	0.0358
2018	3.120	2.808	1.8252	1.58	0.250	0.0358
2019	3.014	2.713	1.7634	1.52	0.241	0.0358
2020	2.922	2.630	1.7096	1.48	0.234	0.0358
2021	2.842	2.558	1.6625	1.44	0.227	0.0358
2022	2.771	2.494	1.6212	1.40	0.222	0.0358
2023	2.709	2.438	1.5850	1.37	0.217	0.0358
2024	2.655	2.389	1.5531	1.34	0.212	0.0358
2025	2.607	2.346	1.5249	1.32	0.209	0.0358
2026	2.564	2.308	1.5001	1.29	0.205	0.0358
2027	2.527	2.274	1.4782	1.28	0.202	0.0358
2028	2.494	2.244	1.4587	1.26	0.199	0.0358
2029	2.464	2.218	1.4415	1.24	0.197	0.0358
2030	2.438	2.194	1.4262	1.23	0.195	0.0358
2031	2.415	2.173	1.4126	1.22	0.193	0.0358
2032	2.394	2.155	1.4005	1.21	0.192	0.0358
2033	2.376	2.138	1.3897	1.20	0.190	0.0358
2034	2.359	2.123	1.3801	1.19	0.189	0.0358
2035	2.345	2.110	1.3716	1.18	0.188	0.0358
2036	2.332	2.098	1.3640	1.18	0.187	0.0358
2037	2.320	2.088	1.3572	1.17	0.186	0.0358
2038	2.310	2.079	1.3512	1.17	0.185	0.0358
2039	2.300	2.070	1.3457	1.16	0.184	0.0358
2040	2.292	2.063	1.3409	1.16	0.183	0.0358

LearningCurve Analysis – Munich, Germany

Table 53F

Current solar PV system cost for Germany

1 Euro	1.31 US$
2014 System Cost Euro/W	1.64
2014 System Cost US$/W	2.15

Table 54F

Learning curve parameters used for Germany

PR	90%
LR	10%
Learning Parameter b	-0.152003093
Inflation	2%

Table 55F

Solar PV learning curve analysis working for Munich, Germany

Year	System Cost 2014 $/W	System cost minus 11% Inverter cost $/W 2014	Inverter $/W	Maintenance Cost 1% of 2015 System cost
2014	2.148			
2015	2.089	1.860	0.230	0.021
2016	2.040	1.815	0.224	0.021
2017	1.996	1.777	0.220	0.021
2018	1.957	1.742	0.215	0.021
2019	1.926	1.714	0.212	0.021
2020	1.898	1.689	0.209	0.021
2021	1.873	1.667	0.206	0.021
2022	1.851	1.647	0.204	0.021
2023	1.831	1.630	0.201	0.021
2024	1.814	1.614	0.200	0.021
2025	1.798	1.600	0.198	0.021
2026	1.784	1.588	0.196	0.021
2027	1.772	1.577	0.195	0.021
2028	1.761	1.567	0.194	0.021
2029	1.751	1.558	0.193	0.021
2030	1.742	1.551	0.192	0.021
2031	1.734	1.544	0.191	0.021
2032	1.727	1.537	0.190	0.021
2033	1.721	1.532	0.189	0.021
2034	1.715	1.527	0.189	0.021
2035	1.710	1.522	0.188	0.021
2036	1.706	1.518	0.188	0.021
2037	1.702	1.515	0.187	0.021
2038	1.698	1.511	0.187	0.021
2039	1.695	1.509	0.186	0.021
2040	1.692	1.506	0.186	0.021

Learning Curve Analysis – Hyderabad, Pakistan

Table 56F

Current solar PV system cost for Pakistan

1 PKR	0.0097 US$
2014 System Cost PKR/W	252.155
2014 System Cost US$/W	2.45

Table 57F

Learning curve parameters used for Pakistan

PR	85%
LR	15%
Learning Parameter b	-0.234465254
Inflation	11%

Table 58F

Solar PV learning curve analysis working for Hyderabad, Pakistan

Year	System Cost 2014 $/W	System cost minus 5.6% Inverter cost $/W 2014	Inverter $/W	Maintenance Cost 1% of 2015 System cost
2014	2.446			
2015	2.343	2.21	0.131	0.0234
2016	2.257	2.13	0.126	0.0234
2017	2.184	2.06	0.122	0.0234
2018	2.119	2.00	0.119	0.0234
2019	2.066	1.95	0.116	0.0234
2020	2.020	1.91	0.113	0.0234
2021	1.979	1.87	0.111	0.0234
2022	1.944	1.83	0.109	0.0234
2023	1.912	1.80	0.107	0.0234
2024	1.884	1.78	0.105	0.0234
2025	1.859	1.75	0.104	0.0234
2026	1.837	1.73	0.103	0.0234
2027	1.817	1.72	0.102	0.0234
2028	1.800	1.70	0.101	0.0234
2029	1.784	1.68	0.100	0.0234
2030	1.770	1.67	0.099	0.0234
2031	1.758	1.66	0.098	0.0234
2032	1.747	1.65	0.098	0.0234
2033	1.737	1.64	0.097	0.0234
2034	1.728	1.63	0.097	0.0234
2035	1.721	1.62	0.096	0.0234
2036	1.714	1.62	0.096	0.0234
2037	1.708	1.61	0.096	0.0234
2038	1.702	1.61	0.095	0.0234
2039	1.697	1.60	0.095	0.0234
2040	1.693	1.60	0.095	0.0234

