Microgrid Utilities for Rural Electrification in East Africa: Challenges and Opportunities

Submitted in partial fulfillment of the requirements for

the degree of

Doctor of Philosophy

in

Engineering and Public Policy

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May, 2017

Dedication

To my wife, Mihloti, and my parents, Kurt and Brenda.

Acknowledgements

I would like to thank my advisor, Paulina Jaramillo, for her guidance and support during my PhD studies. In addition, I would like to acknowledge the contributions of the rest of my committee, Jay Taneja, Tim Brown, and Eric Hittinger. In particular, I would like to note my appreciation of the close collaboration and frequent discussions with Jay who is a co-author of two already published works and another that is under review. Thanks are also due to Alex Davis whose advice on the statistical modeling in Chapter 5 was invaluable.

The entire faculty and staff of the Carnegie Mellon University – Africa campus are due my gratitude for several productive visits during my studies. In particular, I would like to thank Bruce Krogh, Tim Brown, and Taha Selim Ustun. I am grateful to Selim for his encouragement early on to publish a review paper that helped me frame my research going forward. Bruce opened many doors for me in Rwanda and beyond, in particular by funding my initial visit to Rwanda through his Scott Institute grant. This trip allowed me to collect important data from the Rwanda Energy Group, who I gratefully acknowledge.

The Infrastructure Systems for Global Development group and its members were a great help in developing my thinking around issues of infrastructure and development and providing critical feedback on my work. In particular, I would like to thank Chukwudi Udeani, Jesse Thornburg, Rebecca Ciez, Jeremy Keen, Brian Sergi, Aviva Loew, and Matt Babcock.

A special thanks is due to PowerGen Renewable Energy for their generosity and enthusiasm in providing data and their precious time. I am appreciative of the collaborative efforts of Ben

Cornell, Isaiah Lyons-Galante, and Ella Wynn in developing the predictive demand model in Chapter 5. I am especially grateful to the PowerGen survey and community engagement team, Enosy, Daniel, and James, for allowing me to observe their work in the field and helping me out of a sticky situation.

I would like to acknowledge the financial support from the Carnegie Mellon University College of Engineering, the Department of Engineering and Public Policy, and the Scott Institute for Energy Innovation.

Finally, I would like to thank my wife, Mihloti, my parents, Kurt and Brenda, and my grandparents, Ebby and Jean, for their continued support and patience during my long academic journey.

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Abstract

Expanding access to electricity is central to development in East Africa but massive increases in investment are required to achieve universal access. Private sector participation in electrification is essential to meeting electricity access targets. Policy makers have acknowledged that grid extension in many remote rural areas is not as cost effective as decentralized alternatives such as microgrids. Microgrid companies have been unable to scale beyond pilot projects due in part to challenges in raising capital for a business model that is perceived to be risky. This thesis aims to identify and quantify the primary sources of investment risk in microgrid utilities and study ways to mitigate these risks to make these businesses more viable. Two modeling tools have been developed to this end. The Stochastic Techno-Economic Microgrid Model (STEMM) models the technical and financial performance of microgrid utilities using uncertain and dynamic inputs to permit explicit modeling of financial risk. This model is applied in an investment risk assessment and case study in Rwanda. Key findings suggest that the most important drivers of risk are fuel prices, foreign exchange rates, demand for electricity, and price elasticity of demand for electricity. The relative importance of these factors is technology dependent with demand uncertainty figuring stronger for solar and high solar penetration hybrid systems and fuel prices driving risk in diesel power and low solar penetration hybrid systems. Considering uncertainty in system sizing presents a tradeoff whereby a decrease in expected equity return decreases downside risk. High solar penetration systems are also found to be more attractive to lenders.
The second modeling tool leverages electricity consumption and demographic data from four microgrids in Tanzania to forecast demand for electricity in newly electrified communities.
Using statistical learning techniques, improvements in prediction performance was achieved over the historical mean baseline. I have also identified important predictors in estimating electricity

consumption of newly connected customers. These include tariff structures and prices, pre-connection sources of electricity and lighting, levels of spending on electricity services and airtime, and pre-connection appliance ownership. Prior exposure to electricity, disposable income, and price are dominant factors in estimating demand.

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1 Introduction

Access to affordable and high quality electricity is essential for the development of modern economies. Low rates of electricity access in the developing world pose a significant barrier to sustainable economic and social development, particularly in rural areas. Yet the International Energy Agency (IEA) estimates that about 1.3 billion people in the world, primarily in South Asia and Sub-Saharan Africa, still lack a connection to electricity [1].

Electricity access has been linked to many positive developmental and welfare benefits including greater economic opportunities and increased income, higher quality of life and access to information, improved health, and greater educational attainment [2]-[9]. Lack of electricity in rural communities has also been linked to disparities in regional development within countries and increased rural to urban migration, thus putting further stress on already strained urban infrastructure systems [10]-[12]. For this reason, access to electricity has taken greater prominence in recent years on the global development agenda.

State-owned utilities have traditionally carried out electrification projects driven by a mandate to expand social access to electricity services. Power sector reforms in the 1990s, advocated by organizations such as the World Bank, led to the commercialization and privatization of many state-owned utilities. This led to a shift in the treatment of electricity from a social service to a commodity [13]. Because rural electrification projects are rarely economically attractive, power sector reforms generally has a negative effect on electrification activities [14]. In some cases, countries have seen the number of people without access actually increase as population growth in unelectrified areas exceeded the number of new connections [15].

More recently, many countries have recognized that if electricity access is to be expanded into rural areas, resources need to be allocated for projects of a social rather than a commercial nature [14]. This has led to the establishment of dedicated rural electrification agencies whose mandates are to expand access to electricity for the purpose of long-term social and economic development [16]. Limited public and donor funds, however, have proven insufficient to meet the aggressive access goals that governments and international organizations have set. Increasing attention has now focused on how to encourage the private sector to invest in electricity access projects in developing countries. Because of the typically unattractive risk-return profiles of these investments, efforts to accelerate access by securing private capital have been largely unsuccessful [17]. As a result, several scholars have pointed out the need for greater academic work exploring barriers and solutions to unlocking private sector investment in electrification activities [18], [19].

In the absence of legacy systems, many developing countries have the opportunity to leverage decades of technological advancement and experience in developed countries as they build innovative modern infrastructure systems. Microgrids, small electricity networks that have the ability to operate autonomously, can play a key role in developing an electricity infrastructure built around decentralized renewable energy technologies. At the same time, microgrids can accelerate electricity access to areas the central electricity grid cannot reach in the short to medium term. As these microgrids develop, they can be easily interconnected, creating a decentralized network that can aggregate loads and generation capacity, while maintaining the ability to operate as isolated systems should the need arise. Many developed nations are now devoting significant resources to retrofit existing infrastructure and permit the integration of decentralized technologies [20]. Countries with underdeveloped electricity systems are well positioned to leapfrog outdated centralized approaches.

Many of the barriers to private sector investment in microgrid utilities are related to perceived high levels of risk and uncertainty about key inputs into microgrid financial models. This thesis identifies key drivers of risk in microgrid business models and ways to mitigate these risks through system design using a tool called the Stochastic Techno-Economic Microgrid Model (STEMM). Demand for electricity in as yet unelectrified communities is among the important sources of risk identified. Using data from PowerGen Renewable Energy, a developer of microgrid utilities in East Africa, this thesis also develops a predictive model of demand for electricity for electrified businesses and households.

Chapters 1 and 2 are based on a paper, *Enabling private sector investment in microgrid-based rural electrification in developing countries: A review*, published in Renewable and Sustainable Energy Reviews [21]. These chapters present a review of the benefits of the microgrid-based electrification, barriers to attracting capital into the sector, and potential policies and business models to overcome these challenges. Chapter 3 develops the modeling tool, STEMM, and applies the model to perform a risk assessment of microgrid utilities in four technology scenarios. Chapter 4, based on a paper presented at the 2016 IEEE PowerAfrica Conference in Livingstone, Zambia [22], applies STEMM to study the sizing of hybrid diesel/solar/battery microgrids under uncertainty. Chapter 5 presents a predictive model of electricity demand using consumption and demographic data from four PowerGen micgrogrids in Tanzania using various statistical learning techniques. Chapter 6 concludes the thesis with a discussion of the implications of this work as well as recommendations for future work.

2 Enabling Private Sector Investment in Microgrid-based Rural Electrification in Developing Countries: A Review

This chapter examines the benefits of and the challenges faced by private sector participation in the deployment of microgrids for rural electrification in developing countries. It further explores various solutions that have been proposed and tested to unlock the potential for private sector-driven microgrid-based electricity access projects. The chapter is intended to provide a global perspective with an understanding that many solutions are very context-specific and must consider unique geographical and cultural conditions.

2.1.1 Advantages of Microgrid Electrification

The decentralized nature of microgrids is viewed as having several inherent advantages over traditional centralized infrastructure. These advantages include improved economics, technical performance, environmental sustainability, and regional equity in the context of rural electrification. In many countries, the reach of the electricity grid is extremely limited and almost exclusively serves urban areas. Sub-Saharan Africa is a prime example of electricity access disparity between rural and urban communities. The World Energy Outlook 2011 [23] reports the urban electrification rate in this region is 59.9% whereas the rural access rate is only 14.2%. Without a decentralized approach to expanding access, many communities located far from existing grid infrastructure will be left in the dark for decades to come.

The proximity of load to generation in a microgrid is also an economic advantage. While it may be technically feasible to pursue an entirely grid-based electrification program, several studies have found that the cost of building distribution and transmission infrastructure to deliver power from centralized power stations often exceeds the cost of decentralized solutions. The low levels of rural electricity demand and the energy losses incurred en route do not justify the cost of building the long power lines to remote areas. Parshall et al. [24] found the average grid connection cost for a household in Kenya to be about $1,900, with more remote and sparsely populated communities having much higher connection costs. Decentralized solutions such as microgrids are often more cost effective solutions to delivering electricity to these areas [25], [26]. Further, unlike other decentralized technologies such as solar home systems, microgrids can be more easily integrated into larger grids in the future when economic development takes hold, the central grid expands, and/or demand for electricity rises. Upon connection to the main grid, the microgrid then has the ability to feed excess electricity into the network or draw electricity to meet shortfalls. This aggregation of loads and generators on a larger scale unlocks greater economies of scale and more efficient management of the power system. By maintaining the ability to operate microgrids in an islanded mode once interconnected, the security of the power system is enhanced. The rolling blackouts often associated with centralized grid networks in developing countries could be avoided by distributing energy generation resources in semi-autonomous microgrids.

From a development perspective, the ability of microgrids to produce grid-quality power also presents benefits over other decentralized alternatives. While there are several companies operating in developing countries that offer energy services from solar home systems on a “fee for use” and “lease to own” basis, these systems are limited in the type of energy services they can provide. For example, M-KOPA, a company with over 100,000 customers in East Africa, offers small 8W solar home systems (SHS) that power LED lights, a cell phone charger and a radio. These systems are unable to provide electricity for productive use such as refrigeration, mills and food processing, sewing machines, and electric tools for carpentry and construction, which are key to stimulating rural economies and reducing poverty [7]. The service level limitations of SHS have also resulted in high levels of customer dissatisfaction where grid level service was expected [27].

From an environmental perspective, microgrids may have lower environmental impacts than traditional systems. Microgrids are well suited to use local renewable energy resources like wind, small hydro, and solar power. They may also be suitable for the application of advanced generation technologies like modular nuclear reactors, biomass-based systems, and combined heat and power. While most developing nations only contribute to a small fraction of global greenhouse gas emissions, the early adoption of renewable energy technologies presents an opportunity to pursue a cleaner and more environmentally-friendly developmental path than the developed economies of today. Should developing regions pursue fossil fuel-based solutions to meet their energy needs, the problem of climate change would only be exacerbated in the long term as economies grow and energy demand increases. Furthermore, it is developing nations that tend to face the greatest consequences of climate change while at the same time being the least prepared to adapt [7].

In addition to providing environmental benefits, the use of renewable resources also enhances energy security. Many developing countries depend on imported diesel for a large portion of their electricity generation. This dependence on diesel and other imported fossil fuels exposes economies to price shocks resulting from the volatility of the price of oil and risks due to supply chain disruption. Renewable energy technologies rely primarily on freely available local resources and are, therefore, not vulnerable to the price of primary energy sources.

2.1.2 Advantages of Private Sector Participation

Despite the apparent advantages of microgrids and several public sector efforts encourage their deployment in rural areas, microgrid electrification has not yet contributed significantly to the alleviation of energy poverty in developing countries. There is growing interest in understanding how to encourage private sector participation in rural electrification efforts. One of the primary motivations for pursuing private sector investment in energy access projects is to tap into the large amounts of capital available in the private sector [19], [28]. Electrification is a capital-intensive activity and one of the major constraints to rolling out electricity access projects is the limited availability of resources in the public sector and donor community. The private sector is therefore viewed as a source of capital to finance these infrastructure projects.

The advantages of private sector participation go beyond access to capital. Publicly-owned utility companies have also been known to suffer from inefficiency and poor technical performance [14]. Common reasons for failure in publicly-owned electrification projects are a lack of technical capability to properly maintain and operate the technology and poor service quality [29]. This has been found both in community-operated cooperatives and grid extension projects operated by public utilities. India has even experienced instances of de-electrification due to poor maintenance and vandalism [30]. Privately-operated microgrids, on the other hand, often benefit from technical skills, management capabilities, and efficiency that are lacking in community-run projects and even large, state-owned utilities [14]. Private sector participation in electrification projects could thus lead to both an increase in the availability of capital as well as improved technical and managerial performance. However, the private sector has not been quick to answer the call of governments in developing countries to invest in electrification projects. The next section will provide a broad summary of the barriers to private sector involvement in decentralized electrification.

2.2 Barriers to Private Sector Investment in Electrification via Microgrids

Despite some clear advantages of private sector participation in electrification efforts, there are several challenges that must be overcome to make these projects attractive to potential investors and project developers. Expanding electricity access to rural areas in developing countries is often motivated by social concerns, but as with any investment opportunity, the private sector will measure the attractiveness of a project by its expected financial return and its associated risks. The security of revenue streams, long-term risks and policy certainty, regulatory transparency and complexity, as well as practical challenges relating to local organizational structures and technical implementation are issues of significant concern. This section examines various issues that must be overcome to create an enabling environment for private sector participation in microgrid electrification. Though many of these challenges are codependent, I divide them into three broad categories as represented in Figure 2-1: financial barriers, institutional and policy obstacles, and technical challenges.

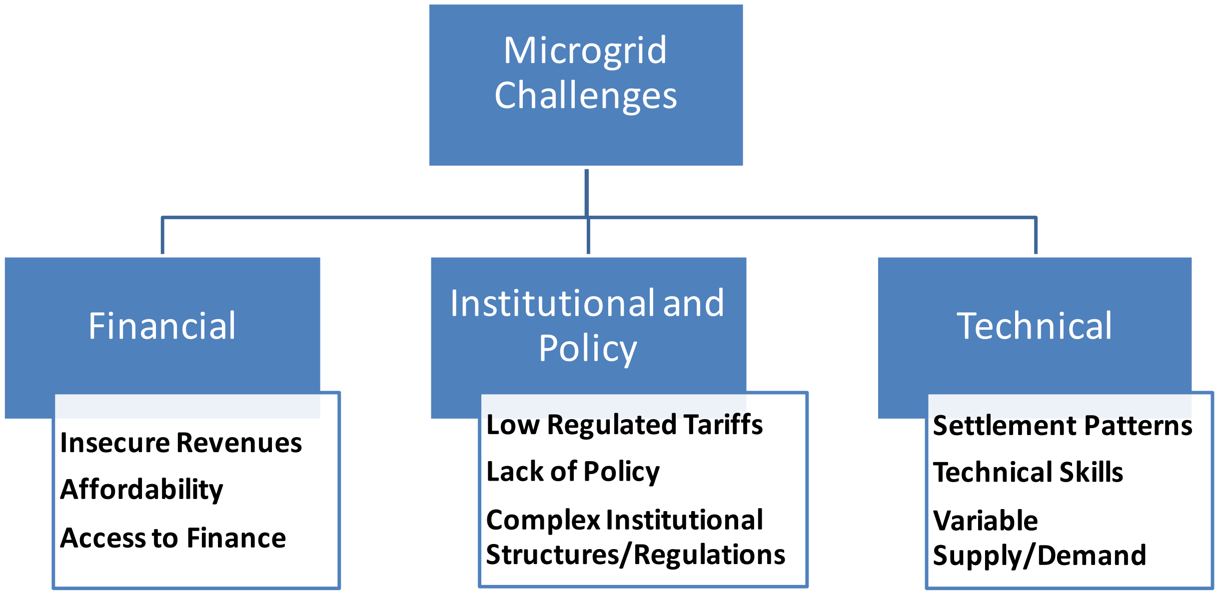

Figure 2-1 Challenges to private sector microgrid electrification.

2.2.1 Financial Barriers

Private sector investment decisions primarily hinge on the balance between risks and expected returns. In building a business case for microgrid electrification projects, concerns about both high levels of risk and low expected returns are likely to be raised. In the first place, a project must have a secure stream of revenue to fund operating costs, repay project debt, and provide a return to equity investors. Rural microgrids often serve poor populations with limited means to pay for electricity services. While it is well documented that poor unelectrified rural populations often pay more for the same energy services than their urban counterparts [8], [10], [31]-[33], ability to pay, electricity demand levels, and the potential for non-technical losses due to electricity theft are still of concern to private investors.

Ability to pay varies between countries, regions, and even within communities. It is often the case that rural communities depend highly upon activities such as subsistence farming, with only a small fraction of the population receiving regular cash income. As a result, the seasonality of income poses challenges to revenue collection during certain times of the year. With typical interest rates for locally sourced debt exceeding 10%, and at times exceeding 20%, in sub-Saharan Africa, late payment can be costly to project owners [34]-[38].

The level of electricity demand in rural communities is also typically very low. This results in a high unit cost to generate and distribute electricity, which in turn amplifies problems related to the ability of rural consumers to pay for energy services. The level of demand itself is highly uncertain [19]. It is not possible to directly measure the electricity demand in a community that has never had access. When assessing potential demand, it is therefore necessary to employ methods such as surveys of current energy use or to base assumptions on experiences in other villages [29]. Fabini et al. [39] have developed a technique to map predicted demand in unelectrified communities using demographic and socioeconomic data. Since the profitability of a project is highly dependent on the amount of electricity that is produced and sold, uncertainty regarding electricity demand in microgrids represents a significant risk to investors. Should demand fall short of expectations, the microgrid may turn out to be unprofitable. On the other hand, should demand exceed expectations, the installed generation capacity may fall short of demand, resulting in poor performance and customer satisfaction which could jeopardize the sustainability of the project [40].

Revenue security risks are amplified due to the capital-intensive nature of electrification, particularly if they include large amounts of renewable energy generation such as wind and photovoltaic systems, though the costs of these technologies is rapidly falling [41]. This means that several years may be required for the project to break even and start generating profits, which exposes project owners to long-term risks that could cause a project to fail before the recovery of initial capital investments [42]. Furthermore, such projects are often funded by project finance, which is based upon projected future cash flows rather than physical assets or collateral. Project developers will therefore need to demonstrate to debt providers that revenue streams are secure throughout the loan tenor.

Securing finance for rural electrification projects is often challenging. Electrification projects are seen as high risk by both debt and equity funders. These project-specific risks are often compounded by a generally poor local investment climate in developing countries resulting from perceived political risks and other country specific challenges. This frequently results in projects being unable to secure the capital required for implementation. When they do, it is often on unfavorable terms with high interest rates and short debt tenors, which exacerbates the challenge of achieving sustainable, affordable tariffs [37], [43]. Investors in microgrid projects will thus need assurances that their investments will be protected over the medium- to long-term [42]. Risks to overcome include grid encroachment, unregulated competition, loss of operating subsidies, changes in regulated tariffs, and other sources of policy and regulatory uncertainty. Addressing these risks requires a sound policy and regulatory environment that is often lacking in developing countries. The next section includes a discussion of these issues.

2.2.2 Institutional and Policy Challenges

Creating an enabling policy and regulatory environment is essential to stimulating private investment in infrastructure projects with low profitability and strong social welfare motivations. If private investment is to take place, the electricity sector must be open to the private sector and not subject to state-owned monopolies. Progress has been made in this regard in many countries under World Bank pressure for power sector reform. However, these reforms often lead to the treatment of electricity purely as a commodity and not as a public good. Such policies have been disastrous for rural electrification where access to electricity should be motivated primarily by social rather than commercial motives [14]. Consequently, there must be a balance between the needs of the private sector and the goals of public policy in providing social services.