Learning Curve Analysis – Johannesburg, South Africa

Table 59F

Current solar PV system cost for South Africa

1 ZAR Rand	0.091 US$
2014 System Cost ZAR/W	36.8
2014 System Cost US$/W	3.35

Table 60F

Learning curve parameters used for South Africa

PR	85%
LR	15%
Learning Parameter b	-0.234465254
Inflation	6%

Table 61F

Solar PV learning curve analysis working for Johannesburg, South Africa

Year	System Cost 2014 $/W	System cost minus 13% Inverter cost $/W 2014	Inverter $/W	Maintenance Cost 1% of 2015 System cost
2014	3.35			
2015	3.208	2.79	0.417	0.0321
2016	3.091	2.69	0.402	0.0321
2017	2.990	2.60	0.389	0.0321
2018	2.901	2.52	0.377	0.0321
2019	2.829	2.46	0.368	0.0321
2020	2.766	2.41	0.360	0.0321
2021	2.710	2.36	0.352	0.0321
2022	2.661	2.32	0.346	0.0321
2023	2.617	2.28	0.340	0.0321
2024	2.579	2.24	0.335	0.0321
2025	2.545	2.21	0.331	0.0321
2026	2.515	2.19	0.327	0.0321
2027	2.488	2.16	0.323	0.0321
2028	2.464	2.14	0.320	0.0321
2029	2.443	2.13	0.318	0.0321
2030	2.424	2.11	0.315	0.0321
2031	2.407	2.09	0.313	0.0321
2032	2.392	2.08	0.311	0.0321
2033	2.379	2.07	0.309	0.0321
2034	2.367	2.06	0.308	0.0321
2035	2.356	2.05	0.306	0.0321
2036	2.346	2.04	0.305	0.0321
2037	2.338	2.03	0.304	0.0321
2038	2.330	2.03	0.303	0.0321
2039	2.323	2.02	0.302	0.0321
2040	2.317	2.02	0.301	0.0321

Appendix G

Battery Price Working

The following tables show battery price working for each location. Figures in each table are from different sources. The final figures used in the analysis for a given location are the total average numbers for data from each of the sources.

Germany

Table 62G

Lead Acid battery price working - $/Wh for Germany

Lead Acid battery price	
2013 Euro/kWh	150
2014 Euro/kWh	153
2014 $/kWh	200.43
2014 $/Wh	0.200

Table 63G

Lead Acid battery price working - $/Wh for Germany

Battery Size AH	Voltage V	Battery Energy Wh	Price Euros	Euro/Wh	$/Wh
26	12	312	53.95	0.173	0.227
24	12	288	52.75	0.183	0.240
10	12	120	27.75	0.231	0.303
12	12	144	25.35	0.176	0.231
18	12	216	35.95	0.166	0.218
22	12	264	53.5	0.203	0.265
				Average	0.247

Source: http://www.reichelt.de/Lead-Acid-Batteries-12V-Kung-Long/2/index.html?&ACTION=2&LA=2&GROUP=P571&GROUPID=4232&START=0&OFFSET=16&SHOW=1;SID=14VAtX1n8AAAIAABc40ds163ed9ba9d1b7a3d253efa5035ac24c1

Table 64G

Current US battery prices in Euro/Wh. This is then converted to $/Wh

US Price	Euro/Wh	0.16
	$/Wh	0.210

Total Average: **0.219 $/Wh**

Pakistan

Table 65G

Lead Acid battery price working - $/Wh for Pakistan

Battery Size AH	Voltage V	Battery Energy Wh	Price PKR (2011)	Price PKR (2014)	Price US$ (2014)	$/Wh
200	12	2400	32,000	43,646.0	423.4	0.176
150	12	1800	24,500	33,416.5	324.1	0.180
120	12	1440	18,500	25,232.9	244.8	0.170
100	12	1200	15,500	21,141.0	205.1	0.171
55	12	660	12,000	16,367.3	158.8	0.241
					Average Price	0.188

Source: http://www.pakssolarpower.com/prices.html

Table 66G

Lead Acid battery price working - $/Wh for Pakistan

Battery Size AH	Voltage V	Battery Energy Wh	Price PKR	PKR/Wh	$/Wh
12	250	3000	52000	17.33	0.1681

Source: TSK Engineering Pvt. Limited

Table 67G

Lead Acid battery price working - $/Wh for Pakistan

Battery Size AH	Voltage V	Battery Energy Wh	Price PKR	PKR/Wh	$/Wh
100	12	1200	20000	16.67	0.162
135	12	1620	26000	16.05	0.156
150	12	1800	29000	16.11	0.156
200	12	2400	38000	15.83	0.154
250	12	3000	45000	15.00	0.146
				Average $/Wh	0.155

Source: TSK Engineering Pvt. Limited

Total Average: **0.170 $/Wh**

South Africa

Table 68G

Lead Acid battery price working - $/Wh for Pakistan

Voltage V	Battery Size AH	Battery Energy Wh	Price Rand (ZAR)	Rand/Wh	$/Wh
12	100	1200	4023	3.35	0.305
12	40	480	1199	2.50	0.227
12	100	1200	2504	2.09	0.190
12	120	1440	1846	1.28	0.117
12	100	1200	3179	2.65	0.241
				Average $/Wh	0.216

Source: http://www.pricecheck.co.za/search/?search=lead+acid+battery

Appendix H

German Standard Load Profile (SLP) Working

In order to de-normalize the Standard Load Profile (SLP) time series data, a typical German single household load profile (referred to as HLP here) obtained from (Gottwalt, Ketter, Block, Collins, & Weinhardt, 2011) is used.

The maximum and minimum load values from both the SLP and the HLP are used to de-normalize data using the following relation:

$$Load\ (i) = \ Min.HLP\ Load + \left[\frac{(Max.HLP\ Load\ \ - Min.HLP\ Load)}{(Max.SLP\ Load\ \ - Min.SLP\ Load)}\right] \times (SLP\ Load(i) - Min.SLP\ Load)$$

where $Load\ (i)$ and $SLP\ Load(i)$ correspond to the ith time series data entry.

With the following maximum and minimum values, a 102.115 kW SLP data entry, when de-normalized returns a load value of 0.305 kW. This is shown in the following working:

$$Min.HLP\ Load = 0.15\ kW \qquad Max.SLP\ Load = 240.17\ kW$$

$$Max.HLP\ Load = 0.72\ kW \qquad Min.SLP\ Load = 50.45\ kW$$

$$SLP\ Load(i) = 102.115\ kW$$

$$Load\ (i) = \ 0.15 + \left[\frac{(0.72\ \ - 0.15)}{(240.17\ \ - 50.45)}\right] \times (102.115 - 50.45) = 0.305\ kW$$

The same working is applied to each entry of the SLP to get the final load profile for Germany

Appendix I

Pakistan Temperature Time Series Data

The following table shows the average high and low monthly temperatures for Hyderabad, Pakistan, as reported by Hong Kong Observatory (Hong Kong Observatory , 2012).