In order to ensure financial sustainability for private investors, tariff regulations must permit cost recovery and subsidies may be necessary to promote affordability to consumers. These policies must balance the need to protect and attract investment and the obligation to promote social and economic development among the rural poor. A lack of regulatory independence has often led to unsustainably low electricity tariffs due to political pressure to maintain affordability. Unfortunately, these low tariffs have made the electricity sector in many countries unprofitable and unattractive to the private sector [44].

It is also important to minimize regulatory and licensing complexity. Bureaucratic red tape increases transaction costs, unnecessarily extends timelines, and deters investment [17]. Clear policy and regulatory frameworks and long-term policy certainty permit the development of bankable business plans and financial models. Policies and regulations that are frequently changing or are poorly-defined lead to a breakdown in investor confidence that the policies on which they are building their business case will be respected. Well-developed policies and regulations however, are only one of the prerequisites. Effective administration of policy and regulation relies on clear institutional structures with well-defined allocation of roles and responsibilities. All too often, institutional structures and regulatory processes are complex and difficult to navigate, acting as a barrier to potential project developers and investors [19]. Furthermore, where state-owned utilities exist, it is essential to have clearly-defined relationships between private and public actors in the sector. For example, the creation of the Agence Sénégalaise d'Électrification Rurale (ASER), which was meant in part to relieve the utility SENELEC of its electrification mandate and attract private sector participation, was initially a source of conflict and resentment as the utility viewed the new arrangement as a threat [45].

Beyond the state institutions, it is important that any electrification project involve the local community in the project from an early stage. Poor coordination and consultation with target customers has frequently resulted in projects that do not meet community needs and do not achieve local acceptance or participation. The consequences of this have been low uptake of energy services, poor payment morality, low collection rates, and high incidence of electricity theft [19]. Creating effective local organization and stakeholder consultation is a challenge in remote areas where there is often a cultural gap between project sponsors and project beneficiaries. Bridging this gap is essential to creating a sustainable project that meets the needs of beneficiary communities.

2.2.3 Technical Challenges

This review does not focus on the technical design of microgrids. However, there are several technical issues that affect the feasibility of microgrids for rural electrification that should be noted. For any gridded system, population distribution patterns are an important determinant of the technical design specifications and capital investments required to build physical infrastructure. Low density and highly dispersed settlement patterns result in higher distribution infrastructure costs per customer when compared to more densely populated areas. Population density and settlement patterns are therefore an important factor to consider when evaluating the appropriateness of a microgrid as a technical solution for electrification [46].

Microgrids are also more sensitive to local energy consumption patterns than interconnected grid systems. Because loads are aggregated over smaller geographical areas, the variability of demand is more pronounced than in large national and regional grids. Combined with potentially high proportions of variable and intermittent renewable energy sources, grid management becomes a greater challenge. This complicates the generation system design process, which must maximize service quality while minimizing cost. Uncertain load profiles add to this problem, making it difficult to size the generators required to meet the demand.

Once the project has been built, a lack of local technical skills creates challenges in maintaining and operating the system [19], [47]. The remoteness of some sites can make maintenance and repairs challenging, with high costs and long lead times for the delivery of replacement parts, which may not be available in local markets. Teferra [36] notes that in some cases in Ethiopia, utilities have stepped in as a supplier due to the difficulty of sourcing materials for construction.

Local skills and supply chains are important to the long-term sustainability of microgrids. Even when these skills have been developed, experience has shown that newly trained technicians may be tempted to take their new found skills to urban areas with higher salaries [48]. Meeting the technical challenges of rural microgrids thus requires the preparation and retention of local technicians and operators.

2.3 Business Models and Policy Support for Private Microgrids

Despite the aforementioned challenges, many strategies have been put forward to overcome these barriers to private sector participation in electrification generally, and microgrids specifically. This section examines various models that have been proposed or tested in the field, including various subsidy and finance models, strategies to secure and stimulate electricity demand, and innovative revenue models. It also highlights important considerations relating to organizational and institutional approaches, as well as technical and skills development solutions. Figure 2-2 provides an overview of public policy interventions and Table 2-2 links the barriers from section 2.2 to the interventions described in section 2.3.

2.3.1 Financing and Subsidy Models

While subsidization is often not a preferred intervention due to concerns about economic sustainability and market distortion, the need for subsidies to make electricity affordable to the rural poor is most often a reality. Subsidies for microgrids can take a number of different forms, but they typically support either capital or operating expenditures. A number of non-subsidy financial supports, such as loan and partial risk guarantees and concessionary debt to overcome failures in capital markets, exist as well [49]. The implications of these financial supports are diverse and must be carefully considered when designing programs to encourage private sector investment in electrification. Table 2-1 summarizes the various interventions reviewed in this paper.

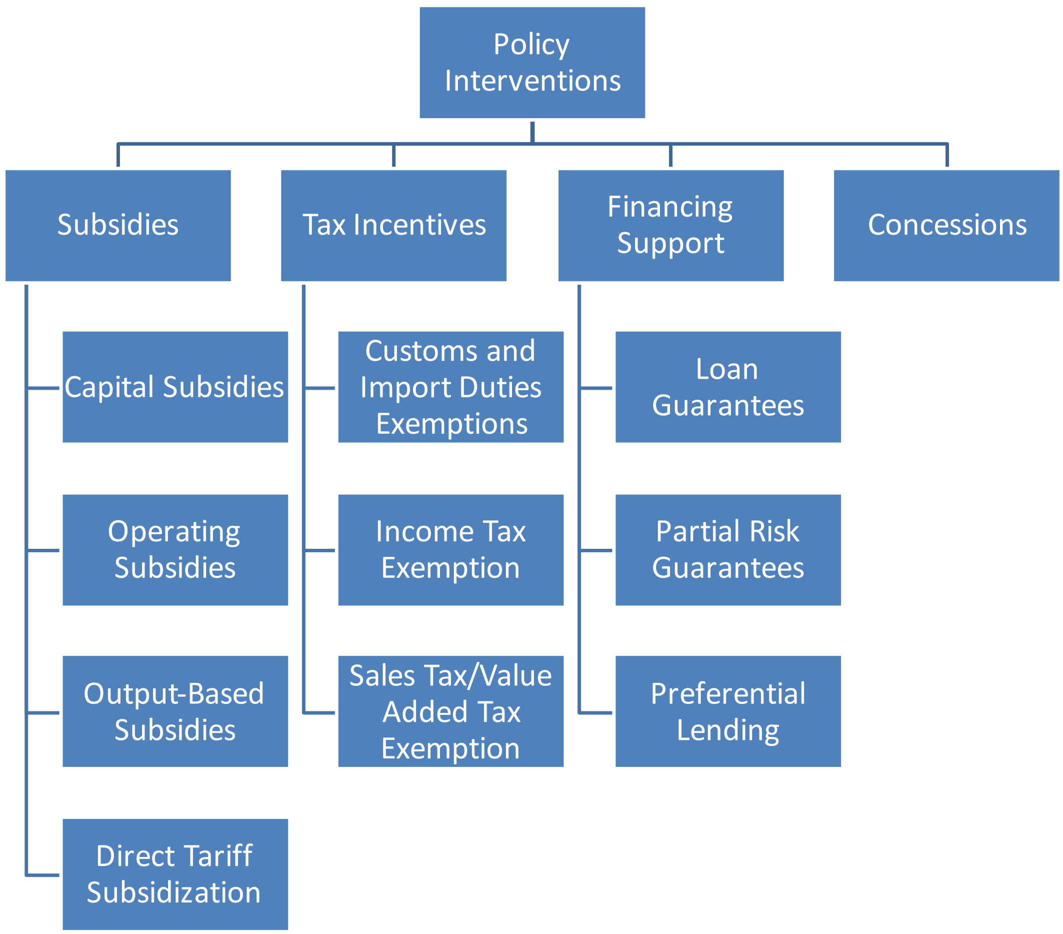

Figure 2-2 Policy interventions in support of private sector microgrid electrification.

Table 2-1 Summary of Public Microgrid Support Interventions

	Description	Advantages	Disadvantages
Subsidies			
Capital subsidies	Subsidization of capital costs for project realization.	Reduces capital burden and time to capital recovery. Promotes affordable tariffs to end-uers.	Lack of public sector capital is a motivation for private sector subsidization but also a limitation on funding subsidies. Reduced incentive for fiscal discipline.
Operating subsidies	Subsidization of operating costs during operations. Includes fuel subsidies.	Promotes affordable tariffs to end-users.	Exposes project to risk of subsidy discontinuation. Viewed as unsustainable and a continuous burden on public funds.
Output-based subsidies	Subsidization of capital and/or operating costs after project realization based on fulfillment performance of criteria.	Ties subsidies to specific policy objectives such as connection rates.	Exposes developers to high cost at risk as subsidies are not paid until after project realization.
Direct tariff subsidies	Direct subsidization of consumers through instruments such as electricity vouchers or via sale of power to a subsidized 3rd party retailer.	Can be targeted to specific customer classes in the case of vouchers. Expands access to grid subsidies if sold to state owned retailer. Long-term PPA with third party reduces revenue insecurity.	Essentially an operating subsidies with similar associated risks.
Guarantees and Preferential Lending			
Loan guarantees	Assists project in securing debt by assumption of debt obligation in event of default.	Enables microgrid to secure debt finance or secure debt finance on more favorable terms. No upfront cost.	Transfers risk of project failure to guarantor. Cost is difficult to quantify.
Partial risk guarantees	Guarantee to private lenders by third party to fulfill contractual obligations of government in case of nonperformance.	Enables projects to secure debt by reducing risk related to government nonperformance on subsidies and other obligations.	Government incurs additional cost in securing partial risk guarantee.
Preferential lending	Direct lending on concessionary terms to projects.	Provides access to debt finance at reduced interest rates and/or longer tenors.	Transfers risk of project failure to debtor.
Tax Incentives			
Customs/Duties exemptions	Reduction or exemption of microgrid equipment from customs and import duties.	Reduces capital costs. No reduction in public revenue if project would not otherwise be realized.	Reduces public tax revenue if the project would have been realized without incentive. Vulnerable to abuse if exempted equipment has multiple applications.
VAT/Sales tax exemptions on equipment	Reduction or exemption of microgrid equipment from VAT/sales tax.	Reduces capital costs. No reduction in public revenue if project would not otherwise be realized.	Reduces public tax revenue if the project would have been realized without incentive.
Income tax exemption/reduction	Reduction of operating expenses through reduction in tax burden.	Reduces operating costs. No reduction in public revenue if project would not otherwise be realized.	Reduces public tax revenue if the project would have been realized without incentive.
VAT/Sales tax exemptions on electricity sales	Reduction or exemption of electricity sales from VAT/sales tax.	Reduces electricity prices for consumers.	Reduces public tax revenue from taxes on substituted unsubsidized forms of energy.
Concessions	Award of exclusive rights to service a geographic area for a fixed term with minimum service level obligation.	Protects microgrid investments from competition in medium to long-term. Often accompanied by subsidies.	Provides monopoly status to a single private sector operator. Proper regulation necessary to protect consumers.

Table 2-2 Summary of public microgrid support interventions

Barrier	*Interventions*
Access to finance	Loan guarantees Climate finance Partial risk guarantees Preferential lending
Affordability	Public subsidization Tax exemptions/reductions Financing of connection fees
Grid encroachment	Public service concessions
Revenue security	Long-term PPAs Anchor customers Fixed service based tariffs Financing of appliances
Revenue collection	Prepayment meters Mobile phone payments

2.3.1.1 Subsidy Models

Capital subsidies, which reduce the initial investment cost for project implementers, are frequently cited as preferred to operating subsidies for reasons of long-term sustainability. Capital subsidization corresponds well to the cost structure of microgrids, which require large investments in electricity distribution and generation equipment. Capital subsidies also tend to promote the use of capital-intensive generation technologies such as wind, solar, and hydropower. Compared to fossil-based generating technologies, these renewable energy technologies have lower exposure to fuel price volatility and operating costs uncertainty. The reduction of capital requirements and the fuel price certainty of renewables leads to affordable electricity tariffs without the need for continued subsidization throughout the life of the project [50]. Greater uptake of renewable energy technologies has the positive side effect of improved environmental performance as well. The use of low carbon technologies also has the potential to attract carbon emissions reduction credits, which can be an additional source of revenue for the microgrid.

One of the primary motivations for attracting private sector participation is to overcome a lack of capital in the public and donor spheres. This shortage of public capital for electrification projects is therefore also a limitation on capital subsidies. However, using public funds to provide capital subsidies may permit the limited amount of public capital available for electrification to be stretched farther by coupling it with private sector investment. The level of capital subsidization offered should seek to deliver affordable electricity to consumers with a reasonable return to investors, while at the same time maximizing the number of projects that public funding can support.

Experience has shown that full subsidization of capital costs of privately owned systems is a disincentive to fiscal discipline. For example, a program in Peru that offered fully subsidized solar home systems found that many of the systems provided to the poor were later sold [51]. While the technology is different, the principle is still applicable to microgrids, where a developer may be tempted to, for example, install more generation capacity than is necessary to meet demand. Capital subsidies have also received criticism, primarily in the context of community ownership. There is evidence that indicates that projects fully financed by the owners and beneficiaries are more likely to be well taken care of [52]. Such examples have also led to the implementation of output-based subsidies.

Output-based, or performance-based, subsidies are only paid out if certain goals or milestones are reached. They allow governments to align subsidies with specific policy goals such as expanding access [49]. For example, subsidies can be linked to the number of customers connected to the microgrid, therefore incentivizing microgrid operators to connect as many customers as possible rather than focusing on a small group of more profitable high-consumption users [53]. To the developer and investor, output-based subsidies involve more risk than upfront capital subsidies. Projects must be financed, built, and operating before the subsidies can be accessed. The German development organization Gesellschaft für Internationale Zusammenarbeit (GIZ) is currently developing such a subsidy scheme for microgrid development in rural Rwanda [54]. Output-based subsidies must therefore be based on clear and transparent criteria and policies to mitigate these risks.

Subsidization of operating costs can take several forms. The subsidization of fuel is a commonly used subsidy, which is primarily used to reduce the cost of diesel. Diesel subsidies are often applied nationally and are not necessarily specific to electricity generation. Such subsidies reduce the cost of diesel-based electricity generation, which is then reflected in lower tariffs to customers. The use of subsidized diesel, however, comes with an environmental cost and can create a long-term burden on national budgets [19]. Several studies have shown the levelized cost of electricity from renewable energy is frequently lower than the cost of diesel-generated electricity [26], [55], [56]. While conventional generation technologies such as diesel have many technical advantages over variable and intermittent renewable energy technologies such as wind and solar power, subsidization of diesel has the potential to increase the total economic and environmental cost of electricity generation by making lower cost clean technologies less attractive.

Another form of operational subsidy is direct subsidization of tariffs. This typically takes the form a power purchase agreement whereby the owner of the power generation sells the electricity generated to a third party, often a state subsidized utility, which then sells this electricity at a lower rate. Grid-based electricity in developing countries is often supported by public subsidies so that electricity can be sold at rates below the cost of production. Subsidizing privately owned and operated microgrids in this way ensures that all electricity consumers have access to public subsides and equal tariffs. The power purchase agreements (PPAs) that typically accompany this arrangement are designed to ensure long-term revenue security to independent power producers (IPPs). PPAs will be discussed in greater detail in section 3.3 on revenue models.

An alternative form of direct tariff subsidization is the use of "energy coupons" provided by the government. These "coupons" can be redeemed for the purchase of electricity from a microgrid. This form of subsidy is given directly to consumers and can be targeted to people with the least ability to pay [57]. Such a model grants policy makers a greater ability to create subsidies that target the most vulnerable while requiring those with greater means to make greater financial contributions to the microgrid. For the microgrid operator, these subsidies serve to broaden their customer base and increase revenue.

2.3.1.2 Tax Incentives

Tax incentives can also be applied as a way of indirectly subsidizing microgrid electrification projects, either in addition to, or in lieu of direct subsidies [58], [59]. They can act as both capital and operating cost subsidies. Exemption from and reductions in customs, duties, and other taxes on the importation and procurement of equipment for electrification projects has become a common incentive used by governments to reduce the capital costs of such projects. Nepal, for example, has exempted certain technologies, such as generators and solar and hydro power equipment, from import duties [58]. India has a similar policy provided that the required equipment is not produced domestically. Both China and India have reduced value-added tax rates for renewable energy equipment [59]. To the extent that such projects would not be realized without public support, these tax exemptions do not necessarily reduce government revenue. These tax exemptions, however, are vulnerable to abuse. Many microgrid components have multiple applications and could result in exemptions being exploited for unintended uses. Batteries are one example of possible microgrid components that have a much wider range of applications. The World Bank suggests that such abuses can be mitigated by limiting exemptions to equipment meeting certain specifications and quality standards [10]. Exemption of microgrids from payment of income taxes and other taxes related to the operation of the microgrid is sometimes applied as a form of operating cost subsidy [36]. Electricity consumers can be subsidized directly by exempting electricity purchases from value-added and sales taxes.

2.3.1.3 Climate and Carbon Finance

With the high level of interest in integrating renewable energy technologies into rural microgrids, it is natural to consider carbon finance as a means of subsidizing the use of clean technologies for rural electrification. Carbon finance is based on the value of avoided carbon emissions that can be traded on carbon markets, giving the holder the ability to offset emissions in developed countries where such emissions are capped or regulated. Credit for emissions reductions is measured by establishing a baseline level of emissions. In the context of an isolated microgrid, the baseline could be built around the assumption that the default alternative would be to use diesel-based generation [25]. The difference between the diesel baseline emissions factor, measured in carbon equivalents per kWh, and the emissions factor for the clean technology would then be credited to the project owner based on the amount of electricity generated by the system. The goal of carbon finance programs such as the Clean Development Mechanism (CDM) is to offset carbon emissions in the developed world while supporting cleaner development paths in the developing world [60].

The literature has given mixed reviews on the potential of carbon finance to fund energy access. As it stands, high transaction costs make carbon finance unattractive to small scale energy generation projects [28] with a large majority of registered CDM projects to date being large-scale projects in middle income countries such as China [7]. While the bundling of projects under Programmes of Activities (PoAs) and standardized baselines can reduce these transaction costs [28], [61], price volatility in carbon markets makes it difficult to build a business case reliant on carbon finance [62]. It is therefore unlikely that a private investor would make an investment decision on the basis of the availability of carbon-based revenue.

Multilateral funds such as the Global Environmental Facility (GEF) provide other forms of climate finance. The objective of the GEF is to finance the *incremental cost* (the additional cost of using clean alternatives over traditional technologies) of using environmentally friendly technologies instead of more conventional solutions through grant funding. Because renewable energy technologies are often the lowest cost solution in remote rural areas [25], [26], [56], the incremental cost may in fact be negative which would render the project ineligible for GEF funding. Furthermore, Zerriffi et al. [60] found that GEF funding for energy access projects did not cover the entire incremental cost in roughly half of all cases analyzed. From a purely financial perspective, a private investor would have no incentive to pursue clean technologies if incremental costs are not met. Even in the case where incremental costs are exactly covered by GEF funding, the investor would be neutral between technologies from an economic standpoint. Zerriffi et al. [60], however, did find that in some cases incremental costs were exceeded, providing a net benefit to the project sponsors. Furthermore, the level of GEF funding is not dependent on variable market prices and in this way gives microgrid developers greater certainty for decision making than carbon credits. Other multilateral funds for clean energy development that provide support for energy access projects include the Climate Investment Fund, the Global Energy Efficiency and Renewable Energy Fund, Seed Capital Assistance Facility, and the Renewable Energy Enterprise Development program operated by the United Nations Environment Programme [61].

Climate-based financing of electrification projects has not been significant historically and is only relevant to projects implementing clean energy solutions. Newer mechanisms such as PoAs and other interventions that reduce transaction costs have the potential to increase carbon financing for electrification projects [28]. Despite this progress, building a business case dependent on carbon finance remains challenging. Uncertain long-term carbon prices add further risk to projects that are already considered high risk.

2.3.1.4 Preferential Lending and Risk Guarantees

Even with a favorable cost structure, microgrid projects can be difficult to finance. Governments and development finance institutions (DFIs) have also explored interventions to facilitate the ability of electrification projects to secure finance. This can be done by providing debt facilities directly or through risk and loan guarantees. To overcome difficulties in securing debt funding from commercial banks on acceptable terms, some governments and DFIs have offered investors debt funding at preferential rates [7], [61]. These arrangements typically offer lower interest rates and longer debt tenors than those available commercially. Additionally, they may offer debt finance for projects that would not be able to secure commercial debt under any terms. China has been providing low-interest loans for rural energy projects since 1987 [59]. These loans, provided at around half the commercial interest rate, have supported a variety of renewable energy projects for electricity access in rural areas [63].

Preferential lending, the provision of debt on concessionary terms, may be appropriate when projects are financially viable but perceived to be too risky by commercial lenders. By offering debt to projects at concessionary rates, the lender is assuming default risks at a reduced risk premium. Preferential lending is only effective when the project has a strong business case and attractive return expectation [28]. Concessionary loans can overcome barriers to obtaining debt and enhance returns on strong projects. However, leveraging an unprofitable project with debt will only serve to amplify losses on equity. Gunning [53] also notes that there exists some controversy over interventions that "distort market conditions" such as offering financial services under conditions not available on the market.

As an alternative to direct lending to projects, governments and DFIs have also offered loan or partial risk guarantees to assist projects in securing debt funding from commercial institutions. Under a loan guarantee, the guarantor agrees to become liable for all or a portion of debt to the funding institutions in the case of default. Partial risk guarantees are provided by organizations such as the World Bank and provide private lenders with assurance that the guarantor will fulfill government obligations towards the private sector project in the case of nonperformance [64]. Such guarantees may permit projects unable to obtain debt finance to secure the required funds or, for risky projects, to secure debt on more favorable terms. Loan guarantees transfer risk from project owners or financiers to the guaranteeing government or organization. The expected cost of loan guarantees is much more difficult to gauge than other financial support mechanisms because the probability of default is unknown. Loan guarantees require no initial cost to the guarantor but risk becoming a heavy financial burden should project risks turn into defaults on debt [49]. Partial risk guarantees must be purchased by the government or entity securing the guarantee on behalf of private sector actors therefore increasing the cost of the intervention, be it subsidies or concession contracts [64].

One reason that lenders are averse to providing debt to microgrid electrification projects is that they are unfamiliar with such projects and do not know how to properly assess the project risks [35]. Loan guarantees can help generate the experience and track record necessary for commercial lenders to begin lending to future projects without such strict terms. A unique lending approach was taken by commercial banks in Rwanda to obtain security on debt provided for microhydro power projects developed by public-private partnerships. Because of the unfamiliarity of the banks with hydropower investments and the associated risks, they were unwilling to provide debt on the basis of projected cash flows from electricity sales. The agreed-upon solution was that the banks would purchase the turbines used in the projects and lease them back to the project owners as a form of collateral. The assets of the project owner and shareholders were additionally required as loan guarantees. Such extreme conditions such as the inclusion of shareholders' private assets as security are certain to deter many potential investors. However, it is likely that such conditions would be relaxed as lenders gain more experience and comfort with the technology and business model [35].

It is also possible to support access through the provision of microfinance to rural electricity consumers [61]. Part of the capital cost required to establish microgrid connections is shared with customers through the payment of connection fees. Connection fees are meant to cover the cost of physically linking customers to the grid. These costs can be a significant barrier for low-income consumers who may otherwise be able to pay for electricity service. Removing this barrier promotes wider access to electricity service permitting government to achieve social and equity objectives and providing microgrid operators with more customers. Micro-finance for connection costs can be provided by third parties or directly by microgrid operators, who can collect loan payments over time along with service payments. As will be discussed in section 3.2, common electrical appliances can be bundled into this cost to provide greater benefit to users while stimulating increased electricity demand on the microgrid.

2.3.1.5 Public Service Concessions

While not strictly a financial support intervention, the awarding of concessions to private companies for electrification of geographic areas is a means by which governments can mitigate long-term project risks by isolating investors from competition. The concession model awards private companies monopoly rights to distribute and retail electricity in a geographic area. These concessions typically include an obligation on the concessionaire to maintain a specified level of service and to connect all or some minimum number of customers within their concession. At times it has been difficult to attract private sector interest for concessions in rural areas, which are viewed as challenging, risky, or potentially unprofitable. Some countries have therefore elected to bundle concessions. Through this approach, concessions to distribute electricity in dense urban areas are bundled with less attractive rural concessions [16], [27]. For example, in the 1990's, Argentina launched a program to expand rural electricity access by offering concessions to private companies, which would then receive subsidies from the local provincial government. Concessionaires were selected based on predefined criteria, which included the amount of subsidy that they would require to implement the project. The concessions provided for a 15-year monopoly under regulated tariffs. Under the terms of the contract, the concessionaire was required to provide service to all households and public facilities within their concession provided their accounts were in good standing [27].

Due to the long term and regulated nature of private concessions, a transparent tariff and subsidy setting process is essential to providing certainty to concessionaires while ensuring that public money is spent in a responsible manner and consumer interests are protected. Subsidies can include initial connection costs and ongoing tariff and operating expense support. Concession contracts must clearly define the terms of the agreement. Important terms include the way in which risk is shared, incentive schemes, as previously described, and performance standards with associated penalties when these standards are not met [65].

Mostert [16] distinguishes between decentralized and centralized electrification approaches. In the context of concessions, this reflects the size of concessions offered. Large concessions, which divide territories into a small number of large areas, are more likely to attract large foreign utilities that can leverage greater economies of scale. However, in regions that are viewed as particularly high risk, such as sub-Saharan Africa, such public tenders may fail to attract viable bids. Concessions in a decentralized approach may include a mix of small-to-medium and large concession areas and encourage the participation of multiple players including local companies and investors. These smaller projects may suffer from higher relative transaction costs and less favorable economies of scale. This could act as a deterrent to larger international investors, allowing room for domestic businesses to participate. The decentralized approach tends to attract a larger number of participants resulting in a more competitive market at the cost of economies of scale [16].

2.3.2 Securing and Stimulating Demand

One of the key challenges to building a sustainable microgrid model while maintaining an affordable tariff structure is generating sufficient demand for electricity, which will produce enough revenue to cover operating costs, repay debt, and provide returns for investors. Approaches to overcoming this challenge have included simply selecting sites with more energy-intensive customers, taking measures to stimulate demand by enabling customers to use more electricity, and establishing commercial and light industrial facilities that require electricity and generate local income.

The first step in securing sufficient electricity demand is to target communities that are likely to require more energy. Not only does this increase the economic sustainability of the microgrid, it is also likely to result in greater developmental benefits to the electrified community. Communities with higher potential electricity demand have higher levels of commercial and industrial activity, access to markets through transportation infrastructure, and potential to exploit nearby tourist sites or high agricultural potential. Proper site selection may include the identification of one or more anchor customers that have high, reliable electricity demand, and the ability to pay for electricity at an attractive tariff. These anchor customers range from rural industries, to public buildings, to infrastructure systems such as base transceiver stations (BTS) for mobile phone networks [16], [66].

BTSs for mobile networks are particularly promising anchor customers. These facilities are widespread in off-grid areas across developing countries, about 639,000 at the end of 2012. In an off-grid situation, they are typically powered by diesel generators or, increasingly, stand-alone hybrid renewable energy systems [67]. Electricity provision to BTSs is estimated to make up around 40% of mobile network operators' (MNOs) operating costs [68]. MNOs are therefore eager to reduce the cost of electricity provision and have been selling their BTS sites at a rapid rate to independent tower operators, who then lease capacity on the sites back to the operators. This trend has also encouraged tower sharing resulting in larger loads at BTS sites. BTSs have several desirable qualities as anchor customers for microgrids. They provide a high level of certainty regarding electricity demand and have a very predictable and flat load profile for which it is easy to design a power supply [69]. They do require a high level of reliability, but considering their current energy costs, would likely be willing to pay a premium for it. They are expected to have a high payment morality and new off-grid BTS sites are being installed everyday. Given the rapid rate at which new BTS sites are being established [67], it is likely that they will be reliable longer-term customers.

Rural industries such as mineral extraction and agro-processing facilities are also potential anchor customers. These customers typically have substantial electricity demand and, provided they are operating at a profit and rely on electricity for their operations, should exhibit good payment morality. However, they are also more likely to have challenging load profiles with significant variability and intermittency. This may result in higher cost power supply systems. Furthermore, relying on temporary anchors customers like mines, may create a risk to the microgrid, as they are designed around the energy needs of the anchor. Failure of the anchor typically leads to failure of the microgrid. The use of multiple anchors can mitigate this risk.

Public service buildings can also serve as anchors but they typically do not require large amounts of power. Typical loads at schools, for example, may include lighting, a few computers, and perhaps some audio-visual equipment. While loads from schools, health clinics, and administrative offices consume more energy than households and generate daytime demand that complements residential morning and evening peaks, they are not likely to be substantial anchors. Heating and air conditioning loads, while not common in many rural developing country contexts, could represent a significant load. In any case, the existence of such infrastructure is a positive attribute for a potential microgrid site.

Regardless of the presence of an anchor customer, the largest proportion of customers in a microgrid is likely to be households. Households are generally low-demand customers. Particularly after first connection, households do not possess many electrical appliances and the upfront investment required to obtain them is a barrier to increased electricity demand. Many companies offering solar home systems in off-grid areas on a fee-for-service or micro-finance basis have bundled the most desired appliances with their systems. This enables customers to obtain greater utility from their systems and also allows companies to upsell clients to larger systems that can power televisions and sound systems. Microgrid operators could stimulate demand on a microgrid in a similar manner [28]. As discussed in section 2.3.1, the offer of microfinance to fund connection costs can help overcome barriers related to upfront costs. Providing microfinance for both connection costs and appliances simultaneously has the potential to stimulate greater electricity demand in the residential and small enterprise sector.

Providing assistance to community members to invest in and benefit from the productive use of electricity can also generate demand and increase the affordability of electricity to customers [28]. This requires strong integration with the community and a good understanding of community needs. Potential projects include electric mills, water pumping, workshops, and irrigation. Income-generating activities are particularly appropriate as they increase the ability of customers to pay for electricity.

2.3.3 Microgrid Revenue Models

Securing predictable long-term revenue streams is a key determinant of microgrid success. The previous section described different strategies employed to establish demand for electricity. The importance of securing demand stems from the assumption that revenue and electricity demand are closely tied, as is the case in the metered business models used by traditional utilities. The coupling of revenue and demand however, depends on the revenue model microgrid operators adopt. Several private microgrid operators have implemented tariffs based on access to services such as lighting and charging rather than consumption of kWhs. This section reviews several microgrid revenue models followed by a brief overview of revenue collection systems and technologies. Figure 2-3 summarizes the tariff and revenue collection models that are discussed.

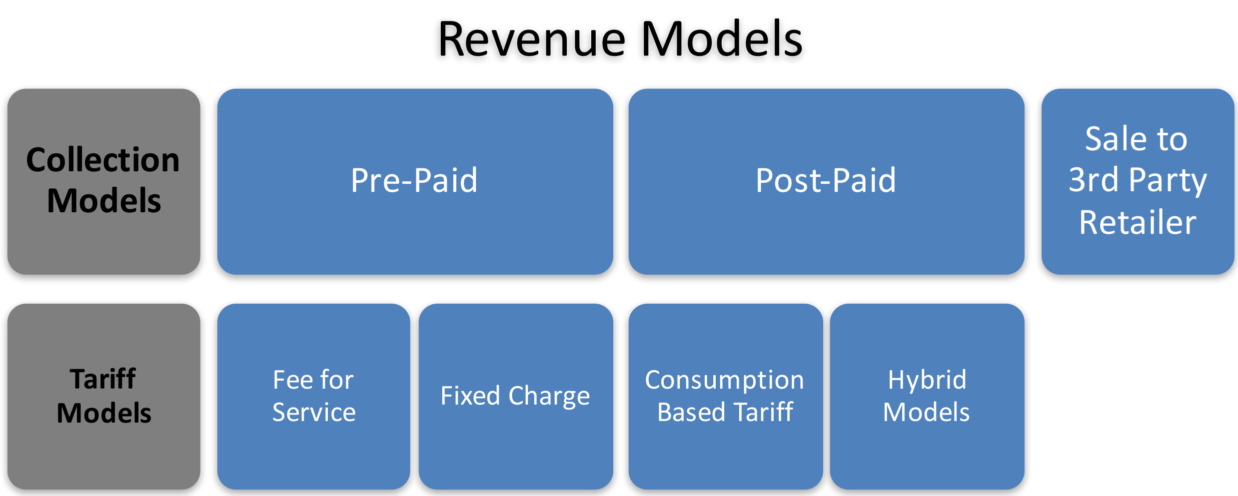

Figure 2-3 Overview of tariff and revenue collection models

Perhaps the lowest risk model for microgrid operators is the sale of electricity to a reliable third party under a long-term PPA. This third party, most often a state subsidized utility, will then retail the power to end-users. PPAs have traditionally been used to encourage private electricity generation in a grid-connected setting. IPPs are privately owned and operated electricity generators who sell power under a PPA to either an electricity trader, an electricity distributor, or directly to an end user. When a public entity is offering the PPA, the payment received by the IPP for each unit of energy delivered is called a feed-in tariff (FIT).

Several countries have attempted to attract IPPs to generate electricity under a PPA to feed into existing utility-owned microgrids. These grids are typically powered at great expense by diesel generators. Current prices for renewable energy such as wind and photovoltaic power can be significantly lower than the cost of diesel generation depending on local energy resources. Although the generation capacities required for these microgrids are much lower than those required for systems connected to the main grid, a price premium is often offered for generators on microgrids. Kenya, for example, offers $0.12/kWh for a system connected to the main grid but $0.20/kWh for systems connecting to microgrids [70]. Tanzania also offers significantly higher rates for IPPs feeding into microgrids [71].

However, it is not just the FIT that is important in attracting private sector investors. The counterparty to these agreements must be 'bankable' and there must be long-term certainty regarding tariffs to ensure that the project will produce a reasonable return on investment. As an example, Tanzania offers PPAs to IPPs on different terms for generators linked to grid-connected and isolated microgrid systems. A major shortcoming of the Tanzanian standardized PPA is that, in the event that isolated microgrids are connected to the main grid, PPAs for IPPs feeding into microgrids will be terminated and given the option to sign a new PPA under the terms and tariffs for grid-connected systems [64], [72]. The low tariff for grid-connected systems is not viable for most renewable energy projects. The risk that the main grid may arrive before the project is fully amortized is likely to prevent would-be project developers from securing debt finance.

Another important attribute of the PPA is the duration of the agreement, which should be at least as long as the debt tenor. In the case of renewable energy projects, such as wind and solar photovoltaic power, this is typically 15 years or more due to the capital-intensive nature of these technologies. Having standardized documents setting out the terms and conditions for IPPs and clearly defined processes for the development, approval, and interconnection of these generators can greatly reduce the transaction cost of these projects as well. Transaction costs can be a major barrier for small projects where these costs may represent a significant portion of the total project development and capital cost.

The limited size of microgrid loads also creates the possibility that at times the full power being produced by an embedded renewable energy IPP might not be required or would cause conventional generators to operate below minimum load factors. In this case, these renewable energy generators might be required to curtail their output. Project investors and financiers will therefore likely insist that the IPP be compensated even for energy that is curtailed to de-risk the project from uncertainties related to electricity demand. This risk is particularly important to mitigate in microgrids that are fully owned and operated by private companies. In such instances, risks related to electricity demand on the system fall entirely on the owner of the microgrid. To eliminate this risk and encourage investment in microgrids that are entirely owned and operated by the private sector, Rwanda has embarked on an innovative pilot project that offers privately operated projects compensation based on the availability of power on the microgrid. The detailed terms of the arrangement have not yet been made public but based on pre-qualification documents released by Rwanda's public utility Rwanda Energy Group (REG), the microgrids will be owned and operated privately but the power will be purchased and retailed to consumers by REG [73]. This relieves the microgrid operator of risks related to demand and the complexity of setting up revenue collection systems. Furthermore, REG will retail the electricity to consumers at the regulated tariff thereby providing microgrid customers access to subsidies afforded to grid-connected consumers. Public subsidies of electricity are significant in Rwanda where the costs of generating and delivering a kWh of electricity are currently 200 Rwf (US$0.29) and the retail tariff (at the time the work was completed) is 134 Rwf (US$0.20) [74]. While this system increases the cost of public subsidization of electricity, it does provide equal access to such subsidies to the so-called "geographically disadvantaged" [30].

Most often, long-term PPAs with a third-party retailer have not been available to privately owned and operated microgrids. For microgrids that retail electricity directly to end users, there are various revenue models that have been explored to meet the needs of both consumers and microgrid operators. Tariff models typically fall into two categories: tariffs based on energy consumption and tariffs based on maximum power consumption. There are arguments for the appropriateness of both revenue models. Energy-based tariffs could be seen as more equitable. Those who consume the most electricity pay the most. Others have observed that the predictability of a fixed monthly rate for a connection limited by the amount of power that can be drawn makes it easier for consumers to budget their limited incomes. Furthermore, it has been argued that fixed tariffs are more appropriate for microgrids because the cost structure of microgrids is largely composed of fixed costs [50].

Fixed monthly payments can be based on the demand from a certain number of appliances, most often light bulbs, or on a maximum allowable power draw from the microgrid. Microgrids with tariffs based on maximum power consumption often enforce this policy by installing load limiting devices that disconnect the customer when their demand exceeds the limit to which they have subscribed [40], [75]. In the absence of a physical limitation on power consumption, some microgrid operators have instituted strict penalties for those found to have installed unauthorized appliances that exceed their allotted power [40]. With such an arrangement, customers are limited in how they can use the microgrid, but are not limited in how long they can use it. This revenue model may be less appropriate for microgrids powered by operating expense-intensive generation technologies such as diesel generators for which operating cost is closely tied to the amount of electricity generated. However, with a capital-intensive generator such as a solar array, the operating cost is not related to the electricity produced but rather the installed generation capacity. Higher than anticipated electricity consumption in a diesel powered microgrid using fixed tariffs, could result in revenues that are insufficient to meet operating costs.

The more traditional tariff structure is based on the number of kWhs consumed by the customer. This system requires the installation of electricity meters, which increases the cost of connections. Energy consumption-based tariffs can use either prepaid or postpaid revenue collection systems. The literature emphasizes the need for tariffs that can at least recover the cost of operation while remaining as affordable as possible [50]. Keeping tariffs at affordable but sustainable levels permits broader access to energy services within communities. Having more customers spreads fixed costs among a larger pool. Microgrid operators seeking to maximize their return must strike a balance between higher tariffs and a larger customer base.

Lessons can also be learned from fee-for-service solar home system companies. Most of these companies charge a flat rate for their services because their cost structure consists almost entirely of fixed costs associated with financing hardware, providing maintenance, and customer services. Microgrids, particularly those relying on renewable energy, also have high fixed costs. The potential for demand falling short of expectations presents a significant risk for microgrids with high fixed costs. A revenue model similar to that of solar home systems may be appropriate while still permitting user access to electricity services without consumption limitations.

A hybrid revenue model where customers pay a fixed monthly charge that permits the use of a fixed amount of kWhs per month, with excess consumption charged at an energy based tariff, would ensure that fixed costs are met. At the same time, it would ensure that those who consume less do not subsidize more energy-intensive customers. As previously discussed, basic electrical appliances can be financed and bundled into this monthly charge to ensure that consumers have the equipment needed to benefit from the basic electricity allowance.

Regardless of the revenue model employed, revenue collection can be a financial, technical, and logistical challenge in remote rural areas. Prepaid meters have become increasingly popular even in grid-connected settings [76], [77]. In such a system, revenues are collected prior to consumption and customers are disconnected automatically when their credit is exhausted. These meters reduce the cost and complexity of billing and revenue collection and allow customers to avoid consuming more electricity than they can afford [78]. Experience from Peru has shown about a 66% reduction in revenue collection costs using prepayment meters over traditional revenue collection methods. While prepaid meters are more expensive than traditional meters, the operating cost savings were found to pay for the increased cost of meters in 5 years [7].

Community participation has also been found to be crucial to maintaining high collection rates and good payment morality. Cooperatives and projects involving local community committees have shown significantly higher payment rates and lower incidences of electricity theft. In some cases, community management has provided a reduction in electricity theft from as high as 35% down to 15% and settlement of accounts in arrears for up to 5 years [7].

Regardless of the payment method, seasonal income patterns will inevitably create problems for consumers in some regions. The World Bank's Energy Sector Management Assistance Program (ESMAP) advises that flexible payment options be adopted for those who do not receive regular incomes. This can take several forms, including large prepayments when seasonal incomes are received or less frequent collection of payment designed to correspond with influxes of income such as after harvests [40]. Some energy service companies in East Africa that operate solar home system services allow systems to be paid off over a number of years and permit users a fixed grace period during a year to accommodate customers with cash flow problems. Customers who are in a grace period have their services disconnected remotely through the mobile phone network. If the grace period becomes exhausted, the system is repossessed. This is an undesirable result for both the service provider and the customer because collection of systems located in rural areas represents a significant cost.