Table 69I

Average High and Low temperature data for Hyderabad Sind obtained from Hong Kong Observatory

Month	Average High	Average Low
Jan	24.7	11.1
Feb	28.1	13.8
Mar	33.8	18.6
Apr	38.8	22.9
May	41.4	26.1
Jun	40.1	28
Jul	37.3	27.7
Aug	36	26.6
Sep	36.5	25.3
Oct	36.9	22.4
Nov	31	17.3
Dec	26	12.8

Source: http://www.hko.gov.hk/wxinfo/climat/world/eng/asia/westasia/hyderabad_e.htm

In order to translate this to an hourly temperature time series, average high and low temperatures are assumed to occur at fixed times throughout the year. This helps give starting points for splitting data into hourly series. The following hours of the day are chosen for the average high and low temperatures:

Average High Temperature = 2 PM (14:00 Hours)

Average Low Temperature = 4 AM (4:00 Hours)

The difference in the average high and low temperature values for each month is divided into hourly time steps using the following relation:

$$Temperature\ time\ step = \frac{(Avg.\ High\,Temperature - Avg.\ Low\,Temperature)}{Avg.\ High\,Temperature\ time - Avg.\ Low\,Temperature\ time}$$

$$= \frac{(H - L)}{(14 - 4)}$$

The resulting time step is then added for each hour between 4AM to 2PM, signifying a uniform hourly increase in temperature until the average high. From 2PM to 4AM, the same step is subtracted each hour to reflect a uniform fall in temperature until the average low.

The resulting hourly time series for a particular day of each month is then replicated for the entire month. Even though the approach makes the time series conservative, neglecting any highs and lows above or below the average figures respectively, it gives a good estimate. The following table shows the hourly data for single days in each month of the year. The values are replicated to populate the 8760 temperature time series for Pakistan

Table 70I

Constructed hourly temperature time series data for Hyderabad, Pakistan. This time series for a particular day in each month is then replicated for the entire month to get the annual hourly series

Hour	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
24	15.0	17.9	22.9	27.4	30.5	31.5	30.4	29.3	28.5	26.5	21.2	16.6
1	14.0	16.9	21.9	26.3	29.4	30.6	29.8	28.6	27.7	25.5	20.2	15.6
2	13.0	15.8	20.8	25.2	28.3	29.7	29.1	27.9	26.9	24.5	19.3	14.7
3	12.1	14.8	19.7	24.0	27.2	28.9	28.4	27.3	26.1	23.4	18.3	13.7
4	11.1	13.8	18.6	22.9	26.1	28	27.7	26.6	25.3	22.4	17.3	12.8
5	12.5	15.2	20.1	24.5	27.6	29.2	28.7	27.5	26.4	23.9	18.7	14.1
6	13.8	16.7	21.6	26.1	29.2	30.4	29.6	28.5	27.5	25.3	20.0	15.4
7	15.2	18.1	23.2	27.7	30.7	31.6	30.6	29.4	28.7	26.8	21.4	16.8
8	16.5	19.5	24.7	29.3	32.2	32.8	31.5	30.4	29.8	28.2	22.8	18.1
9	17.9	21.0	26.2	30.9	33.8	34.1	32.5	31.3	30.9	29.7	24.2	19.4
10	19.3	22.4	27.7	32.4	35.3	35.3	33.5	32.2	32.0	31.1	25.5	20.7
11	20.6	23.8	29.2	34.0	36.8	36.5	34.4	33.2	33.1	32.6	26.9	22.0
12	22.0	25.2	30.8	35.6	38.3	37.7	35.4	34.1	34.3	34.0	28.3	23.4
13	23.3	26.7	32.3	37.2	39.9	38.9	36.3	35.1	35.4	35.5	29.6	24.7
14	24.7	28.1	33.8	38.8	41.4	40.1	37.3	36	36.5	36.9	31	26
15	23.7	27.1	32.7	37.7	40.3	39.2	36.6	35.3	35.7	35.9	30.0	25.1
16	22.8	26.1	31.6	36.5	39.2	38.4	35.9	34.7	34.9	34.8	29.0	24.1
17	21.8	25.0	30.5	35.4	38.1	37.5	35.2	34.0	34.1	33.8	28.1	23.2
18	20.8	24.0	29.5	34.3	37.0	36.6	34.6	33.3	33.3	32.8	27.1	22.2
19	19.8	23.0	28.4	33.1	35.9	35.8	33.9	32.6	32.5	31.7	26.1	21.3
20	18.9	22.0	27.3	32.0	34.8	34.9	33.2	32.0	31.7	30.7	25.1	20.3
21	17.9	21.0	26.2	30.9	33.8	34.1	32.5	31.3	30.9	29.7	24.2	19.4
22	16.9	19.9	25.1	29.7	32.7	33.2	31.8	30.6	30.1	28.6	23.2	18.5
23	16.0	18.9	24.0	28.6	31.6	32.3	31.1	30.0	29.3	27.6	22.2	17.5

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Appendix J

Electricity Retail Price Projection Figures

The following tables show the retail electricity price projection working for all locations. For recent trends, data is extrapolated up until 2040. Government trends are obtained from various government sources.

United States

The recent trend used is from 2006 onwards. Data is obtained from the EIA.

Table 71J

US recent retail electricity prices 2006-2013

Year	2006	2007	2008	2009	2010	2011	2012	2013
LCOE cent/kWh	9.34	9.57	10.06	10.67	11.31	11.42	11.76	11.91
LCOE $/kWh	0.093	0.096	0.101	0.107	0.113	0.114	0.118	0.119
LCOE 2014 $/kWh	0.109	0.110	0.113	0.118	0.122	0.121	0.122	0.121

Source: Energy Information Administration, US

This trend is extrapolated in MATLAB using the curve fitting tool. The following snapshots show this working.

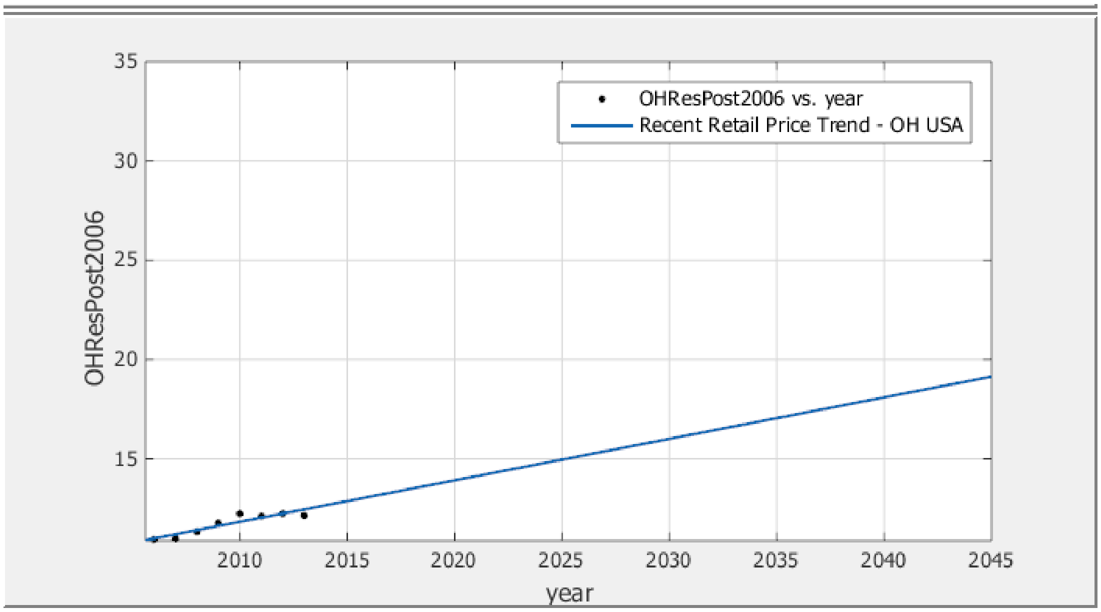
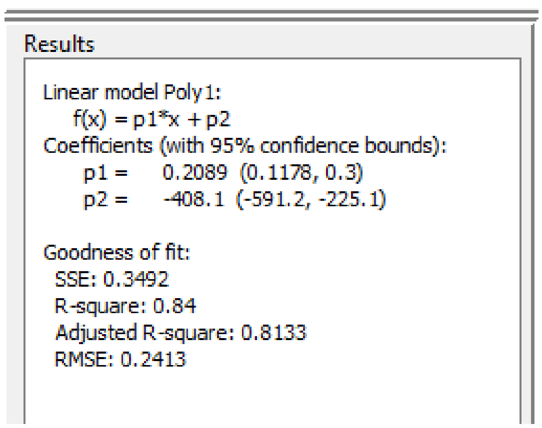


Figure 10J. Extrapolated recent real electricity price trend in the US using the MATLAB curve fitting tool


Results

Linear model Poly1:
f(x) = p1*x + p2
Coefficients (with 95% confidence bounds):
p1 = 0.2089 (0.1178, 0.3)
p2 = -408.1 (-591.2, -225.1)

Goodness of fit:
SSE: 0.3492
R-square: 0.84
Adjusted R-square: 0.8133
RMSE: 0.2413

Figure 11J. MATLAB curve fitting results for recent real electricity price extrapolation for the US

The trend line equation is used to determine the final price trend up until the year 2040. For the Government trend, price projections done by the EIA for the US are used as is. Examining past data, residential electricity prices for Ohio are reflective of the US electricity prices. Therefore the US figures are used.

Germany

Data from (Schlesinger, Dietmar, & Lutz, 2014) gives the government projection figures.

Table 72J

Government future estimates of real grid electricity prices in Germany

Year	2011 Euro/MWh	2011 Euro/kWh	2014 Euro/kWh	2014 $/kWh
2011	259	0.259	0.2749	0.360
2015	273.7	0.274	0.290	0.380
2020	292	0.292	0.3099	0.406
2025	312	0.312	0.3311	0.434
2030	284	0.284	0.3014	0.395
2035	280	0.280	0.2971	0.389
2040	276	0.276	0.2929	0.384

For recent trends, similar to the US, historical prices from 2003 onwards obtained from Eurostat, are extrapolated using MATLAB. The trend line obtained is used to extrapolate figures.

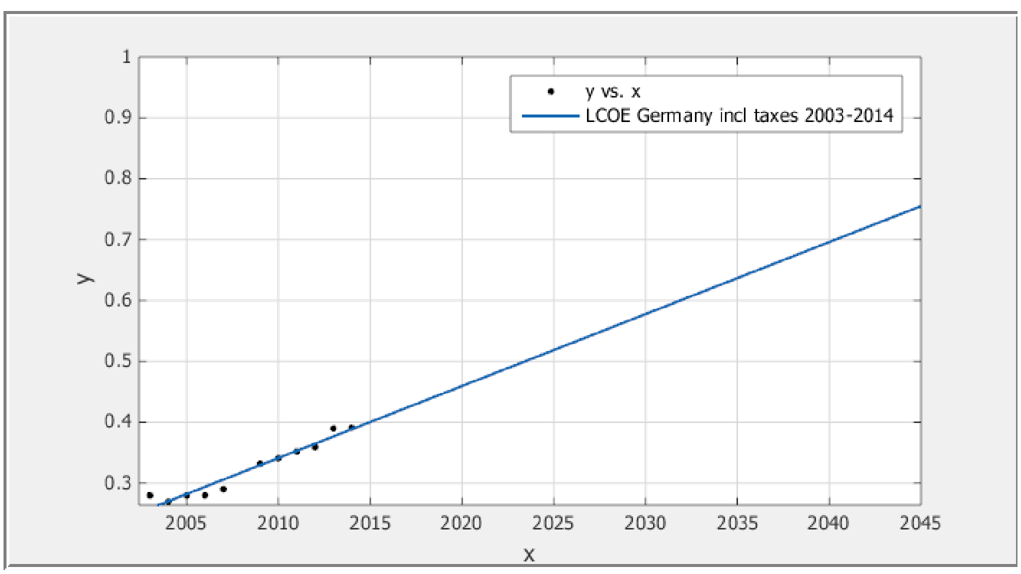


Figure 12J. Extrapolated recent real electricity price trend for Germany using MATLAB