The remote disconnection of service described in the previous example is possible through the integration of mobile communication chips into the solar home system hardware, which permits communication with the device via the mobile phone network. Such technology could also be integrated into microgrids so that users that have not paid for their service can be disconnected without the need for a technician to go to the premises and manually disconnect service. Furthermore, mobile money systems, which began in Kenya and are now growing in popularity around the world, can be used to collect payments through mobile money transfers [79]-[81]. A portion of each transaction will go to mobile network operators as a service fee. This service fee non-withstanding, acceptance and uptake of the technology can simplify revenue collection by leveraging existing mobile network payment infrastructure. Mobile payment paired with remote disconnection through the mobile network can vastly reduce the complexity of revenue collection. Mobisol, for example, provides electricity services through solar home systems ranging in size from 15W to 200W [79]. Using a mobile connection, Mobisol can monitor customer use of electricity and system performance, and remotely unlock systems for use after payment. Remote monitoring of system performance permits remote diagnosis of technical issues and fast response for maintenance and repairs [81]. Such a system, of course, necessitates the existence of a mobile network that offers mobile money services at the microgrid site.

2.3.4 Institutional Models

The effective design and implementation of any rural electrification program depends on the existence of effective institutions. According to Irwin [49], institutions are "the set of rules governing decision making" and includes "who is involved in making which decisions, who has the right to be consulted and make recommendations to the decision makers, what justifications must the decision makers provide about the decision, what monitoring of the results of the decision must be undertaken." Institutional structures for rural electrification will typically include government ministries for finance and energy, regulators, private sector actors (including developers, investors, technology providers and lenders), multilateral institutions, non-governmental organizations, donors, and community representatives. Effective institutional structures must ensure that decision makers have positive incentives to make good decisions. This means establishing accountability, avoiding conflicts of interest, and ensuring that decision makers have access to the information required to make good decisions [49].

Overly complex, opaque, or poorly defined institutional structures can be a significant barrier to private sector participation. Overlapping and conflicting institutional functions and poor interagency coordination can make the institutional landscape difficult and expensive to navigate for project developers [19]. The results are higher transaction costs, more red tape, and often the deterrence of any private sector investment. This has led to many countries developing dedicated rural electrification agencies that are tasked to be a central point of contact for electrification activities and to enforce regulations.

Gridded electricity distribution is a natural monopoly [14]. Given that the purpose of electrification is often to enhance livelihoods and social welfare at the base of the pyramid, public support is generally required to make electricity services affordable to the poor in developing countries. As such, effective regulation of the electricity industry, and rural electrification activities in particular, is essential. The role of the regulator is to create an environment that both promotes investment and protects the public interest. This is a delicate balance that is prone to political interference. Common regulatory functions are tariff setting, granting licenses, guaranteeing service quality through enforcement of standards, and providing a forum for complaints [82].

Tariff setting is one of the most crucial roles that regulators play because the tariffs that microgrid operators are permitted to charge their customers lies at the heart of project profitability. In many jurisdictions, small generators, including microgrids, are exempt from tariff regulation and are permitted to fix their own tariffs or to do so in consultation with the local community [82]. Where exemptions do not exist, microgrids are sometimes subject to blanket tariff regulations that apply to all electricity distributors. These tariffs are generally designed for large utilities that are often state-owned and benefit from public subsidies. While such tariffs promote equitable energy costs nationally, they are not well adapted to microgrid cost structures that are often much higher than grid-based electricity on a per unit basis. Without some sort of subsidization, these tariffs will most often render microgrid projects unviable.

Other regulators make tariff decisions on a case-by-case basis. A "cost plus" model is frequently employed to ensure that investors are able to cover their costs plus a reasonable return [53]. The definition of a reasonable return is left to the regulator but should balance affordability, recognition of the opportunity costs incurred and risks carried by the microgrid investor. Cost plus models can also be tied to subsidies where tariffs are fixed below cost for social reasons. In such a case, the regulator will determine subsidies based on a fixed target return for the microgrid owner. Such a model comes with an administrative burden due to requirements for project operators to furnish detailed financial information that regulators must assess in determining subsidies. It also reduces operator incentive to control cost because a fixed return is guaranteed [53].

Regulators are also commonly tasked with adjudicating applications for electricity generation and distribution licenses. Licensing requirements are meant to ensure that service companies provide a minimum level of service quality and consumer protection. Overly stringent licensing requirements can create large administrative burdens on private operators and increase transaction costs that operators will attempt to pass on to customers. The role of the regulator is to strike a balance between protecting the interests of investors and consumers [82]. These requirements are typically very context-specific and no general prescriptions can be offered.

The creation and enforcement of standards also often falls to regulatory agencies. These standards are meant to ensure service quality and safety. The World Bank advises against over-regulation of microgrids and advocates the use of different standards on the basis of system size, with the smallest systems being required only to register and file annual reports [10]. The regulator must find a balance between ensuring quality service and minimizing costs. If it is envisioned that in the future microgrids will be integrated with a larger grid, standards should ensure compatibility to avoid costs related to infrastructure that must be replaced or upgraded.

Finally, policy makers also have a role in creating an environment conducive to the development of business and industry that supports electrification activities. In many developing countries, the equipment and skills required to implement rural electrification projects are not available locally in sufficient quantity or quality [61], [83]. Importation of equipment and hiring of foreign consultants add cost and complexity to electrification projects, including microgrid-based projects [16]. Steady and predictable investment in electrification activities stimulates the development of local supply chains and skilled labor, which in turn reduces prices and transaction costs. However, supply chains and pools of labor take time to develop and will only take hold when steady investment takes place. This requires a steady flow of funds to projects. Further, institutions of vocational and higher education tied to programs that prevent "brain drain" can also support electricity access and should be a priority for governments.

2.4 Discussion

Active participation and investment from private sector actors are essential if ambitious goals to expand access to electricity in the developing world are to be achieved. Decentralized microgrid-based projects will play an important role in ensuring that people who are far from the grid are not left waiting in the dark for decades to come. As it stands, microgrid electrification projects are not attractive opportunities for the private sector due to high levels of risk and potentially low returns. Unlocking this investment will require innovation on the part of businesses, carefully designed policies as well as incentive programs from the public sector and donor community.

Innovative entrepreneurs will need to find ways to secure reliable revenue streams while minimizing costs. Several opportunities exist including the leveraging of anchor clients such as off-grid cell phone towers, decoupling revenue and demand with service based models and providing microfinance to households and small businesses to purchase electrical appliances.

The objectives of electrification are often social in nature, providing a strong justification for public sector intervention and subsidization. Many subsidy models have been proposed and implemented. Capital subsidies have traditionally been viewed as more sustainable than subsidies on operating costs. Output-based subsidies acting as both capital and operating subsidies have the ability to tie subsidies to performance and specific policy objectives. Long-term power purchase agreements between private operators and public utilities also have the potential to mitigate risks and extend public grid-based subsidies to rural electricity consumers. As has been proposed in Rwanda, private operators can own and operate decentralized grids while selling the power to the state-owned utility that retails the electricity using existing prepaid electricity systems and distribution channels.

Even with a strong subsidy program that improves the profitability of decentralized electrification projects, developers are often unable to secure the required financing to realize the project. Risk-averse lenders that are often unfamiliar with and unable to assess the merits of such projects may require guarantees from a third party. This may come in the form of a loan guarantee from a government or a partial risk guarantee from an organization such as the World Bank. Direct lending from governments and development finance institutions at concessionary rates can address this problem as well.

The allocation of rural electrification concessions has had success in South America in encouraging private sector-based electrification, although not necessarily through microgrids. Concessions provide private operators with protection from competition in the medium to long-term. These have often been accompanied by subsidies or have been attached to more attractive urban concessions.

Strong and effective institutions and policy must support all of these public interventions. Ineffective institutions unnecessarily increase transaction costs and lead times, which could deter investment entirely. A common policy barrier that must be overcome is a blanket electricity tariff cap that renders private projects unviable without access to the same subsidies received by distributors on the central grid.

There is still a lot of work that can be done to reduce uncertainties in microgrid business models and better understand ways that government and the donor community can support sustainable private sector electrification projects. More work is needed to understand the way that rural populations use electricity after first receiving access and how this behavior evolves over time. Uncertainty about electricity demand remains a major challenge in building strong business cases for privately operated microgrids. A greater understanding of factors influencing rural electricity demand and how rural consumers respond to price and different tariff schemes would greatly improve the ability of potential project developers to meet the needs of rural consumers and create sustainable and bankable projects.

Additionally, very little quantitative work has been completed to date to understand the comparative costs and benefits of the public interventions described in this thesis and how these interventions affect the risks and returns faced by private sector investors in microgrid electrification projects. In order to ensure that limited public and donor funds are allocated in the most cost effective manner, more work is needed to quantify the risks and benefits of the various support measures that could be pursued. All of the above mentioned challenges have to be addressed in a collective manner. Only after that will it be possible to use the untapped energy resources in developing countries. Large masses will be energized with microgrids that rely on the distributed energy resources and operate in a sustainable and reliable manner.

3 An Investment Risk Assessment of Microgrid Utilities for Rural Electrification Using the Stochastic Techno-Economic Microgrid Model: A Case Study in Rwanda

3.1 Introduction

As discussed in Chapter 2, access to electrical energy is an enabler and driver of economic growth and development [84] and yet, more than 1.2 billion people in the world today still lack access to reliable electricity services [85]. The regions most affected are also the least urbanized in the world [86] and the cost of reaching rural populations with a centralized grid are high [24]. With the decreasing cost of distributed generation technologies such as photovoltaics (PV) and wind, decentralized systems are now, in many cases, a lower cost solution to rural electricity service provision than extension of the electricity grid [25], [26]. However, a barrier for both centralized and decentralized electrification programs has been a scarcity of capital from public sources and the donor community [87]. As a result, the pace of progress towards meeting ambitious energy access goals has been slow. Governments have looked to the private sector to fill the gap, but high-perceived risk has been a stumbling block [87]. Unfortunately, there is a lack of quantitative analysis to critically evaluate the key drivers of risk in microgrid utilities, or how different business models and technologies affect the potential for these projects to attract finance and scale up deployment. Using a Stochastic Techno-Economic Microgrid Model (STEMM), this chapter presents a risk analysis of the key uncertain factors affecting microgrid utility business models. The key contributions of this work are the identification of important risk factors in microgrid utility projects and how choices of technology and tariff models affect these risks.

3.2 Methods

STEMM models microgrid utilities as ring-fenced corporate entities. The model consists of two primary components: a technical model and a financial model. These models are linked to simulate connections between technical design and performance and financial outcomes. STEMM is designed from an investor's perspective; therefore, primary model outputs are financial indicators meant to shed light on the attractiveness of the microgrid as an investment opportunity to equity investors and lenders. The core strength of STEMM is its ability to compute these metrics probabilistically so as to account for risk and uncertainty. Debt Service Coverage Ratio (DSCR) measures the "bankability" of the project. Lenders use the DSCR to determine whether or not the expected project cash flows will be sufficient to repay a loan on schedule. The DSCR is the ratio of cash available to repay debt to the debt payment owed in a period. A DSCR of less than one indicates that the project cannot pay its debt from project revenues. Similarly, the net present value (NPV) of projected equity cash flows measures the attractiveness of the project to equity investors. The equity NPV is the net present value of equity cash flows discounted by a target return on equity. An equity NPV greater than or equal to zero means that project meets or exceeds the target return or cost of equity. In addition to equity NPV and DSCR, STEMM also computes a levelized cost of electricity (LCOE). While LCOE serves as a metric to compare the costs of different generating technologies, it is not widely used as an investment metric and is thus excluded from the analysis in this chapter.

STEMM is implemented in Analytica [88], a flexible modeling tool in which any input can be modeled as uncertain (as a distribution) or deterministic (as a point value). This provides the user flexibility in determining which uncertainties to model explicitly as distributions or parametrically. STEMM explicitly models some inputs, including fuel price, exchange rates, electricity demand, and solar resource as uncertain. The model propagates uncertainties using Monte Carlo simulation. In this chapter, I use a 10-year model horizon, based on the assumption of a 10-year debt tenor and that equity investors will take a relative short-term view, given risks that are more difficult to quantify such as grid encroachment. Shorter debt tenors result in larger debt payments early in the project life and lower DSCRs. Longer debt tenors have higher DSCRs but are exposed to similar risks as equity such as grid encroachment and will therefore be difficult to secure. The 10-year debt tenor has been selected as a realistic value that balances these considerations.

3.2.1 Technical Model

The technical module in STEMM simulates microgrid performance at an hourly resolution over the model horizon. It is currently capable of modeling multiple AC loads, a solar photovoltaic generator, multiple diesel generators, and battery-based energy storage. Figure 3-1 depicts the general system configuration of STEMM. Key outputs of the technical model that feed into the financial model include satisfied and unsatisfied customer demand, fuel consumption, and microgrid component runtimes.

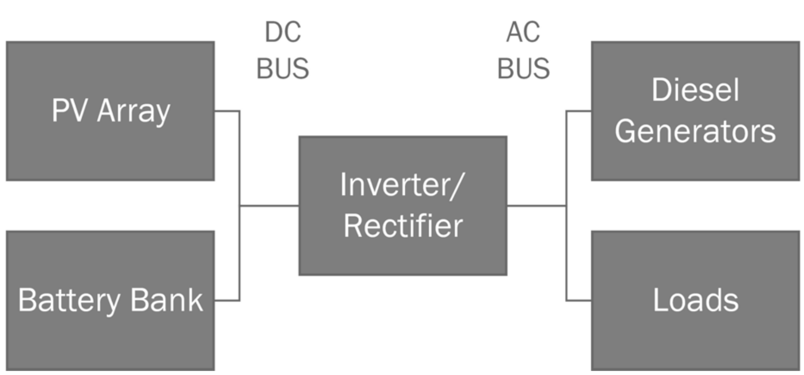

Figure 3-1 General microgrid technical configuration in STEMM.

STEMM allows the use of multiple diesel generators while aggregating all photovoltaic generation into a single array. STEMM operates under the assumption that diesel generators are available to supply power at any time step at load factors between a user specified minimum and 100%. The case studies in this paper assume a typical minimum load factor of 30%. The diesel generator's fuel consumption is linearly related to electrical output with a non-zero, no-load fuel consumption of the form

$$F_{tot} = F_{marg} \cdot P_{gen} + F_{nl}$$

where F_{tot} is the total fuel consumption at each time step, F_{marg} is the marginal fuel consumption per kW of generator output at each time step (P_{gen}), and F_{nl} is the no-load fuel consumption at each time step.

The PV generator module in STEMM relies on equations that estimate PV module fill factor, and therefore assumes the PV array operates at the maximum power point (MMP). The outputs of the model include hourly AC and DC maximum PV power availability, which feed into the dispatch model to determine the schedule for meeting demand and charging the batteries. Uncertainty in the PV module results from uncertainty in the meteorological data and as well as uncertain loss and module degradation inputs. The case studies in this paper use hourly solar resource data from the HelioClim-3 database and include temperature corrections and uncertainty, as described in Appendix A. In addition, STEMM includes a storage model that simulates the performance of a lead-acid battery bank using a version of the kinetic battery model (KiBaM) [89] and a capacity fade model to estimate battery lifetime and capacity degradation [90], also described in more detail in Appendix A.

Demand on the microgrid can be modeled as a single load or as multiple loads that can be controlled independently. This allows the STEMM user to prioritize certain loads over others in the case of a shortfall in supply, and/or to implement different tariff structures for each load. Expected load profiles are user-defined on an hourly basis for each month of the year. Because electricity demand is usually a key uncertainty for microgrids, STEMM accounts for uncertainty in the load profiles, as described in more detail in Appendix A. In addition, STEMM can model tariffs changing in real terms over time (for example, if tariffs move with the price of diesel), in which case the model relies on a constant price elasticity of demand to adjust customer demand. Finally, STEMM has the ability to account for demand growth over time as an annual growth rate. Demand growth in newly electrified communities is poorly studied and inputs are difficult to estimate. Furthermore, accurate modeling of demand growth should include decisions to expand generating capacity on the grid over time. In the future, such functionality will be added to STEMM. This chapter, however, only includes case studies in which there is a single aggregate load without prioritization between customers and without demand growth. The chapter also includes cases with tariffs both fixed in real terms and linked to fuel prices.

The core of the technical module in STEMM is the dispatch model, which determines how generation and storage resources operate to meet demand and charge the battery bank. In the case of a shortfall in generation capacity, it also determines which loads to serve and which loads to shed. The manner in which load-shedding occurs depends on the technology deployed in the grid. Figure 3-2 provides an overview of the data flows between other technical modules and the dispatch module. The details of the dispatch algorithm are available in Appendix A. It is also worth noting that STEMM models the distribution system as having technical and non-technical losses equal to a percentage of the total energy delivered on the system. Strictly speaking, non-technical losses are not losses due to the distribution system, as they represent electricity theft and uncollected revenue; however, both losses represent load that does not generate revenue.

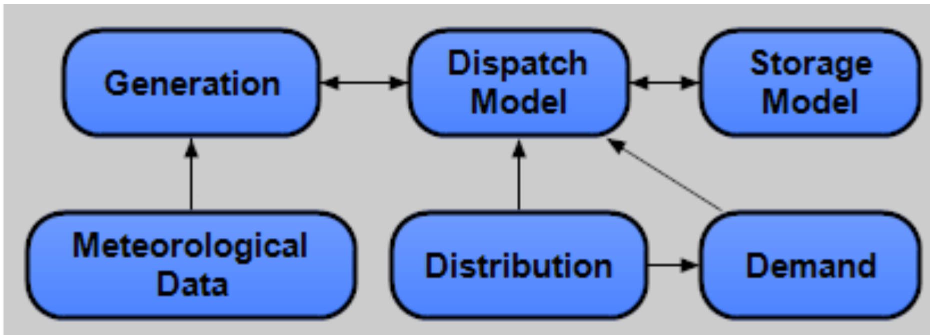

Figure 3-2 STEMM technical model influence diagram.

The dispatch algorithm in STEMM currently provides two load-shedding algorithm options for cases when supply is not sufficient to satisfy demand. The algorithms depend on the level of control the grid operator can exert on demand. In the simplest case, the operator is only able to shed entire circuits on the grid, represented in the model as loads. Deployment of smart meters can enable microgrid operators to control demand on a finer scale. In the case where operators are able to disconnect individual customers, the system is able to serve partial loads. Figure 3-3 illustrates the load-shed algorithms available in STEMM. For this chapter I use the "shed by load" algorithm with a single load.

When dispatchable generators are combined with battery storage, STEMM offers two options for the way in which generator and battery dispatch/charging is done. In the 'load following' algorithm, batteries are dispatched last and recharged only with solar power. In the 'charge cycling' algorithm, batteries are dispatched after solar and before diesel generation subject to constraints on battery state of charge. Excess generation capacity on dispatched diesel generators is used to charge batteries when they are not discharging. Further details can be found in Appendix A. The simulations in this chapter use the charging cycling algorithm.

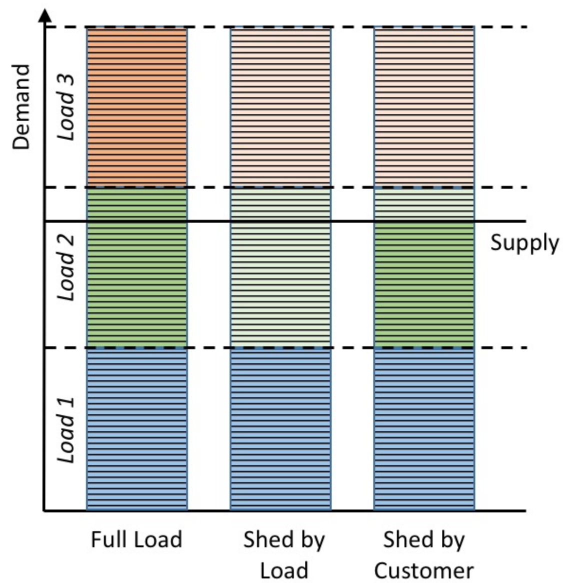

Figure 3-3 Comparison of load shedding algorithms. In the shed by load scenario, any load that cannot be met completely is shed; while in the shed by customer scenario, partial loads can be supplied. The lighter colors in the figure represent loads shed.

3.2.2 Financial Model

The primary outputs of the technical model that feed into the financial model are revenue generating demand, fuel consumption, generator runtimes, battery capacity fade, and, in cases where a penalty is applied to unmet demand, the amount of load shed due to insufficient generating capacity. The STEMM financial model simulates cash flows over the model horizon, on a monthly resolution, using these technical model outputs and financial inputs. Because most of the financial parameters (described in detail in Appendix A) are decision variables, STEMM currently treats most of these input parameters (with the exception of fuel costs, price indices~~,~~ and exchange rates) as deterministic values. It is however possible to model these probabilistically if desired.

Cash flows in STEMM include capital costs, operating costs, revenues, income tax, and debt payments. STEMM models not only initial capital costs but also calculates timings for replacement of capital assets at end-of-life (as described in Appendix A). Operating costs, also described in more detail in Appendix A, include fixed operating costs, fuel costs, PV operation and maintenance (O&M), battery O&M, diesel generator O&M, and unmet demand penalties With the exception of fuel costs, the current assumption is that costs are fixed in real terms. As many microgrid projects are financed in hard currency such as dollars and euros, the model allows for the use of two currencies, one local and one foreign. Consumer price indices and foreign exchange rates are simulated using a version of the Wilkie Investment Model [91]. Because fuel price uncertainty is a key driver of risk in microgrids with significant amounts of fossil fuel-based generation, STEMM models real fuel price uncertainty using a geometric Brownian motion (GBM) model, described in Appendix A. In this chapter, I rely on fuel price volatility from a long term study of US oil prices [92]. Globally, petroleum products are traded in US dollars so the fuel price is modeled in US dollars and converted to local currency at the prevailing exchange rate at each time step.

STEMM accounts for three different types of revenue: energy consumption-based tariffs, fixed monthly service charges, and connection fees. The case studies in this chapter use only consumption-based tariffs. While many microgrid entrepreneurs are experimenting with alternative revenue models, there is not sufficient knowledge about consumer behavior in these situations to model these scenarios. STEMM also accounts for corporate income taxes payable on microgrid profits, as described in Appendix A. Finally, the financing model assumes that microgrid capital costs are financed with a combination of debt and equity. Key inputs include the percentage of capital financed by debt, the cost of debt and equity, and the debt tenor. These parameters are fixed for all capital expenses. Loan repayments are calculated based on a constant monthly payment method. The cost of debt and equity can be specified as either real or nominal. Nominal rates are fixed whereas real rates move with the rate of inflation modeled with the Wilkie Investment Model.

3.3 Risk Assessment Methods and Case Study Inputs

The risk assessment presented in this chapter relies on two different sensitivity analysis methods to analyze the relative importance of key uncertain inputs. In the first sensitivity analysis, I hold all variables but one at their expected value in STEMM; I then set the uncertain variable being tested to their 5th and 95th percentile values based on estimated probability distributions and repeat this process for each uncertain variable of interest. I refer to this as a deterministic sensitivity analysis. The result is a tornado chart describing the sensitivity of model outputs (equity NPV and minimum DSCR) to each uncertain input. The second method involves running a Monte Carlo simulation while holding a single input variable in STEMM at its expected value. This provides an estimation of how much the uncertainty of outputs could be reduced by eliminating the uncertainty of an individual variable. I refer to this as a probabilistic sensitivity analysis.

For the sensitivity analyses in this chapter, I rely on a case study in rural Rwanda. The load profile used came from planning documentation from the Rwandan electric utility, the Rwanda

Energy Group (REG), and represents a typical rural load center of 500 households described in Figure 3-4. I built four generation scenarios (described in

Table 3-1) to compare financial outcome sensitivity to different technologies. Appendix B provides a detailed description of the process used to determine generator sizings in each generation scenario. I also determined an initial tariff for each generation scenario such that equity NPV is approximately zero when the model is run deterministically.

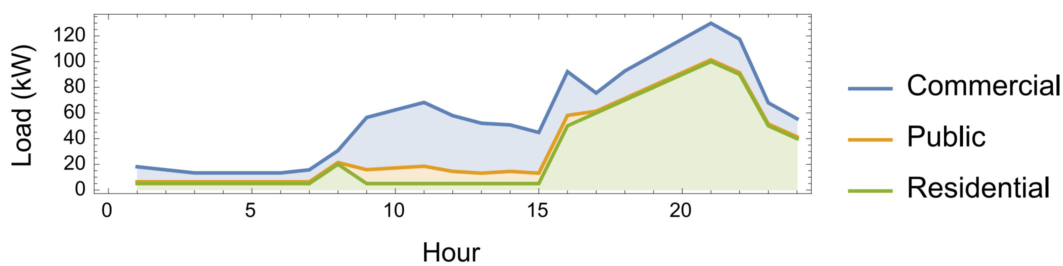

Figure 3-4 Average load profile for a typical load center from REG electricity master plan.

In addition to the generation technology scenarios, I also evaluate cases with tariffs fixed in real terms and tariffs that are linked to diesel prices. In the fixed tariffs case, I include an annual escalation factor, equal to inflation, to the initial tariffs in

Table 3-1. In the linked tariffs case, I escalate a portion of the tariff at a rate equal to the change in annual average fuel price, in addition to inflation. The portion of the tariff that scales up/down with fuel prices is equal to the average contribution of diesel to the overall generation mix on the microgrid when running STEMM in deterministic mode. Whether or not tariffs are fixed in practice depends on the local regulatory environment. On the central grid, many countries have fixed national tariffs. Kenya includes a fuel surcharge in their tariffs that links electricity prices to the cost of fuel.

Table 3-2 summarizes the uncertain inputs considered in the sensitivity analysis. Appendix B provides a more detailed list of inputs. Finally, Table 3-3 summarizes the finance structure assumptions.

Table 3-1 Summary of generation technology scenarios for sensitivity analysis.

Scenario	Diesel	Hybrid (small PV)	Hybrid (large PV)	Solar/Battery
Diesel Gen 1 (kW)	50	50	50	
Diesel Gen 2 (kW)	25	25	25	
Diesel Gen 3 (kW)	25	25	25	
PV Array (kWp)		50	100	200
Inverter (kW)		50	50	75
Battery Strings		1	4	22
Tariff (RWF/kWh)	1,137	1,137	1,219	1,665
Diesel Weight	1	0.69	0.46	0
Initial Capex (k$)	432.1	607.9	790.4	1,297

USD is approx. 800 RWF

Table 3-2 Uncertain inputs considered in sensitivity analysis.

Input	Distribution	Parameters
Mean Daily Demand (kWh)	Normal	mean: REG profile rel. std. dev.: 20%
Fuel Price (USD/liter)	Geometric Brownian Motion	drift: 0% volatility: 20%
Annual PV Degradation	Triangular	min: 0.2% mode: 0.5% max: 0.8%
DC PV Losses	Beta	α: 12.8 β: 96.7
Generator Life	Triangular	min: 20,000hrs mode: 25,000hrs max: 30,000hrs
Battery Capacity Fade Rate	Triangular	min: 0.017%/cycle mode: 0.023%/cycle

		max: 0.029%/cycle
Solar Resource Bias	Normal	mean: 0.6% rel. std. dev.: 2.6%
Price Elasticity of Demand	Triangular	min: -0.35 mode: -0.25 max: -0.15
Non-Technical Losses	Triangular	min: 0% mode: 2% max: 4%
Exchange Rate	1st Order Autoregressive[1]	XA: 0.891261 XV: 0.00037489

[1] See Appendix A for further details.

Table 3-3 Financing assumptions for sensitivity analysis cases.

Input	Value
Leverage (% of capital financed by debt)	50%
Debt tenor	10 years
Cost of debt (real)	10%
Cost of equity (real)	15%

3.4 Results

Figure 3-5 and Figure 3-6 show the results of the deterministic sensitivity analysis. Figure 3-5 presents the case with tariffs fixed in real terms while Figure 3-6 presents results with tariffs linked to diesel prices. The red bars represent the change of the equity NPV and minimum DSCR (the minimum DSCR for a month over the model horizon) from their baseline value (in the case of equity NPV, tariffs are selected such that this baseline value is zero), with the corresponding variable set to its 5th percentile value based on the distributions in

Table 3-2. The orange bars represent the 95th percentile value. All other variables are fixed at their median values with the exception of the load profile time series, which I allowed to vary randomly around the median load profile to account for load variability. The baseline value is the indicator value with all variables fixed to their median values with the aforementioned exception.

Figure 3-5 and Figure 3-6 show that, in all scenarios, both the equity NPV and minimum DSCR are highly sensitive to mean daily electricity consumption, price elasticity, and the exchange rate. In the scenarios incorporating diesel generation with fixed tariffs, the fuel price is also highly influential. As expected, this sensitivity to diesel prices decreases with increasing solar penetration as fuel consumption decreases. Linking tariffs to fuel prices reduces the sensitivity of the financial performance to fuel price. In cases where tariffs depend on diesel prices, we can see that both increases and decreases in diesel prices negatively affect NPV and DSCR. This is due to lower tariffs that are collected when fuel prices are low. Furthermore, lower tariffs result in higher demand, which may also lead to more load shedding and lost revenues. On the other hand, higher fuel prices still have a larger negative effect because, while price increases compensate for higher fuel prices, the higher tariffs reduce demand for electricity. DSCR is particularly sensitive when solar penetration is low. When tariffs are linked to fuel prices, solar plays a less significant role as a risk mitigant for equity (because tariff increases are proportional to the contribution of diesel to the overall energy mix) but is still important to lenders. Whether or not microgrid utilities can freely adjust their tariffs with fuel prices is a matter of policy and regulation.

Price elasticity and mean daily consumption are both variables related to the amount of electricity sold on the microgrid. As previously described, the change in indicators due to variation in price elasticity results from uncertainty in how demand estimated at a certain tariff level, in this case grid tariffs, changes with increased or decreased tariffs. In this case study, because the cost of electricity on the microgrid is higher than the regulated grid tariff, consumption would be lower than it would be on the grid. The importance of these variables increases with solar penetration and the solar/battery scenario is the most sensitive to the assumption about the elasticity. This is due to the high capital costs of solar panels and batteries, which may remain unused if demand falls short of expectations.

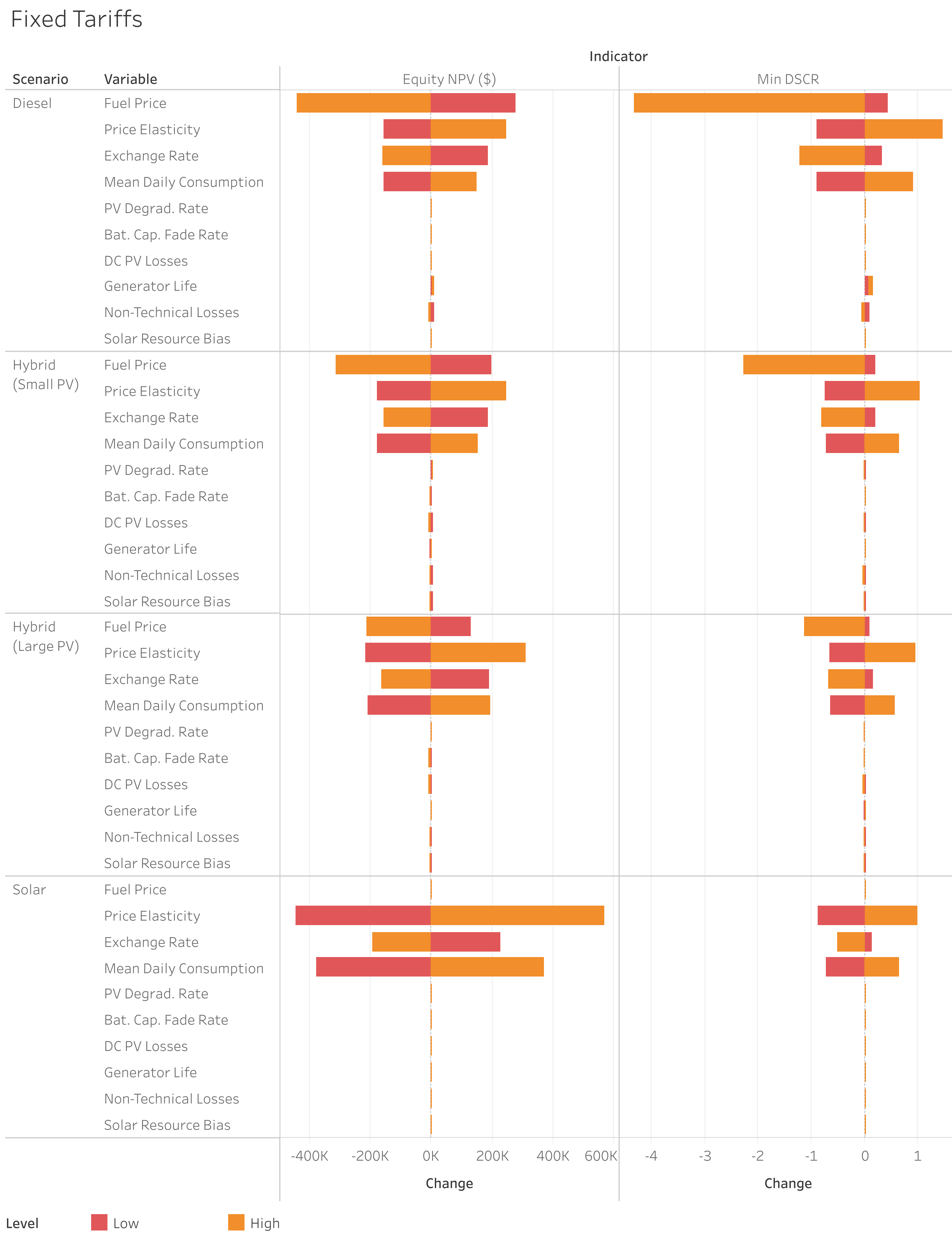

Figure 3-5 Deterministic sensitivity analysis results with fixed tariffs. The scenarios are set up such that the baseline NPV is zero. Baseline DSCR varies by scenario.

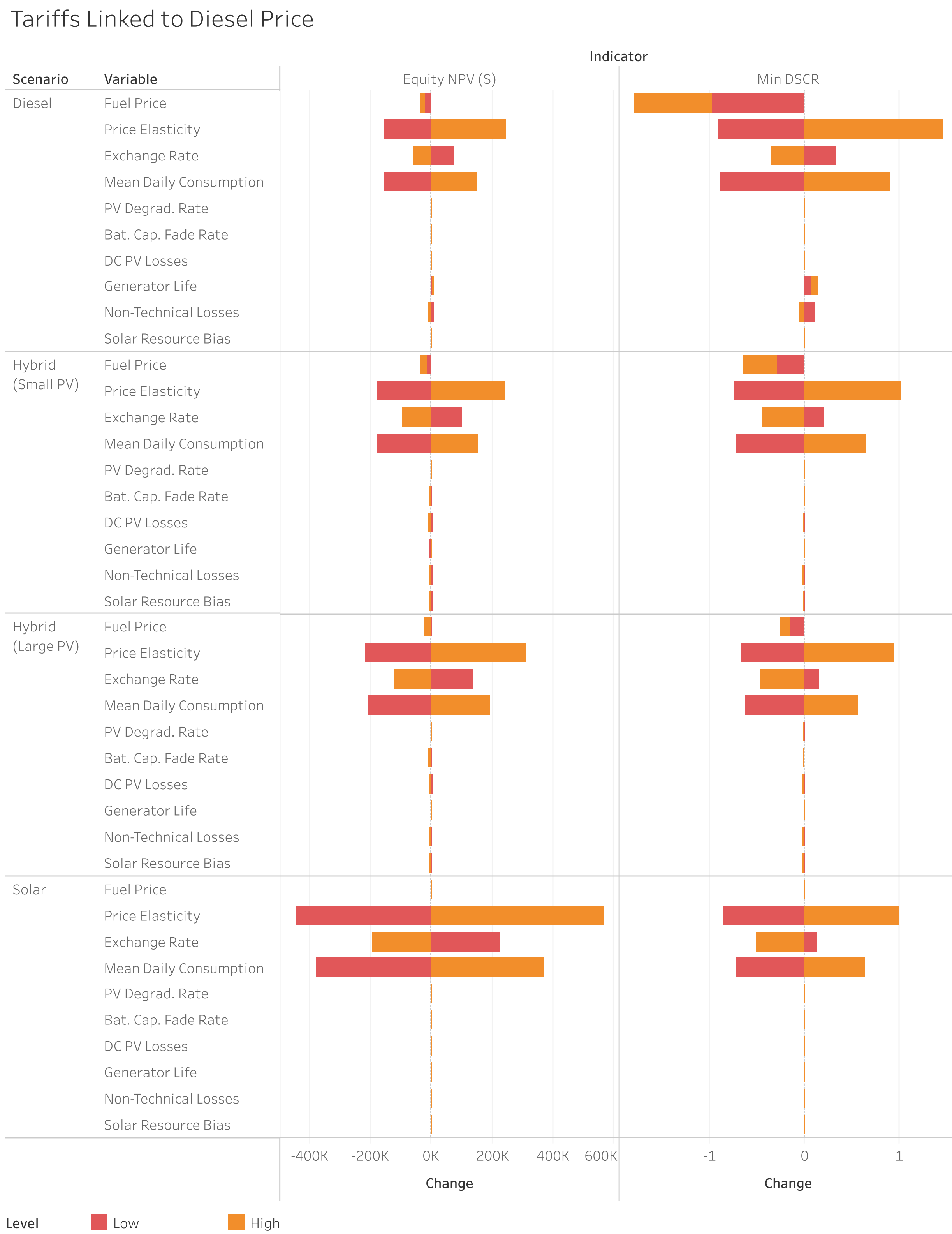

Figure 3-6 Deterministic sensitivity analysis results with tariffs linked to diesel price. The scenarios are set up such that the baseline NPV is zero. Baseline DSCR varies by scenario.

The fourth dominant variable is the exchange rate between local currency and the hard currency in which capital investments are made. Here, the effect of moving from low capex (capital expense)/high opex (operating expense) diesel to high capex/low opex solar is different for the fixed and diesel-linked tariff scenarios. In the fixed tariffs scenario, sensitivity of NPV to exchange rates is relatively constant moving from the diesel to solar scenario, while DSCR sensitivity decreases. The trend is reversed in the linked tariffs cases. The DSCR sensitivity does not change significantly with increasing solar penetration but NPV sensitivity increases. Exchange rates also affect fuel prices because fuel prices are set globally in US dollars. When tariffs are fixed, equity bears the foreign exchange risk not just for repayment of debt denominated in foreign currency, but also for local fuel prices that are affected by exchange rates. When tariffs are linked to fuel prices, a portion of foreign exchange risk is passed on to consumers. In this case, the foreign exchange risk is due primarily to repayment of foreign currency denominated debt, which affects capital intensive solar microgrids more strongly. Lenders face greater risk with fixed tariffs because higher fuel prices reduce cash flow available for debt service, thereby reducing the DSCR. With fuel price-linked tariffs, higher fuel prices are partially offset by increased electricity tariffs.

Other variables are of relatively minor importance. Non-technical losses are most important in scenarios reliant on diesel because non-revenue generating consumption incurs a fuel cost. Technical factors affecting the performance of the solar array such as PV losses, PV array degradation, and solar resource are relatively more important in solar based hybrid scenarios but less important for the solar/battery scenario. This is because in the solar/battery scenario, components are oversized to ensure high reliability that diesel generators supply in the hybrid cases. Only in extreme cases do these losses result in capacity shortfall. Battery capacity fade is strongest in the large solar hybrid scenario. The battery bank in the small solar hybrid scenario is relatively small and therefore does not represent as large of a capital expenditure as in the large solar hybrid scenario with a larger battery bank. In the solar/battery case, the battery bank is so large that the number of equivalent full cycles completed is relatively small and therefore results in less capacity fade and less frequent replacements.

Figure 3-7 and Figure 3-8 present the results of the probabilistic sensitivity analysis. The upper panel provides results for simulations using tariffs fixed in real terms and the lower panel gives results for tariffs linked to diesel prices with equity NPV on the left and minimum DSCR on the right. The boxplots show the interquartile range of the indicators in the orange box. The whiskers show the maximum and minimum values obtained in the simulations. The median value is the dividing line between the light and dark orange blocks within the box. A smaller distribution of outcomes, as described by the boxplots, indicates higher sensitivity of uncertainty to the corresponding variable. The dashed line in the DSCR plot indicates a ratio of one.

The equity NPV probabilistic sensitivity results in Figure 3-7 and Figure 3-8 highlight the same important variables as the deterministic sensitivity analysis: fuel price, exchange rates, mean daily electricity consumption, and price elasticity. With fixed prices, fixing the fuel price significantly reduces downside risk with limited effect on the upside for diesel heavy scenarios. When tariffs are linked to fuel prices, fuel price is not a strong contributor to equity risk and in diesel heavy scenarios seems to even slightly increase the upside.