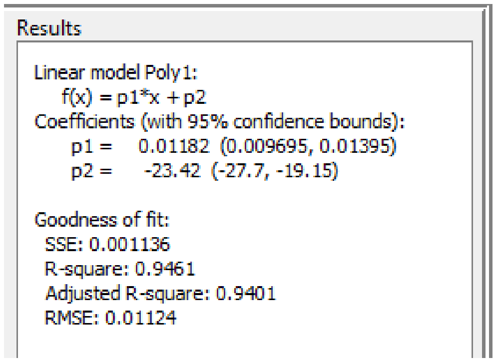


Figure 13J. MATLAB curve fitting results for recent real electricity price extrapolation for Germany

The final projected values from the trend line are as follows:

Table 73J

Extrapolated recent real electricity prices for Germany

Year	Recent Price Trend $2014/kWh
2015	0.397
2020	0.456
2025	0.515
2030	0.575
2035	0.634
2040	0.693

Pakistan

The following table summarizes the working behind the two edges of the parity region for Pakistan.

Table 74J

Projection working for recent trend and government estimates of real grid electricity prices in Pakistan. These are used to calculate the effective costs of the unreliable grid

Year	Recent Real % Increase	Recent Price Trend PKR/kWh	NTDC Projected Real % Increase	NTDC Govt. Projection PKR/kWh	Recent trend 2014 $/kWh	Govt. Trend 2014 $/kWh
2014	9%	14.9	2.20%	13.97	0.145	0.136
2015	9%	16.2	2.20%	14.28	0.158	0.139
2016	9%	17.7	2.20%	14.60	0.172	0.142
2017	9%	19.3	2.20%	14.92	0.187	0.145
2018	9%	21.0	2.20%	15.25	0.204	0.148
2019	9%	22.9	2.20%	15.58	0.222	0.151
2020	9%	25.0	2.20%	15.92	0.242	0.154
2021	9%	27.2	1.10%	16.10	0.264	0.156
2022	9%	29.7	1.10%	16.28	0.288	0.158
2023	9%	32.4	1.10%	16.46	0.314	0.160
2024	9%	35.3	1.10%	16.64	0.342	0.161
2025	9%	38.5	1.10%	16.82	0.373	0.163
2026	9%	41.9	1.10%	17.00	0.407	0.165
2027	9%	45.7	1.10%	17.19	0.443	0.167
2028	9%	49.8	1.10%	17.38	0.483	0.169
2029	9%	54.3	1.10%	17.57	0.527	0.170
2030	9%	59.2	0%	17.57	0.574	0.170
2031	9%	64.5	0%	17.57	0.626	0.170
2032	9%	70.3	0%	17.57	0.682	0.170
2033	9%	76.6	0%	17.57	0.743	0.170
2034	9%	83.5	0%	17.57	0.810	0.170
2035	9%	91.0	0%	17.57	0.883	0.170
2036	9%	99.2	0%	17.57	0.963	0.170
2037	9%	108.2	0%	17.57	1.049	0.170
2038	9%	117.9	0%	17.57	1.144	0.170
2039	9%	128.5	0%	17.57	1.247	0.170
2040	9%	140.1	0%	17.57	1.359	0.170

South Africa

Using the 2013 price figure of 9.1 cents/kWh as a basis, the price trend from the years 2008 - 2013 is extrapolated to determine the recent price trend projection for South Africa using MATLAB. The figure below shows a snapshot of the extrapolated curve.

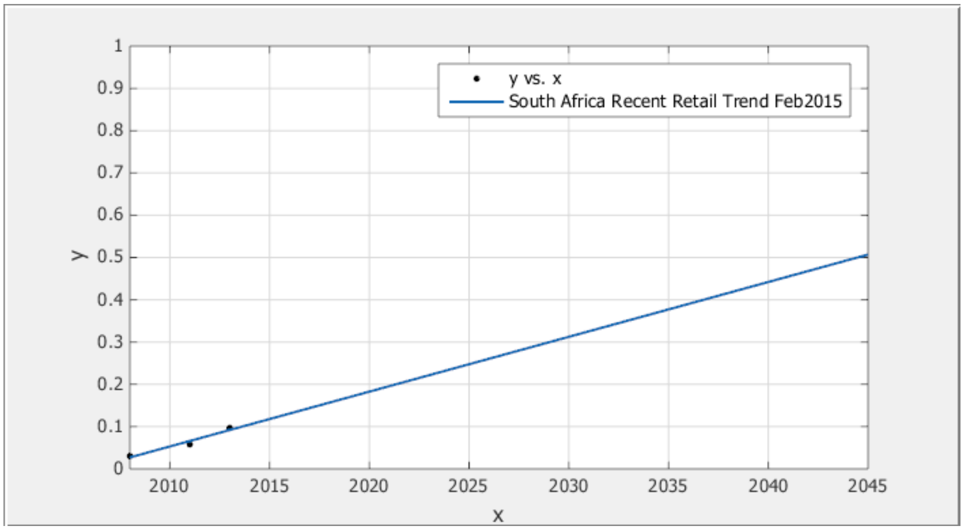


Figure14J. Extrapolated recent real electricity price trend for South Africa using MATLAB

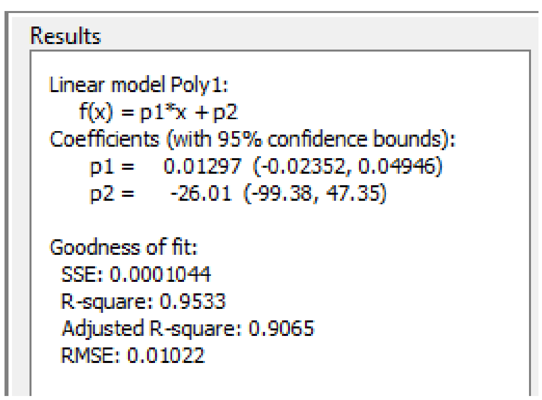


Figure 15J. MATLAB curve fitting results for recent real electricity price extrapolation for South Africa

Table 75J

Extrapolated recent real electricity prices for South Africa

Year	Recent Trend 2014 $/kWh
2015	0.125
2020	0.189
2025	0.254
2030	0.319
2035	0.384
2040	0.449

The government price projections use a 12.59% annual increase up until 2040. The same 2013 base price figure is used in this case. It is important to note that in most cases, price figures available are those charged by ESKOM. The local municipality adds on average around 5-6 South African cents/kWh (Trollip, Butler, Burton, Caetano, & Godinho, 2014) to these rates to cover for operational costs. A nominal 6 South African cents figure is added to the prices to prevent any over estimation of the final price figure. The following table shows this working.