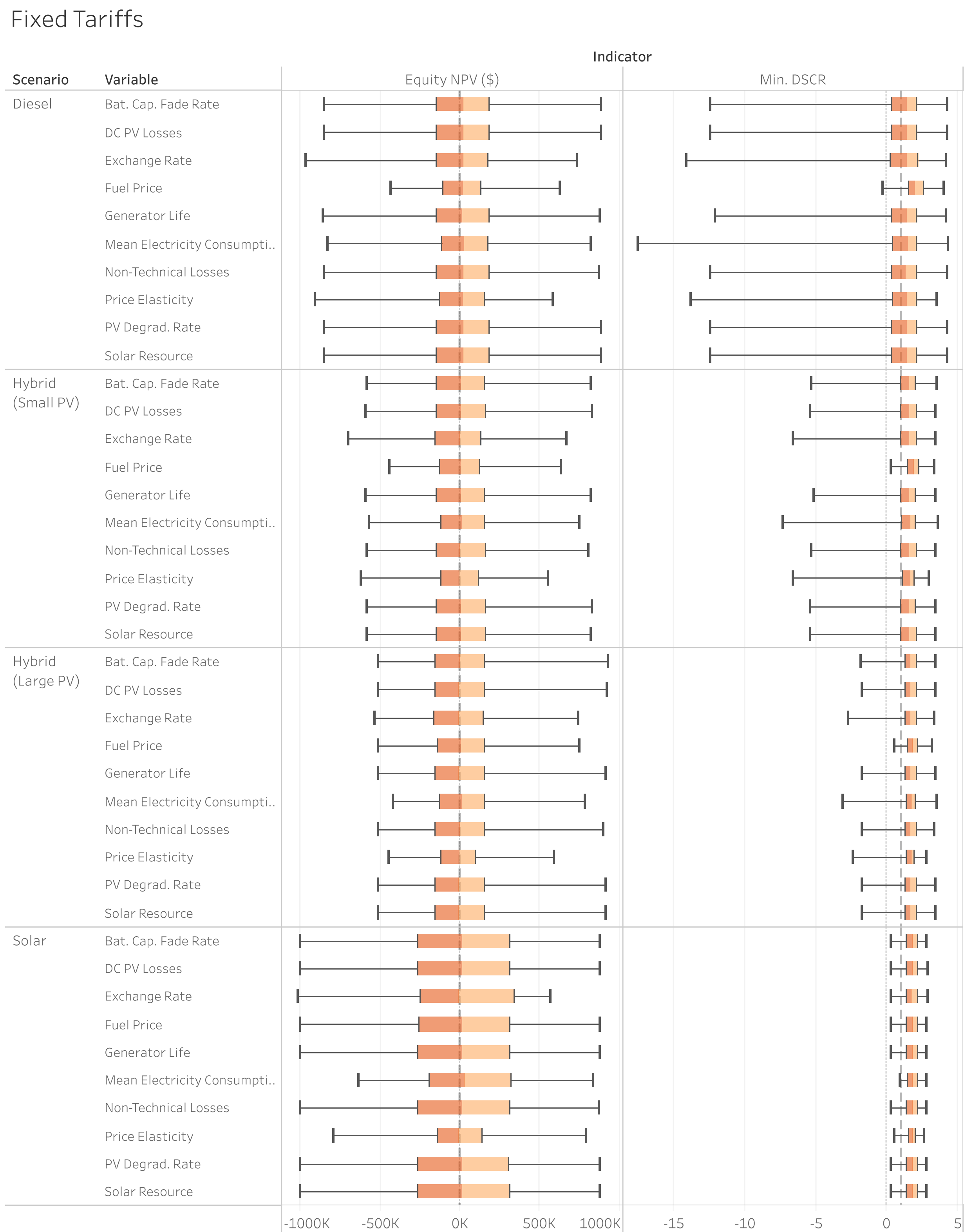

Figure 3-7 Probabilistic sensitivity analysis results with fixed tariffs.

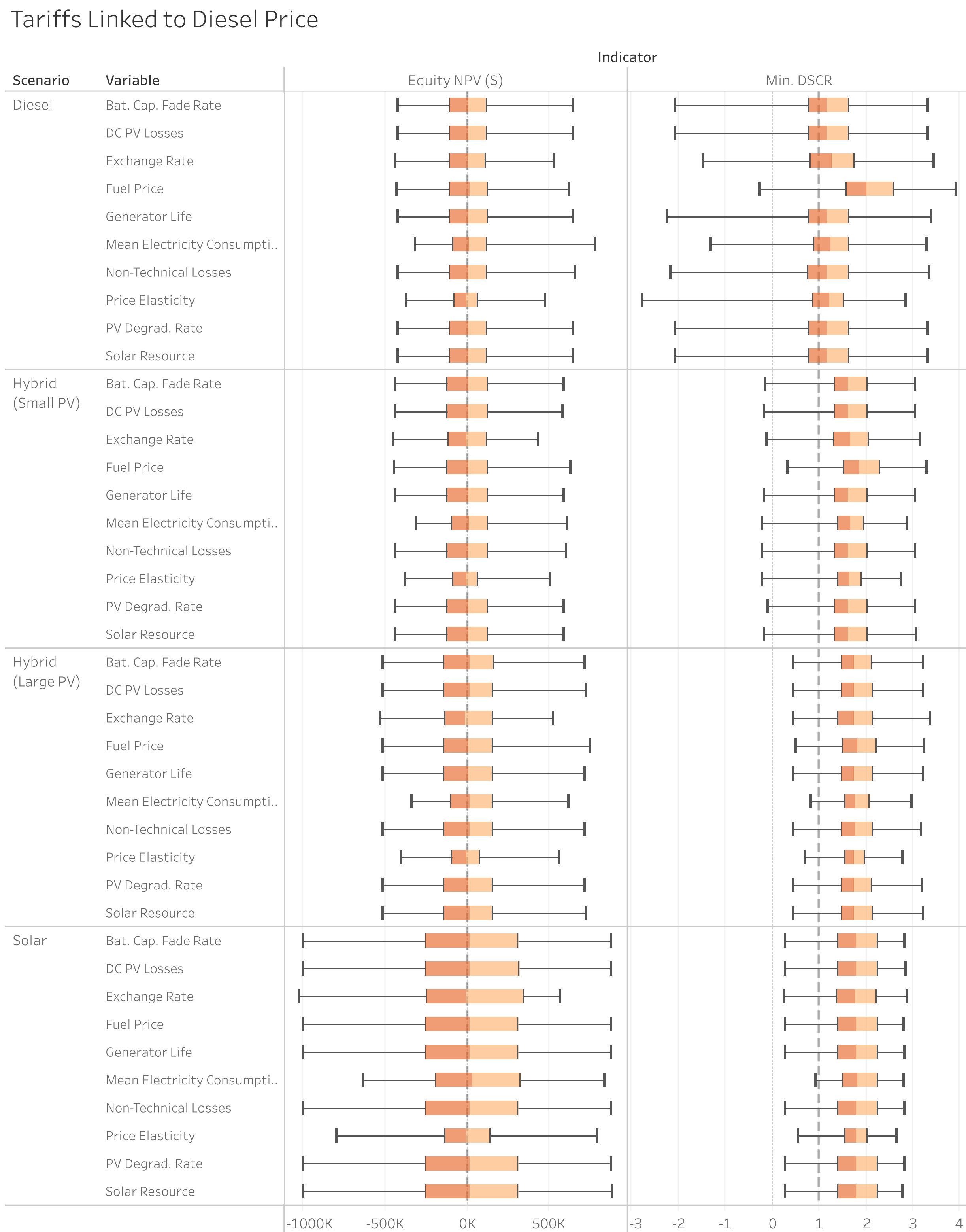

Figure 3-8 Probabilistic sensitivity analysis results with tariffs linked to diesel price.

In both tariff escalation scenarios, fixing exchange rates reduces upside potential more than it mitigates downside risk. The effect is stronger with larger solar penetration because of the greater capital cost incurred and repaid (for the debt financed portion) in hard currency. Price elasticity and mean daily consumption also affects upside disproportionally for diesel dependent scenarios whereas the solar/battery case sees significant risk reduction. Overall, with fixed tariffs, the hybrid scenarios are less risky to equity compared to solar and diesel. The solar and diesel scenarios have similar ranges from maximum to minimum NPV but solar has a larger interquartile range. When tariffs are linked to fuel prices, equity risk exposure is greatly reduced because fuel price risks are passed on to consumers through tariff adjustments. The diesel and small solar hybrid scenarios then become more attractive.

In contrast to the equity NPV, lenders face greater risk in diesel heavy scenarios as seen in the DSCR results in the right panel of Figure 3-7 and Figure 3-8. Particularly with fixed tariffs, the fuel price is clearly the most significant contributor to risk in diesel-based cases. Interestingly, fixing mean daily consumption increases the minimum DSCR noticeably compared to other variables when tariffs are fixed in diesel cases. In the solar case, eliminating mean daily consumption uncertainty results in a minimum DSCR across simulations that is greater than the benchmark value of one. If reliable demand for electricity can be secured, solar/battery microgrids appear to be safe investments for lenders.

3.5 Discussion

The risk assessment presented in this chapter has identified four important uncertain variables in microgrid utility business models that contribute significantly to project risk. These variables are fuel price, foreign exchange rates, demand for electricity, and price elasticity of demand. The relative importance of these factors varies between technologies and tariff structures. Allowing tariffs to vary with fuel price in an unregulated environment mitigates fuel price risk for equity investors. Linking tariffs to fuel prices is also effective in mitigating risk to debt providers but to a lesser extent. Introducing solar generators into a diesel powered microgrid further reduces lenders' exposure to fuel price risk.

Price elasticity and mean electricity consumption risk are both related to the level of electricity demand on the microgrid. These variables are more critical to solar and high penetration solar/diesel hybrid microgrids. These systems have high capital costs that will be either underused if demand for electricity falls short of expectations or unreliable if demand exceeds design specifications. Diesel-dominated systems require less capital investment and their operating costs are linked to revenue via fuel consumption. Because most microgrids being deployed in Africa are financed with hard currency but collect revenue in local currency, microgrid investors are exposed to significant foreign exchange risk.

There are various ways to mitigate these risks that merit further investigation. Fuel subsidies could mitigate fuel price risk but they are controversial, costly, and inefficient [93]. Introducing or increasing solar penetration into diesel powered microgrids is effective in mitigating fuel price risk exposure [22]. Securing reliable anchor customers could reduce uncertainty of electricity demand and price elasticity [21]. Further research is also needed to better understand consumer behavior in these settings. The case studies presented in this chapter assume energy-based tariffs but entrepreneurs in the field have experimented with other tariff structures to reduce revenue uncertainty. Introducing fixed monthly charges that come with credit for a certain number of kWhs partially decouples electricity consumption from revenue. These scenarios are currently difficult to model as it is unclear how consumers respond to different tariff structures. Exchange rate exposure can decrease by sourcing local capital. However, this is often in short supply. There are hedging products available to address foreign exchange risk.

Microgrids have enormous potential to accelerate access to electricity in rural areas of Africa and, through the integration of renewable energy technologies, set the region on a cleaner energy pathway. In order to scale up their deployment, microgrid companies will need access to large amounts of capital. Understanding and mitigating investment risk is essential. This paper has identified key contributors to investment risk to both debt and equity such as fuel prices, electricity demand, price elasticity, and foreign exchange. This knowledge should then be applied in further research to identify strategies to mitigate these risks and improve access to finance for microgrid companies. For example, in the next chapter, I show how these companies can balance fuel price and demand risk by appropriately sizing hybrid systems and how policy makers can mitigate project risk and promote the use of renewable energy by offer concessional debt.

4 PV-array Sizing in Hybrid Diesel/PV/Battery Microgrids under Uncertainty

4.1 Introduction

Chapter 3 presented the Stochastic Techno-Economic Microgrid Model (STEMM) as a tool to assess the financial performance of microgrid utilities and applies the tool to identify important drivers of risk in these business models. Technology choice was found to be an important factor influencing the risk profile of these businesses. Considering how technology choice affects project risk and the ability of projects to raise capital early in the design process is therefore important. This chapter examines how STEMM can be used to make system design decisions accounting for uncertainty and how consideration of this uncertainty may change design decisions from common approaches relying on point value estimates of uncertain inputs.

There is extensive literature on techno-economic models of hybrid microgrids [94]. Many conclude that hybridizing diesel powered microgrids with photovoltaic (PV) generators and battery storage offers significant cost advantages. In addition, hybridization has the potential to mitigate the risks related to uncertainty about future diesel fuel prices. Most previous work to evaluate the economic viability of rural microgrids relies on a cost-minimization framework using point value inputs. It thus excludes considerations of the additional risk mitigating benefit of hybridization, which could lead to different microgrid design decisions. Furthermore, the financial metrics used in other studies, such as levelized cost of energy (LCOE) [95] and life cycle cost (LCC) [96], [97], are often of limited interest to potential debt and equity investors. Equity investors are more often interested in the short- to medium-term net present value (NPV) or internal rate of return, while debt financiers want to know whether the project generates sufficient revenues to repay debt on schedule, often measured by a debt service coverage ratio (DSCR).

Using STEMM, this chapter examines PV array and battery bank sizing decisions for hybrid microgrids while explicitly accounting for risk, particularly to enhance the perspective of investors.

4.2 Case Studies

The case studies in this paper are based on a typical rural Rwandan load center of 500 households. The load profile, shown in Figure 4-1, comes from planning documentation from Rwanda's electricity utility, the Rwanda Energy Group (REG) [98]. Two primary drivers of uncertainty in financial outputs are fuel price and total electricity demand. Total demand on the microgrid is modeled as uncertain using a normal distribution with hourly load profiles scaled accordingly. The relative standard deviation of this distribution is treated parametrically to account for different levels of demand uncertainty. Volatility in the GBM fuel price model is also treated parametrically to examine the effect of different levels of fuel price volatility on financial risk. The base case volatility assumption is taken as 20% based on long term oil price data [92]. The model horizon and debt tenor used is 10 years.

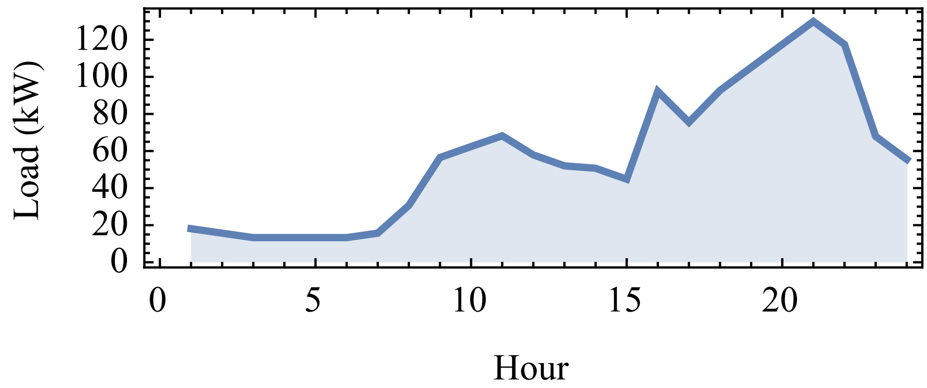

Figure 4-1 Load profile for 500 household rural community used in the case studies

Table 4-1 summarizes uncertain model inputs and their distributions. Table 4-2 describes the cost assumptions for these case studies. The microgrid relies solely on revenues from energy consumption with a tariff of US$1/kWh, fixed in real terms over the model horizon. These case studies rely on fixed tariffs as a simplifying assumption because if tariffs could vary with, for example, fuel prices, consumer behavior may change in response. Price elasticity of demand for electricity in these settings is currently poorly understood and therefore difficult to model. To understand how PV array and battery sizing decisions affect risk and financial performance, PV array and battery bank size are treated parametrically as described in Table 4-2. The technical configuration assumes three diesel generators of capacities 25kW, 50kW, and 100kW and power inverters of capacity 225kW. Diesel generator sizings were determined by running HOMER [99] in a diesel based scenario. The inverter capacity is oversized in the model to simplify the analysis and prevent clipping in any scenario. Solar resource data is taken from the HelioClim-3 database [100] for the coordinates 2°S, 30°E. Temperature data is drawn from the NASA SSE database for the same coordinates [101].

Table 4-1 Probabilistic model inputs.

Input	Distribution	Parameters
Solar resource rel. bias	Normal	μ: 5.9%, σ: 2.6% [102]-[106]
Solar resource rel. st. dev.	Lognormal	μ: 20%, σ: 5.0% [102]-[106]
Max. daily temp.	Normal	μ: NASA SSE Data, σ: 3.1°C [101], [107]
Min. daily temp.	Normal	μ: NASA SSE Data, σ: 2.5°C [101], [107]
Lifetime battery throughput	Triangular	min: 2.2MAh, mode: 2.7MAh, max: 3.3MAh [108]
Generator operating life	Triangular	min: 20,000 hrs, mode: 25,000 hrs, max: 30,000 hrs
Non-technical losses	Triangular	min: 0%, mode: 2%, max: 4% [109]
PV system losses	Beta	α: 12.8, β: 96.7 [110]
PV annual degradation	Triangular	min: 0.2%, mode: 0.5%, max: 0.8% [111]
Fuel price	GBM Model	drift: 0%, volatility: parametric [92]
Daily electricity demand (DED)	Normal	μ: EARP Data, σ: parametric [98]
Hourly load profile (HLP)	Trunc. Normal	μ: EARP Profile, σ: 10% × μ scaled to DED, truncated at zero
Demand time step variability	Trunc. Normal	μ: HLP σ: 8% × μ truncated at zero

Table 4-2 Cost and parametric model inputs.

Cost/Revenue Inputs				Parametric Inputs	
Capital Costs	***Value***	**Operating Costs**		**Input**	**Levels**
PV system	$,2700/kWp	Initial fuel cost	$1.41/liter	Demand uncertainty	10%, 25%
Power electronics	$500/kW	Generator O&M	$0.15/hour	Fuel price volatility	10%, 20%
Batteries	$250/kWh	PV/battery O&M	$8/kWp/month	Cost of debt	0%, 5%, 10%
Diesel generators	$4,400 + $475/kW	Fixed costs	$300/month	Leverage	0%, 25%, 50%, 75%, 100%
Meters	$40/customer			Cost of equity	5%, 10%, 15%
LV distribution	$580/customer	**Revenue**		Battery strings	1, 20, 40
Connection cost	$92/customer	Tariff	$1.00/kWh	PV Array Size (kW)	0, 50, 100, 150, 200, 250, 300

4.3 Results

Figure 4-2 presents results of Monte Carlo simulations for both equity NPV and the 90% exceedance value (P90) of the minimum DSCR as a function of PV capacity installed in the microgrid. Because lenders are more risk averse than equity investors, they use higher exceedance values in their investment criteria. So where an investment may be attractive to equity investors at a P50 level, the P90 DSCR may not meet lender requirements in high-risk scenarios. The blue and orange bands represent small (91kWh) and large (1.8MWh) storage cases, respectively. For equity NPV, dashed lines represent the median values and the lower and upper bands plot the 10^{th} and 90^{th} percentile values, tracing out an 80% confidence interval. The upper panel shows results when the microgrid is levered 75% with concessional debt (0% real cost of debt); the center panel represents a commercial debt case with a 10% real cost of debt and 50% leverage; and the lower panel gives the unlevered (100% equity) case. In all cases, the real cost of equity is 15%. Concessional lending rates lower the cost of borrowing, thereby increasing the amount of debt that the project can carry while meeting DSCR targets. The columns represent cases with different levels of demand uncertainty and annual fuel price volatility.

Examining the DSCR plots in Figure 4-2, it is clear that demand certainty is important in establishing bankability for these projects. The only bankable cases, those having at least a minimum DSCR greater than one, are those with large storage capacity, high PV penetration, and low demand uncertainty. Low PV penetration levels do not generate the fuel consumption savings necessary to mitigate downside fuel price risk in the P90 case. At high PV penetrations, the small storage scenario again limits reductions in fuel consumption and the associated risk mitigation benefit. Because these scenarios are based on an energy tariff-based revenue model, demand uncertainty equates to revenue uncertainty. High levels of PV penetration are capital-intensive and therefore more sensitive to demand uncertainty than low penetration scenarios that rely more heavily on diesel, as can be seen in the divergence of DSCR curves in the low- and high-demand uncertainty cases. In low-capital, diesel-heavy scenarios, demand uncertainty is mitigated by the fact that operating costs are highly correlated with revenues.