Table 76J

Projection working for government future estimates of real grid electricity prices in South Africa

Year	Nominal Govt. Approved % increase	Nominal cents/kWh ESKOM rates	Nominal cents/kWh Muni rates	Real 2014 cents/kWh	Real 2014 Rand/kWh	Real 2014 US$/kWh
2013		94.00	100.00	106.46	1.06	0.097
2014	8%	101.52	107.52	107.52	1.08	0.098
2015	12.59%	114.30	120.30	113.00	1.13	0.103
2016	12.59%	128.69	134.69	118.84	1.19	0.108
2017	12.59%	144.89	150.89	125.06	1.25	0.114
2018	12.59%	163.14	169.14	131.67	1.32	0.120
2019	12.59%	183.68	189.68	138.70	1.39	0.126
2020	12.59%	206.80	212.80	146.17	1.46	0.133
2021	12.59%	232.84	238.84	154.10	1.54	0.140
2022	12.59%	262.15	268.15	162.51	1.63	0.148
2023	12.59%	295.15	301.15	171.44	1.71	0.156
2024	12.59%	332.31	338.31	180.91	1.81	0.165
2025	12.59%	374.15	380.15	190.94	1.91	0.174
2026	12.59%	421.26	427.26	201.58	2.02	0.183
2027	12.59%	474.30	480.30	212.86	2.13	0.194
2028	12.59%	534.01	540.01	224.80	2.25	0.205
2029	12.59%	601.24	607.24	237.45	2.37	0.216
2030	12.59%	676.94	682.94	250.84	2.51	0.228
2031	12.59%	762.16	768.16	265.02	2.65	0.241
2032	12.59%	858.12	864.12	280.04	2.80	0.255
2033	12.59%	966.16	972.16	295.93	2.96	0.269
2034	12.59%	1087.80	1093.80	312.76	3.13	0.285
2035	12.59%	1224.75	1230.75	330.56	3.31	0.301
2036	12.59%	1378.95	1384.95	349.41	3.49	0.318
2037	12.59%	1552.56	1558.56	369.35	3.69	0.336
2038	12.59%	1748.02	1754.02	390.45	3.90	0.355
2039	12.59%	1968.10	1974.10	412.77	4.13	0.376
2040	12.59%	2215.88	2221.88	436.39	4.36	0.397

Appendix K

Cost of Reliability Working for Pakistan and South Africa

Battery back-up scenario

The following relations are used to determine the cost of reliability for power grids in Pakistan and South Africa. Since such costs cannot be simply added, the LCOE needs to be calculated using the load shedding pattern for the entire year.

The following table summarizes data that may be used to incorporate this reliability cost to the final price figures.

Table 77K

ESM system operation statistics obtained from modelling an unreliable grid using the solar PV output as the grid and a battery back-up system for Pakistan

Total Energy Required	418655.71 kWh
Available Grid Energy	175747.98 kWh
ESM LCOE	0.295 $/kWh
Energy lost in Charging	194315.39 kWh

The following working uses 2015 figures for Pakistan as an example to demonstrate the mathematics behind the final numbers. Similar working is done for other years and for South Africa to determine the final cost of unreliable power to the end consumers with a battery back-up option.

For the case of a battery-backup, the LCOE obtained from the ESM can be expressed mathematically as:

$$LCOE_{ESM} = \frac{Cost_{\ batt}}{kWh_{batt} + kWh_{PV}}$$

The following table shows this comes out to be 0.295 $/kWh. This relation helps determine the cost of power output from the battery such that:

$$Cost_{\ batt} = \ LCOE_{ESM} \ \times \ (kWh_{batt} + kWh_{PV}) = 0.295 \ \times (418655.71) = \$\ 123503.4$$

It is important to highlight that the above $LCOE_{ESM}$ result cannot be directly added to the retail price since in this case there are multiple power sources that help meet the load (grid and batteries). Therefore, instead of simple addition, both need to be normalized to a new LCOE figure which may capture the proportions in which these sources supply power.

The above relation also shows that it only accounts for the energy supplied by the battery as output and does not include any costs of energy lost during battery charging. For the battery back-up, the load is met from the grid and the batteries. Part of the energy stored in the batteries is lost, the cost of which should be accounted for as well because batteries are charged using power from the grid. Using ESM output operation time series of the system, the net energy in and out of the system is determined to be 194.32 kWh, as shown in the table above. The cost associated with this energy lost in batteries is determined by the relation:

$$Cost_{lost} = Retail\ Price\ \left(\frac{\$}{kWh}\right) \times Energy\ Lost(kWh)$$

$$Cost_{lost2015} = 0.158\ \times 194315.39 = \$30701.83$$

Using these figures for batteries, the cost of substitute power from the battery during outages can be determined using the relation:

$$Cost_{sub\_batt} = \frac{Cost_{\ batt} + \ Cost_{\ lost}}{kWh_{batt}}$$

$$Cost_{sub\_batt} = \frac{\$123503.4 + \$30701.83}{242907.73\ kWh} = 0.634\ \$/kWh$$

The cost of energy from the grid can then be determined from the total energy supplied by the grid (i.e. 175747.98 kWh from the above table) using the relation (for the recent trend trajectory):

$$Cost_{grid} = Retail\ Price\ \left(\frac{\$}{kWh}\right) \times Energy\ Supplied\ by\ the\ grid(kWh)$$

$$Cost_{grid2015} = 0.158\ \times 175747.98 = \$27768.18$$

The final LCOE is then determined by

$$LCOE_{batt} = \frac{Cost_{grid} + Cost_{batt} + Cost_{lost}}{kWh_{total}}$$

$$LCOE_{batt2015} = \frac{\$27768.18 + \$30701.83 + \$123503.4}{418655.71\ kWh} = 0.435\ \$/kWh$$

The following tables show results for the battery back-up option for both countries. These correspond to the recent and government estimate edges of the parity region used in the analysis.

Pakistan

Table 78K

Future estimates of the effective cost of unreliable power based off of recent price trends in Pakistan. Figures are for a battery back-up system. These form the recent trend edge of the parity region

Retail Price Recent Trend	2015	2020	2025	2030	2035	2040
Battery costs	123,587.16	123,587.16	123,587.16	123,587.16	123,587.16	123,587.16
Cost of energy lost	30,701.83	47,024.33	72,479.64	111,537.04	171,580.49	264,074.62
Cost of grid power	27,768.18	42,531.01	65,554.00	100,879.34	155,185.47	238,841.51
Total kWh	418655.71	418655.71	418655.71	418655.71	418655.71	418655.71
Final LCOE	0.435	0.509	0.625	0.803	1.076	1.496

Table 79K

Future estimates of the effective cost of unreliable power based off of government price estimates in Pakistan. Figures are for a battery back-up system. These form the government estimate edge of the parity region

Retail Price Govt. Trend	2015	2020	2025	2030	2035	2040
Battery costs	123,587.16	123,587.16	123,587.16	123,587.16	123,587.16	123,587.16
Cost of energy lost	27,009.84	29,924.57	31,673.41	33,033.62	33,033.62	33,033.62
Cost of grid power	24,428.97	27,065.19	28,646.92	29,877.16	29,877.16	29,877.16
Total kWh	418655.71	418655.71	418655.71	418655.71	418655.71	418655.71
Final LCOE	0.418	0.431	0.439	0.445	0.445	0.445

South Africa

Table 80K

ESM system operation statistics obtained from modelling an unreliable grid using the solar PV output as the grid and a battery back-up system for South Africa

Total Energy Required	516474.97 kWh
Available Grid Energy	489712.87 kWh
ESM LCOE	0.084 $/kWh
Energy Lost in Charging	10112.16 kWh

Table 81K

Future estimates of the effective cost of unreliable power based off of recent price trends in South Africa. Figures are for a battery back-up system. These form the recent trend edge of the parity region

Retail Price Recent Trend	2015	2020	2025	2030	2035	2040
Battery costs	43,487.19	43,487.19	43,487.19	43,487.19	43,487.19	43,487.19
Cost of energy lost	1,264.02	1,911.20	2,568.49	3,225.78	3,883.07	4,540.36
Cost of grid power	61,214.11	92,555.73	124,387.07	156,218.40	188,049.74	219,881.08
Total kWh	516474.97	516474.97	516474.97	516474.97	516474.97	516474.97
Final LCOE	0.205	0.267	0.330	0.393	0.456	0.519

Table 82K

Future estimates of the effective cost of unreliable power based off of government price estimates in South Africa. Figures are for a battery back-up system. These form the government estimate edge of the parity region

Retail Price Govt. Trend	2015	2020	2025	2030	2035	2040
Battery costs	43,487.19	43,487.19	43,487.19	43,487.19	43,487.19	43,487.19
Cost of energy lost	1,041.55	1,344.92	1,759.52	2,305.57	3,043.76	4,014.53
Cost of grid power	50,440.43	65,131.81	85,210.04	111,654.53	147,403.57	194,416.01
Total kWh	516474.97	516474.97	516474.97	516474.97	516474.97	516474.97
Final LCOE	0.184	0.213	0.253	0.305	0.375	0.468

Generator back-up scenario

For a generator back-up, a similar approach is adopted. However, since there is no energy storage involved in a diesel generator, there is no energy lost component to be considered. The following table summarizes the energy statistics obtained from the ESM for Pakistan.

Table 83K

ESM system operation statistics obtained from modelling an unreliable grid using the solar PV output as the grid and a generator back-up system for Pakistan

Total Energy Required	418655.71 kWh
Available Grid Energy	175747.98 kWh
Total Energy Supplied by Generator	242907.73 kWh

As discussed for the case of batteries, the final LCOE can be obtained from the following relation:

$$LCOE_{gen} = \frac{Cost_{grid} + Cost_{gen}}{kWh_{total}}$$

Similar to batteries, the $Cost_{gen}$ component of the final LCOE can be determined from the relation:

$$LCOE_{ESM} = \frac{Cost\ _{gen}}{kWh_{gen} + kWh_{grid}}$$

Using the same 2015 case for Pakistan, and data from table:

$$Cost\ _{gen2015} = \ LCOE_{ESM2015}\ \times \left(kWh_{gen} + kWh_{PV}\right) = 0.398\frac{\$}{kWh} \times 418655.7kWh = \$166499.4$$

Using this figure, the cost of substitute power from the diesel generator can during outages can be determined using the relation:

$$Cost_{sub\_gen} = \frac{Cost\ _{gen}}{kWh_{gen}}$$

$$Cost_{sub\_gen2015} = \frac{\$166499.4}{242907.73\ kWh} = 0.685\ \$/kWh$$

It is important to note here that unlike battery prices (which are assumed to be constant in real 2014 dollars throughout the analysis), diesel fuel prices change, so that the $LCOE_{ESM2015}$

figure is different for different years. Hence the $Cost_{gen}$ figure is also different for different years.

The cost of energy from the grid can be determined from the energy supplied by the grid (i.e. 175747.98 kWh from the above table) using the relation (the following just considers the grid electricity price for the recent trend trajectory):

$$Cost_{grid} = Retail\ Price\left(\frac{\$}{kWh}\right) \times Energy\ Supplied\ by\ the\ grid(kWh)$$

$$Cost_{grid2015} = 0.158 \times 175747.98 = \$27768.18$$

The final LCOE is then determined by

$$LCOE_{gen} = \frac{Cost_{grid} + Cost_{gen}}{kWh_{total}}$$

$$LCOE_{gen2015} = \frac{\$27768.18 + \$166499.4}{418655.7\ kWh} = 0.464\ \$/kWh$$

Similar working helps get the following results for both government and recent retail price projections for the two countries.