In terms of equity NPV, low PV penetrations and small battery banks provide better median returns. However, none of the small storage/low PV cases are bankable, meaning these projects would need to be financed entirely or nearly entirely by equity. The median NPV in the unlevered case falls just short of the target return and favors small storage/low PV cases. The only scenarios that could meet lending requirements are those with low demand uncertainty, large energy storage, and relatively high PV penetration. Of these, only the concessional debt case achieves positive median equity NPVs. Focusing on this case, one observes that median equity NPV peaks around 150kWp while the P90 NPV peaks closer to 200kWp PV penetration. At 150kWp, median NPV is $173,000 and the P90 NPV is $38,000. A larger array of 200kWp produces a slightly lower median NPV of $165,000 but a higher P90 NPV of $71,000. This presents a trade off for microgrid developers. Higher median returns can be achieved with a small PV array. However, for a $8,000 reduction in median NPV, the downside risk can be reduced by about $33,000 in the P90 case. All of this is to say that larger penetrations of PV generation into hybrid microgrids can serve to mitigate downside risk, driven by exposure to volatile fuel prices, by sacrificing some expected returns.

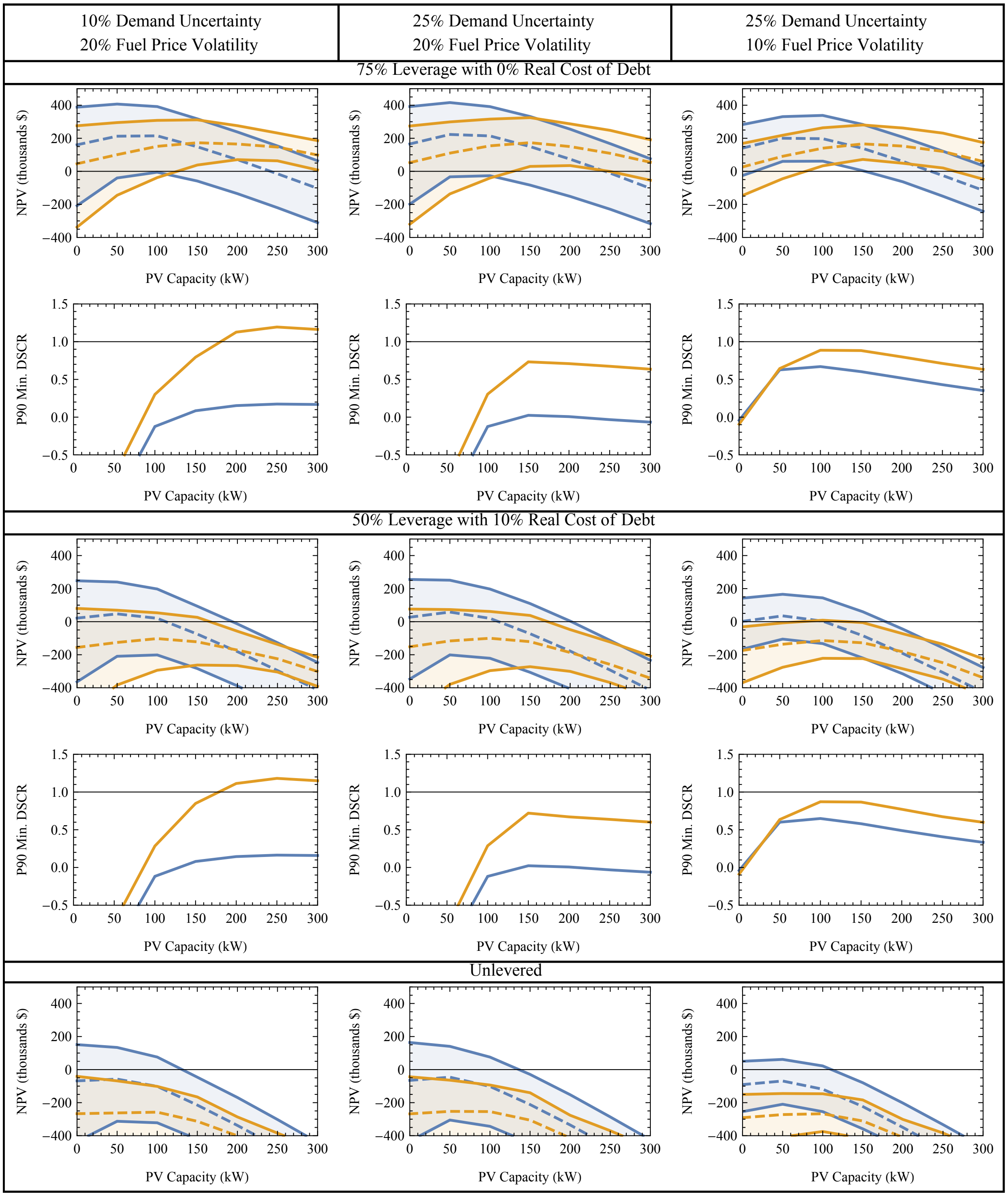

Figure 4-2 80% confidence intervals of equity NPV and P90 min. DSCR. Blue (■) represents the small (91kWh) storage scenario and orange (■) represents the large storage scenario (1.8MWh). In all cases, the real cost of equity is 15%.

4.4 Discussion

From a policy perspective, the results in this chapter suggest that offering concessional debt facilities to microgrid developers can have a two-fold benefit of promoting the use of clean technologies like PV and helping to mitigate fuel price risks faced by microgrid equity investors. From the perspective of investors, this scenario offers reduced risk exposure at the cost of a small reduction in median returns. Because risk is a major barrier to investment in microgrid projects, this may be a tradeoff that investors are willing to make.

As with any investment decision, potential investors in microgrid utilities in developing countries will base their decisions both on expected returns and risk. The findings in this paper suggest that technical design and generator sizing decisions have a significant effect not only on expected returns but also on financial risk. Microgrid developers and system designers should therefore also carefully examine how PV array and storage sizing decisions may affect the risk exposure of the microgrid business and its ability to secure both debt and equity finance. Furthermore, it has been seen that uncertainty around electricity demand strongly affects the bankability of microgrid projects that rely on business models based on energy tariffs. It should therefore be important to lenders that microgrid businesses demonstrate a high level of revenue security. Because consumer behavior in newly-electrified communities is poorly understood, further research should focus on better characterizing the electricity consumption patterns of these new users to reduce demand uncertainty.

5 A predictive model of household-level electricity demand in newly electrified communities in East Africa

5.1 Introduction

In previous chapters, I identified that uncertainty in demand for electricity in newly electrified communities is a key driver of risk for microgrid utilities. This uncertainty makes it difficult for them to raise the capital needed to deploy new systems [19], [21]. As a result, there is interest in developing demand forecasting models for microgrids in these communities. Researchers have developed several methods to estimate demand in areas that have never had electricity, including bottom-up methods based on assumed appliance use, or simple averages of consumption from systems installed in other communities. For example, Louw et al. [112] assessed the determinants of electricity demand in newly electrified households in South Africa, finding that appliance ownership, the price of alternative fuels, income, and access to credit were statistically significantly related to demand. Llanos et al. [113] used clustering algorithms to predict demand in un-electrified communities from similar electrified communities. Mandelli et al. [114] developed a bottom up approach to estimate load profiles based on expected appliance use and the coincidence of use. These approaches have been limited in their ability to forecast demand of individual microgrid customers, and thus are only useful when modeling aggregate demand. Modeling customer level demand is useful, for example, in identifying customers that are likely to consume enough electricity to justify the cost of connecting them. The limited work evaluating customer-level demand has focused on households that are typically low use customers on microgrids, in contrast to commercial customers. Furthermore such work does not assess the predictive power of the models developed.

This chapter analyzes the load characteristics of 11 microgrids and then applies several statistical learning techniques to predict electricity demand for customers, both residential and commercial, on new microgrids using electricity consumption data as well as demographic data at the customer level from four of these microgrids for which detailed demographic data are available. We compare the predictive performance of these statistical techniques to forecast mean daily electricity consumption during the first 30 days after connection to the microgrid. The short time horizon is due to data limitations but is a good starting point for developing longer term forecasts. Finally, we quantify the uncertainty of these forecasts and highlight the important correlates to electricity demand. The data for this chapter came from PowerGen Renewable Energy, a developer of rural microgrids in East Africa. PowerGen collected consumption data using smart meters, while demographic data came from surveys PowerGen deployed during the customer screening process.

5.2 Load Characteristics

Before developing the predictive model, this section presents load characteristics for 11 PowerGen microgrids in Kenya and Tanzania. Where the predictive model I develop in this chapter forecasts average daily demand after connection, the analysis here provides information on hourly load profiles, short term and seasonal variability, and growth patterns. These analyses provide an empirical starting point for developing inputs to STEMM and other software such as HOMER [115].

5.2.1 Load Profiles

Figure 5-1 shows hourly load profiles, normalized to mean hourly demand for each site to facilitate comparison between microgrids of different sizes. Peak demand is consistently between 7PM and 9PM. This is in line with expectations since sunset is consistently around 6PM in the region and it is generally assumed that evening loads from lighting and social activities peak after dark. Consumption decreases significantly between 11PM and 12AM. Several sites also exhibit a second smaller peak from late morning through the afternoon, likely due to commercial activity, as these sites typically have a higher proportion of commercial customers.

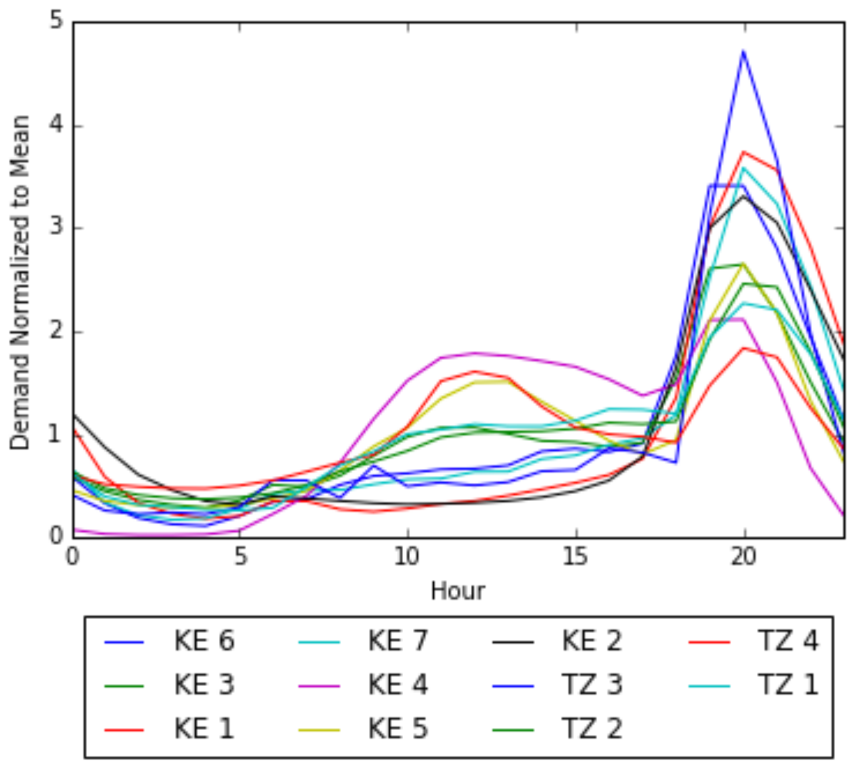

Figure 5-1 Mean hourly load profiles normalized to mean hourly demand.

5.2.2 Load Profile Variability Parameters

The magnitude of variation around these mean load profiles is also an important factor in microgrid design. HOMER models loads with two variability factors while STEMM uses only a single timestep variability parameter. Day-to-day variability is modeled as independent normal distributions around the mean total daily consumption each day, with the standard deviation set to a percentage of the mean value. This percentage is called the day-to-day variability. To estimate this parameter using the empirical data, the daily total electricity consumption is computed for each day at every site. I then compute the day-to-day variability for each site as the standard deviation of the daily consumption values divided by the mean. Table 5-1 shows the results of these computations.

The second variability parameter is the timestep variability. To compute this parameter, I first adjust hourly demand based on the ratio of the electricity consumption on that day to the mean daily consumption. With these adjusted hourly values, I then compute the mean and standard deviation of electricity consumption for each hour of the day at each site. The ratio of standard deviation to mean produces a timestep variability parameter for each hour of the day. HOMER relies on a single value because it assumes that timestep variability is the same across all hours of the day [7]. This is not the case for the sites in our database, which have lower timestep variability during peak times. To combine the hourly time-step variability in the empirical data into a single timestep variability that could be used in HOMER or STEMM, both a simple average and a weighted average are presented. The weighted average weights the hourly timestep variability by the load profile, giving greater weight to high consumption hours. Peak demand is more critical to system design than off-peak demand. The simple average may lead to overestimation of variability of peak load leading to inaccurate system sizing.

Table 5-1 also shows these results. The weighted timestep variability is highly correlated with the number of customers on the microgrid (-0.73) and more weakly correlated with day-to-day variability (-0.13).

Table 5-1 Site sample sizes and HOMER load variability parameters

Site	Customers	Date Connected	Mean Daily Use (kWh)	Day to Day Variability	Timestep Variability	Timestep Variability (weighted)
KE 1	30	Oct. 2015	1.3	27%	61%	40%
KE 2	71	Nov. 2015	9.0	54%	45%	38%
KE 3	32	Jun. 2014	3.9	35%	94%	61%
KE 4	25	Jun. 2014	2.0	44%	98%	70%
KE 5	21	Jun. 2014	2.7	58%	128%	65%
KE 6	28	Mar. 2015	1.2	63%	74%	63%
KE 7	33	Oct. 2015	0.6	37%	74%	51%
TZ 1	70	Jun. 2016	1.1	39%	62%	43%
TZ 2	109	Jul. 2016	7.8	57%	52%	43%
TZ 3	52	Oct. 2016	12	25%	39%	39%
TZ 4	92	Oct. 2016	87	15%	21%	18%

The day-to-day variability and time-step variability parameters estimated with the empirical data suggest that load variability can be high but varies significantly between sites. Time-step variability is strongly negatively correlated with the number of customers on the microgrid. Therefore, increasing the number of customers connected to a microgrid, especially balancing the domestic and commercial customers, could reduce load variability.

5.2.3 Seasonal and Weekly Trends

Simulation tools like STEMM and HOMER also allow the use of different load profiles for weekdays and weekends, and for different months in order to account for weekly and seasonal demand patterns [7]. Using the empirical data, I evaluated the differences in load characteristics during weekdays and weekends, as well as seasonal variability. Figure 5-2 shows monthly electricity demand normalized to the monthly mean for each site and Figure 5-3 shows the electricity demand by day of the week normalized to the daily mean. The number of monthly samples per site is low so trends are difficult to determine at this point. However, no clear patterns are discernable based on this early data. The results suggest that such low frequency variability is not very significant in the PowerGen sites. There are two exceptions in the weekly variation with one site showing significantly greater demand on Mondays and another with increased demand on Fridays, which corresponds to market days in those villages.

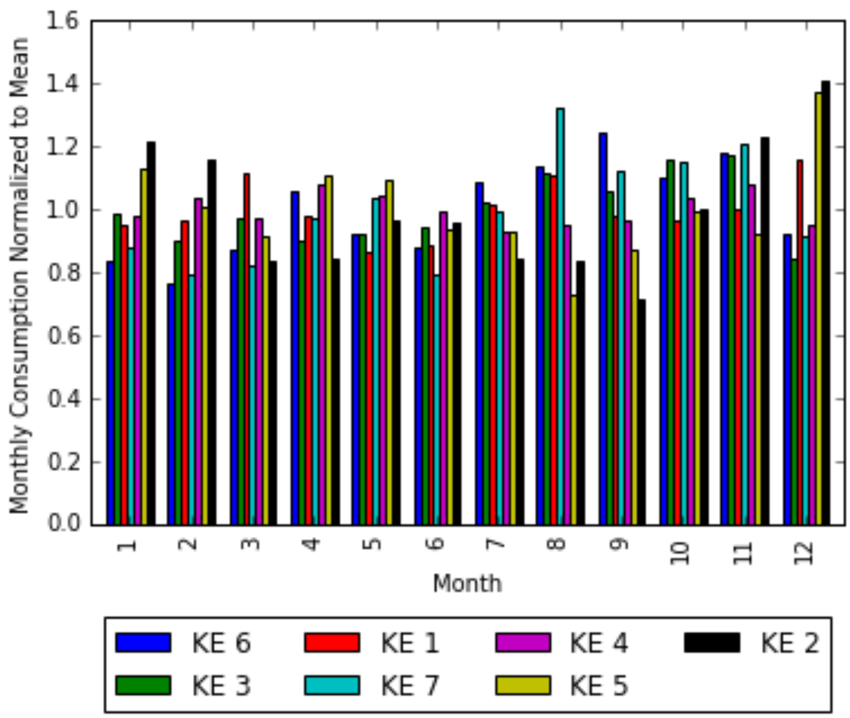

Figure 5-2 Variation in electricity consumption by month (sites with less than 12 months of data have been excluded).

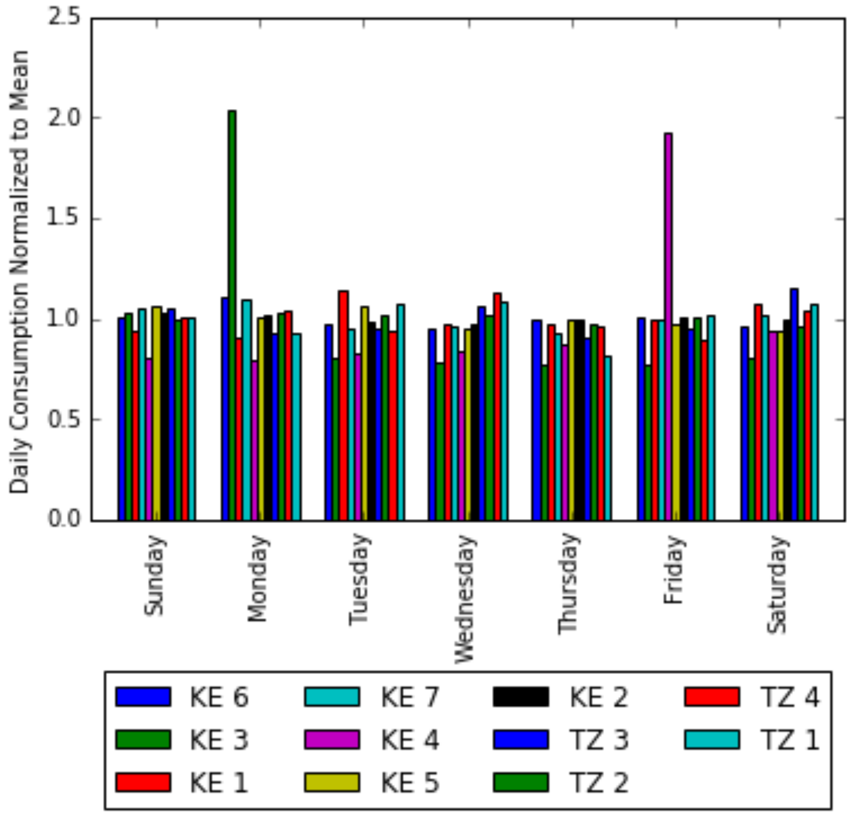

Figure 5-3 Variation in electricity consumption by day of the week.

5.2.4 Load Growth

Microgrid developers like PowerGen are increasingly interested in understanding how demand for electricity evolves after customers are first connected. Figure 5-4 plots the mean daily consumption for each month after connection normalized to the mean daily consumption in the first month. The results suggest that there are microgrids in this study that experienced significant increases in demand following installation. However, I am unable to identify consistent trends in load growth. To create more consistent load growth for all customers, PowerGen is building out various demand stimulation programs, the effects of which will be carefully monitored.

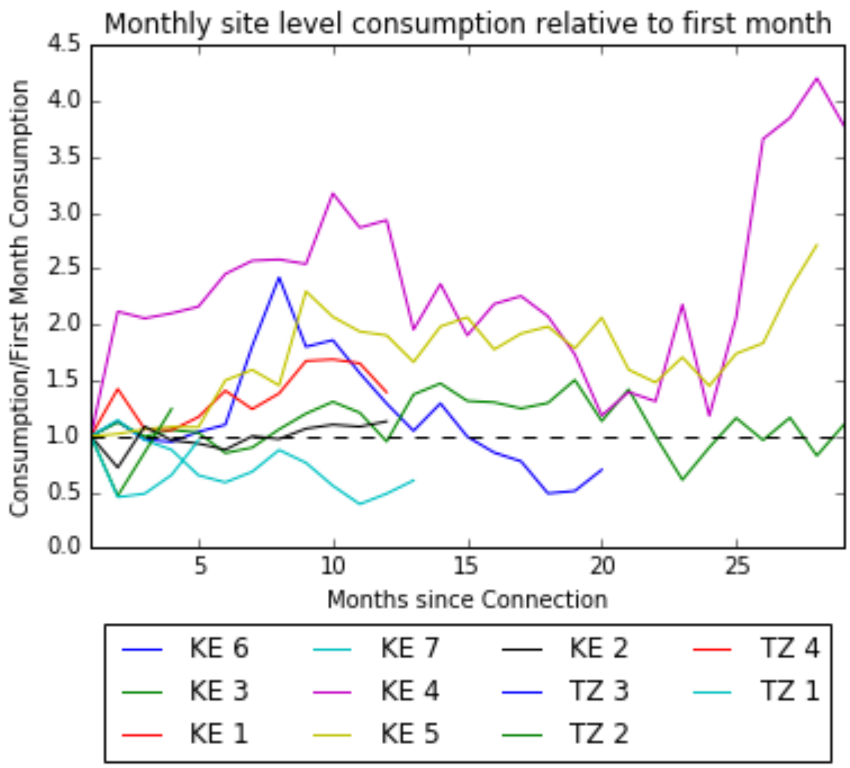

Figure 5-4 Monthly electricity consumption normalized to consumption in first month of access.