Pakistan

Table 84K

ESM system operation statistics obtained from modelling an unreliable grid using the solar PV output as the grid and a generator back-up system for Pakistan

Total Energy Required	418655.71 kWh
Available Grid Energy	175747.98 kWh
Total Energy Supplied by Generator	242907.73 kWh

Table 85K

Future estimates of the effective cost of unreliable power based off of recent price trends in Pakistan. Figures are for a generator back-up system. These form the recent trend edge of the parity region

Retail Price Recent Trend	2015	2020	2025	2030	2035	2040
Generator Costs	166,499.37	173,951.45	188,897.45	200,829.14	214,267.99	227,706.84
Cost of grid power	27,768.18	42,531.01	65,554.00	100,879.34	155,185.47	238,841.51
Total kWh	418655.71	418655.71	418655.71	418655.71	418655.71	418655.71
Final LCOE	0.464	0.517	0.608	0.721	0.882	1.114

Table 86K

Future estimates of the effective cost of unreliable power based off of government price estimates in Pakistan. Figures are for a battery back-up system. These form the government estimate edge of the parity region

Retail Price Govt. Trend	2015	2020	2025	2030	2035	2040
Generator costs	166,499.37	173,951.45	188,897.45	200,829.14	214,267.99	227,706.84
Cost of grid power	24,428.97	27,065.19	28,646.92	29,877.16	29,877.16	29,877.16
Total kWh	418655.71	418655.71	418655.71	418655.71	418655.71	418655.71
Final LCOE	0.456	0.480	0.520	0.551	0.583	0.615

South Africa

Table 87K

ESM system operation statistics obtained from modelling an unreliable grid using the solar PV output as the grid and a generator back-up system for South Africa

Total Energy Required	516474.97 kWh
Total Energy Supplied by Generator	26762.10 kWh
Available Grid Energy	489712.87 kWh

Table 88K

Future estimates of the effective cost of unreliable power based off of recent grid price trends in South Africa. Figures are for a generator back-up system. These form the government estimate edge of the parity region

Retail Price Recent Trend	2015	2020	2025	2030	2035	2040
Generator Costs	21,433.71	21,898.54	23,241.37	24,222.68	25,358.92	26,443.52
Cost of grid power	61,214.11	92,555.73	124,387.07	156,218.40	188,049.74	219,881.08
Total kWh	516474.97	516474.97	516474.97	516474.97	516474.97	516474.97
Final LCOE	0.160	0.222	0.286	0.349	0.413	0.477

Table 89K

Future estimates of the effective cost of unreliable power based off of government price estimates in South Africa. Figures are for a generator back-up system. These form the government estimate edge of the parity region

Retail Price Govt. Trend	2015	2020	2025	2030	2035	2040
Generator Costs	21,433.71	21,898.54	23,241.37	24,222.68	25,358.92	26,443.52
Cost of grid power	50,440.43	65,131.81	85,210.04	111,654.53	147,403.57	194,416.01
Total kWh	516474.97	516474.97	516474.97	516474.97	516474.97	516474.97
Final LCOE	0.139	0.169	0.210	0.263	0.335	0.428

Appendix L

Diesel Price Sensitivity Analysis Working

For diesel price sensitivity, the upper and lower bounds chosen are:

- No price increase so that the real $2014 price continues up until 2014
- Price increase at a rate double that of the current rise in prices over time

The following tables show results for all three diesel price trajectories at the four locations.

United States

Table 90L

Diesel fuel price sensitivity working for the US. In each case, the low end represents no increase in current real fuel prices. The high end depicts twice the increase in real prices compared to the estimated trend in the base case

	2015	2020	2025	2030	2035	2040
Base Case	0.84	0.87	0.95	1.02	1.09	1.16
Base Case % change		4.2%	9.6%	6.5%	7.1%	6.7%
2x Base Case % change		8.4%	19.3%	13.1%	14.2%	13.3%
Double Change	0.84	0.91	1.08	1.22	1.40	1.58
No Change	0.84	0.84	0.84	0.84	0.84	0.84

Germany

Table 91L

Diesel fuel price sensitivity working for Germany. In each case, the low end represents no increase in current real fuel prices. The high end depicts twice the increase in real prices compared to the estimated trend in the base case

	2015	2020	2025	2030	2035	2040
Base Case	1.23	1.35	1.44	1.56	1.70	1.85
Base Case % change		9.6%	7.0%	7.9%	9.3%	8.5%
2x Base Case % change		19.2%	14.0%	15.7%	18.6%	17.0%
Double Change	1.230	1.47	1.67	1.93	2.29	2.69
No Change	1.230	1.230	1.230	1.230	1.230	1.230

Pakistan

Table 92L

Diesel fuel price sensitivity working for Pakistan. In each case, the low end represents no increase in current real fuel prices. The high end depicts twice the increase in real prices compared to the estimated trend in the base case

	2015	2020	2025	2030	2035	2040
Base Case	1.051	1.095	1.201	1.280	1.372	1.463
Base Case % change		4.2%	9.7%	6.6%	7.1%	6.7%
2 x Base Case % Change		8.5%	19.4%	13.1%	14.3%	13.4%
Double Change	1.051	1.14	1.36	1.54	1.76	1.99
No Change	1.051	1.051	1.051	1.051	1.051	1.051

South Africa

Table 93L

Diesel fuel price sensitivity working for South Africa. In each case, the low end represents no increase in current real fuel prices. The high end depicts twice the increase in real prices compared to the estimated trend in the base case

	2015	2020	2025	2030	2035	2040
Base Case	1.06	1.10	1.21	1.29	1.38	1.47
Base Case % change		4.2%	9.7%	6.6%	7.1%	6.7%
2 x Base Case % Change		8.5%	19.4%	13.1%	14.3%	13.4%
Double Change	1.06	1.15	1.37	1.55	1.78	2.01
No Change	1.06	1.06	1.06	1.06	1.06	1.06