5.3 Predictive Demand Model

In order to develop a predictive model of demand to support microgrid-planning efforts, I use a subset of the PowerGen data previously described. In particular, the analysis in this section relies on data collected at four PowerGen microgrid sites in rural Tanzania. PowerGen installs smart meters that record hourly electricity consumption for each customer connected to the microgrid. After the PowerGen team selects communities for microgrid deployment, a survey team collects data on potential customers using their customer application survey. Of the 322 unique meter numbers at the four sites in the consumption data, 269 also have complete demographic data from the customer application survey. Customers with missing or incomplete customer application surveys were excluded from the models. Table 5-2 summarizes the types of customers found at each of the four microgrid sites. The majority of customers are households, typically with a 60/40 split between residential and commercial connections. Some connections include both a household and adjoining business. The most common types of commercial customers are shops, restaurants, bars, and guest houses.

The dependent variable in the statistical models is the mean daily electricity consumption for each customer during both peak and off-peak periods for the first 30 days after connection to the microgrid. We developed two separate models for peak and off-peak periods because about half of the customers in the sample are on time of use (TOU) tariffs that charge different rates based on the time of day. Separate models allow estimation of price elasticities of demand for each time period.

Table 5-2 Customer types by microgrid site

Connection Type	Site 1	Site 2	Site 3	Site 4	Total
Home	37	78	36	58	209
Shop	7	17	9	24	57
Restaurant	7	4	1	4	16
Bar	0	3	2	7	12
Guest house/Hotel	0	2	3	3	8
Hair salon	0	0	0	2	2
Business Services	0	1	0	0	1
Phone charging	1	3	0	1	5
Battery charging	0	1	0	0	1
Milling	0	0	1	0	1
Rental premises	3	0	3	0	6
Office	0	1	0	0	1
Pharmacy	2	1	0	0	3
Dispensary	0	2	1	0	3
Other	2	2	6	4	14
Total Connections	49	86	46	88	269

Table 5-3 lists the categorical variables collected during customer application surveys and used in this study. Such variables include the type of customer (home or type of business), existing and planned electrical appliances, current sources of electricity and lighting, and building type and ownership. Several levels of these categorical variables had low response frequency in the customer surveys, so they were grouped. These groupings were made by mean electricity demand for customers having these attributes and similarity in the nature of the attributes. For example, we grouped the “bar” and “restaurant” levels in the customer type variable and the solar between 50W-150W with solar 150W or greater in the existing appliances/lighting source variable. Numerical variables include the electricity price per kWh, the number of existing light bulbs, and monthly spending on airtime and electricity services. Some variables collected during customer application surveys were not used due to incomplete data collection such as amount and source of income, number of children enrolled in school in the household and asset ownership.

Table 5-3 Categorical variables and levels. Shaded boxes indicate groupings of levels. Response frequency is indicated by the number to the right of the levels.

Connection Type*	
Home	209
Shop	57
Guest house/Hotel	8
Hair salon	2
Restaurant	16
Bar	12
Business services	1
Phone charging	5
Battery charging	1
Milling	1
Rental premises	6
Office	1
Pharmacy	3
Dispensary	3
Other	14

* Multiple responses permitted

Current Electricity/Light Source*	
None	8
Kerosene Lamp	31
Solar (< 50W)	79
Solar (50W – 150W)	57
Solar (> 150W)	4
Generator/Microgrid	50
Solar Lantern	79
Other	24

Building Type	
Brick	96
Sticks and mud	4
Mudbrick	14
Old concrete	18
Irons sheets	1
Well-built concrete	136

Existing Appliances*	
None	45
Phone charging	124
Radio	160
Low watt TV	58
High watt TV	50
CD/DVD player	41
Sound system	15
Printer/Photocopier	2
Computer	5
Refrigerator	15
Shaver	3
Other	25

Building Ownership	
Own	239
Rent	24
Other	6

Planned Appliances*	
None	5
Lights	172
Phone charging	99
Radio	107
Low watt TV	144
High watt TV	7
CD/DVD player	66
Sound system	19
Computer	11
Printer/Photocopier	4
Refrigerator	126
Microwave	5
Shaver	12
Hair clippers	8
Other	62

The cost of electricity is likely a strong determinant of demand. PowerGen implements different tariff structures at different sites and for different classes of customers. Two of the four sites included in the data rely on a bundled tariff structure whereby the more a customer pays in a single purchase, the larger the number of kWhs credited to their account. The other two sites rely on a TOU tariff structure. In this structure, customers receive a lower off-peak rate for electricity consumed between 10am and 4pm. The rate for consumption during the peak period (the peak tariff) is higher than the off-peak rate. Furthermore, PowerGen has three tiers of TOU tariffs on these sites, with higher consumption customers paying a lower rate. The actual price points for these tariff structures are confidential and cannot be published, but the statistical models in this chapter account for such rates. Customers are placed into TOU tiers based on anticipated electricity consumption estimated from anticipated appliance use. Table 3 summarizes the number of customers at each site on each tariff plan. The different tariff structures are the result of a policy change and were not assigned on the basis of any site characteristics.

Table 5-4 Number of customers per site on each tariff plan

	Number of Customers				
Tariff Plan	**Site 1**	**Site 2**	**Site 3**	**Site 4**	**Total**
Bundled	49	86	0	0	135
TOU Small User	0	0	32	0	32
TOU Medium User	0	0	14	27	41
TOU Large User	0	0	0	61	61

5.3.1 Method

The objective of this paper is to develop a predictive model of initial demand for electricity by customers in newly electrified communities using the data collected in customer application surveys as predictors. Using the python package scikit-learn [116], we apply several regression techniques on a training subset of the data representing 70% of the 269 customers with complete survey records. We then evaluate the model performance on the remaining test data using the mean squared error metric.

As previously mentioned, the cost of electricity likely affects demand. Since roughly half of the customers in the database are on the TOU tariff structure (in which they face a lower rate for consumption between 10am and 4pm), we create two models to capture differences between peak consumption (more expensive) and off-peak consumption (less expensive). The dependent variable used in the two models is the log mean daily consumption in each period for each customer during the first 30 days after connection. The 30-day period is chosen because 35 days of data was available for the newest sites when the modeling was completed. Future work will examine how consumption evolves over time after initial exposure.

5.3.2 Regression methods applied

In this analysis we test the performance of different statistical models to predict customer demand during the first 30 days of being connected to the microgrid. We compare all of the models to a base model that assumes that the best prediction of a customer's demand is the average across all customers. This is equivalent to an ordinary least squares (OLS) model with an intercept and no predictors. The other regression techniques applied in this paper include OLS regression, least absolute shrinkage and selection operator (LASSO) regression, ridge regression, principal components regression (PCR), and random forests [117].

5.3.2.1 OLS

Building on the intercept model (base model), OLS minimizes the sum of squared residuals between observations and a model that is linear in parameters

$$\log(y_{peak}) = \beta_0 + \beta_1 x_{TOU} + \beta_2 x_{TOU} log\ x_{tariff_{peak}} + \sum_{k=3} \beta_k x_k$$

$$\log(y_{off-peak}) = \beta_0 + \beta_1 x_{TOU} + \beta_2 x_{TOU} log\ x_{tariff_{off-peak}} + \sum_{k=3} \beta_k x_k$$

where y is mean daily electricity consumption during the first 30 days after connection during each period, x_{TOU} is a dummy variable for customers on TOU tariffs, x_{tariff} is the price per kWh in Tanzanian shillings (TSH) charged to TOU customers in each period, and x_k are the other predictors (listed in Table 5-3). β_0 is the intercept, and β_k are the model coefficients estimated in the model. Numerical variables are incremented by one and logged. This model structure is used for all linear regression techniques applied in this paper. OLS coefficients are determined by solving the minimization problem,

$$\hat{\beta} = \underset{\beta}{argmin} \sum_i \left(y_i - \beta_0 - \sum_{k=1} \beta_k x_{ki} \right)^2.$$

OLS is a widely used technique and provides another point of reference for comparison of more recently developed statistical learning techniques.

5.3.2.2 Ridge

Ridge regression is a coefficient shrinkage method. A penalty term, introduced to the objective function of the minimization problem, shrinks the L_2 norm of the coefficients (the sum of squared coefficients) as follows,

$$\hat{\beta} = \min_{\beta} \left(\sum_i \left(y_i - \beta_0 - \sum_k \beta_k x_{ki} \right)^2 + \alpha \sum_{k=1} \beta_k^2 \right)$$

where α is a tuning parameter that determines the level of coefficient shrinkage.

Ridge regression addresses issues arising from correlated variables that cause coefficients to have high variance in OLS [117]. Figure 5-5 presents the correlation matrices of the model variables showing several large correlations between variables. Appliance ownership, for example, is correlated with source of electricity and lighting. Customers are more likely to have appliances if they have a high quality source of electricity. Certain appliances are correlated as well. Sound system or DVD player ownership is positively correlated with TV ownership. Unsurprisingly, spending on electricity is positively correlated with appliance ownership and having a high quality source of power.

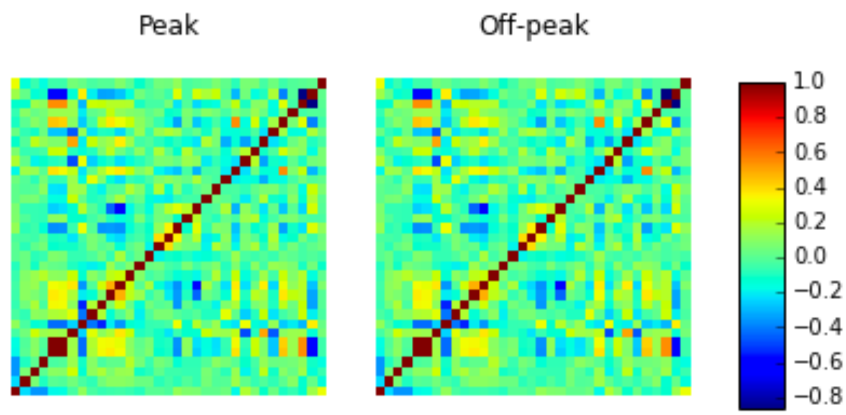

Figure 5-5 Predictor correlation matrices

In this paper, we use 10-fold cross validation for model selection. We normalize all predictors by subtracting the mean and dividing by the standard deviation so that all independent variables are on the same scale. The top panels of Figure 5-6 show the shrinkage of coefficients as a function of the tuning parameter. All coefficients approach zero as the tuning parameter increases. The bottom panels show the cross-validated MSE as a function of alpha. The alpha that minimizes the MSE is the value selected for the model. An alpha value of zero corresponds to an OLS model. On the other extreme, as alpha approaches infinity, coefficients are forced to zero with a non-zero intercept. These end points represent our OLS and intercept models. The OLS model with zero alpha has low bias. Increasing alpha introduces bias while reducing variance. The mean squared error is the sum of squared bias and variance. The minimum MSE in Figure 5-6 balances the introduction of bias with reduced variance.

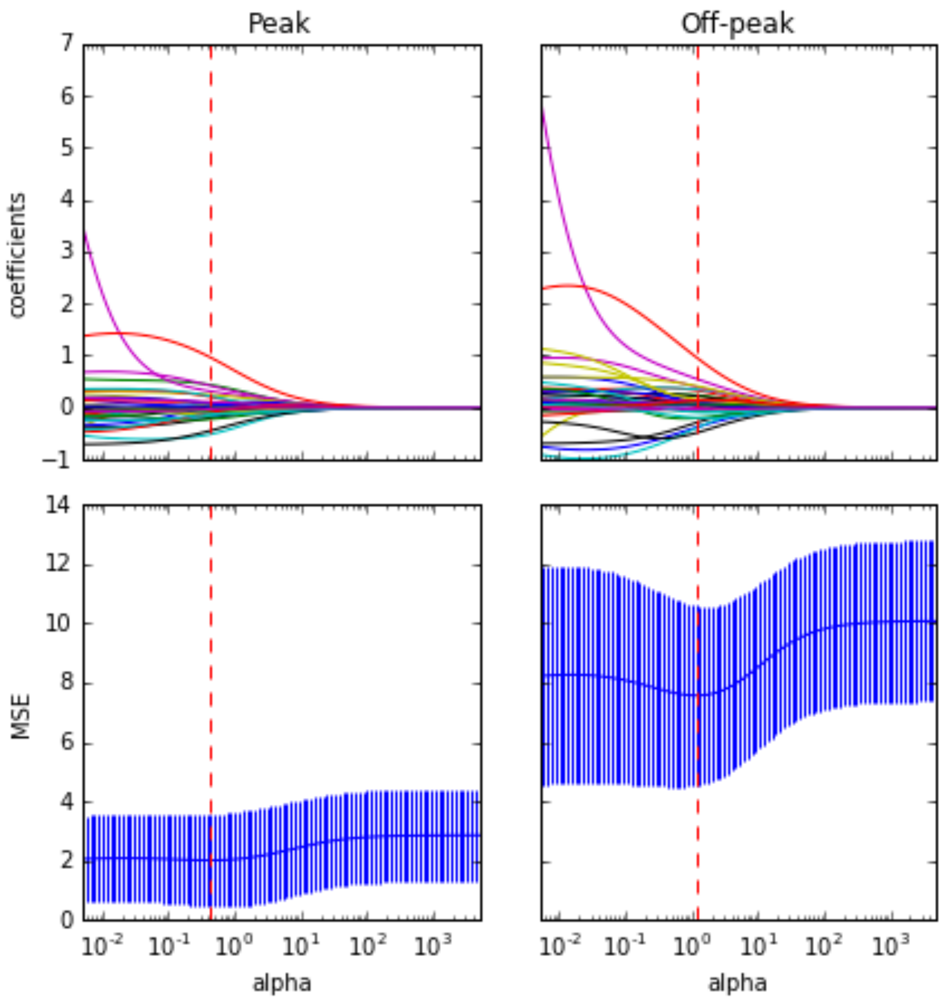

Figure 5-6 Ridge Regression. Top panel: variation of weights (coefficients with tuning parameter. Bottom panel: variation of mean squared error (MSE) on test data with tuning parameter alpha with error bars of one standard error. The dashed line represents the alpha value with minimum test MSE.

5.3.2.3 LASSO

LASSO regression is another shrinkage method, but rather than penalizing the L_2 norm of the coefficients, the L_1 norm (the sum of coefficient absolute values) is penalized leading to the minimization problem,

$$\hat{\beta} = \min_{\beta}\left(\sum_{i}\left(y_i - \beta_0 - \sum_{k}\beta_k x_{ki}\right)^2 + \alpha\sum_{k=1}|\beta_k|\right).$$

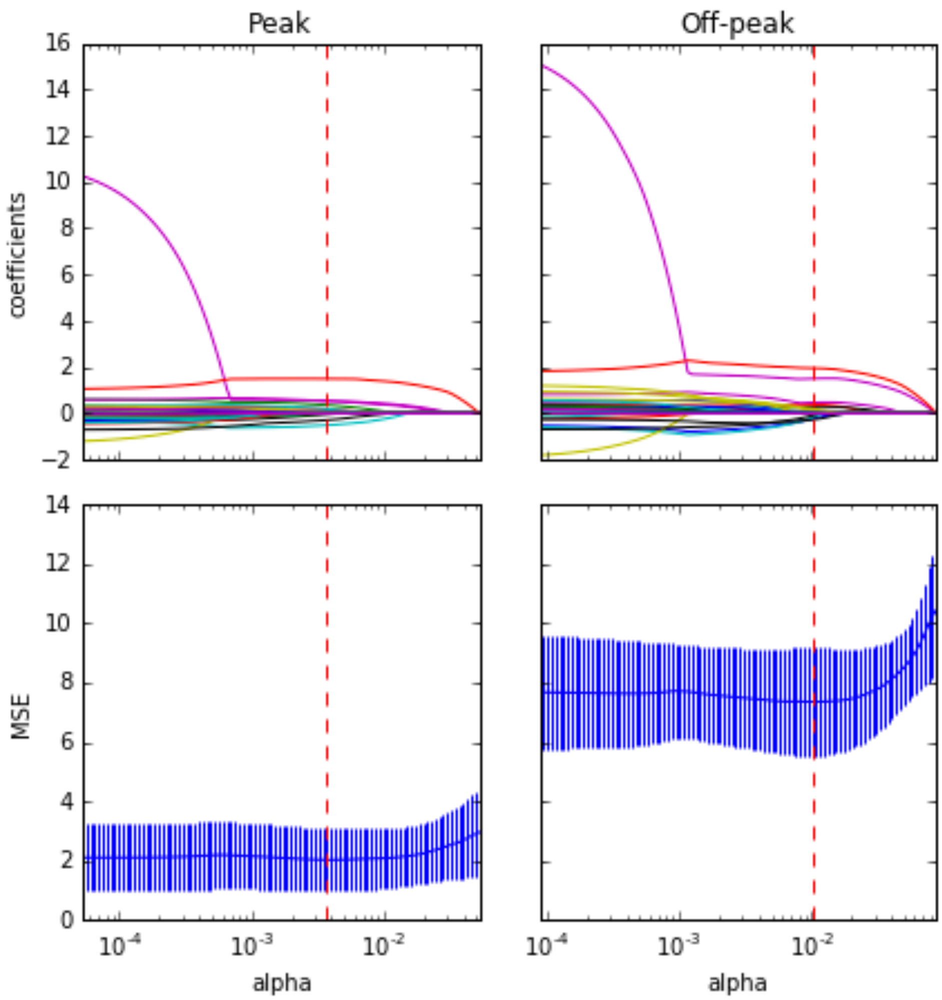

Figure 5-7 LASSO Regression. Top panel: variation of coefficients with tuning parameter. Bottom panel: variation of mean squared error (MSE) on test data with tuning parameter alpha. The dashed line represents the alpha value with minimum test MSE.

The nature of the L_1 constraint leads some coefficients to be set precisely to zero with sufficiently large values of alpha. The LASSO therefore performs variable selection in addition to shrinking coefficients. This leads to fewer predictors and a generally more interpretable model [117]. The value of alpha for the LASSO is also determined using a 10-fold cross validation. Figure 5-7 shows the variation of coefficients and cross-validated MSE for the LASSO. The purple curve is the time of use (TOU) dummy coefficient and the yellow curve is the coefficient for the TOU tariff interacted with the TOU dummy. The TOU dummy coefficient shrinks rapidly from the positive side while the interaction term coefficient shrinks rapidly from the negative side. These variables are clearly positively correlated due to the interaction (when the TOU dummy is zero, the interaction term is zero). In the OLS model, this leads to large coefficients with opposite sign and is a possible source of variance in predictions. The penalty term reduces this effect as seen in the corresponding shrinkage of these coefficients. Most coefficients are set to zero at the alpha value that minimizes the cross validated MSE. As seen in Table 5-5, 12 variables were selected for both the peak and off-peak models. Predictors are normalized in the same way as with the Ridge regression.

5.3.2.4 Principal Components Regression (PCR)

Principal components regression relies on the transformation of variables into a set of orthogonal principal components that are a linear combination of the predictors. The transformation is completed in a way that first components explain the largest amount of variance in the data. We normalize all predictors by subtracting the mean and dividing by the standard deviation prior to applying the principal components transformation. An OLS model is then constructed on the principal components [117]. The number of principal components included in the model is determined using a 10-fold cross validation to minimize cross validated MSE. Figure 5-8 shows the variation of cross-validated MSE as a function of the number of principal components included in the model and the variation of coefficients in terms of the original (untransformed) variables. PCR reduces the dimensionality of the model. At the right most side of the figure, all principal components are included in the model and the solution is equivalent to the OLS case. Zero principal components is equivalent to the intercept model. As more components are added, coefficients grow. The reduction in dimensions reduces the incidence of collinear variables.

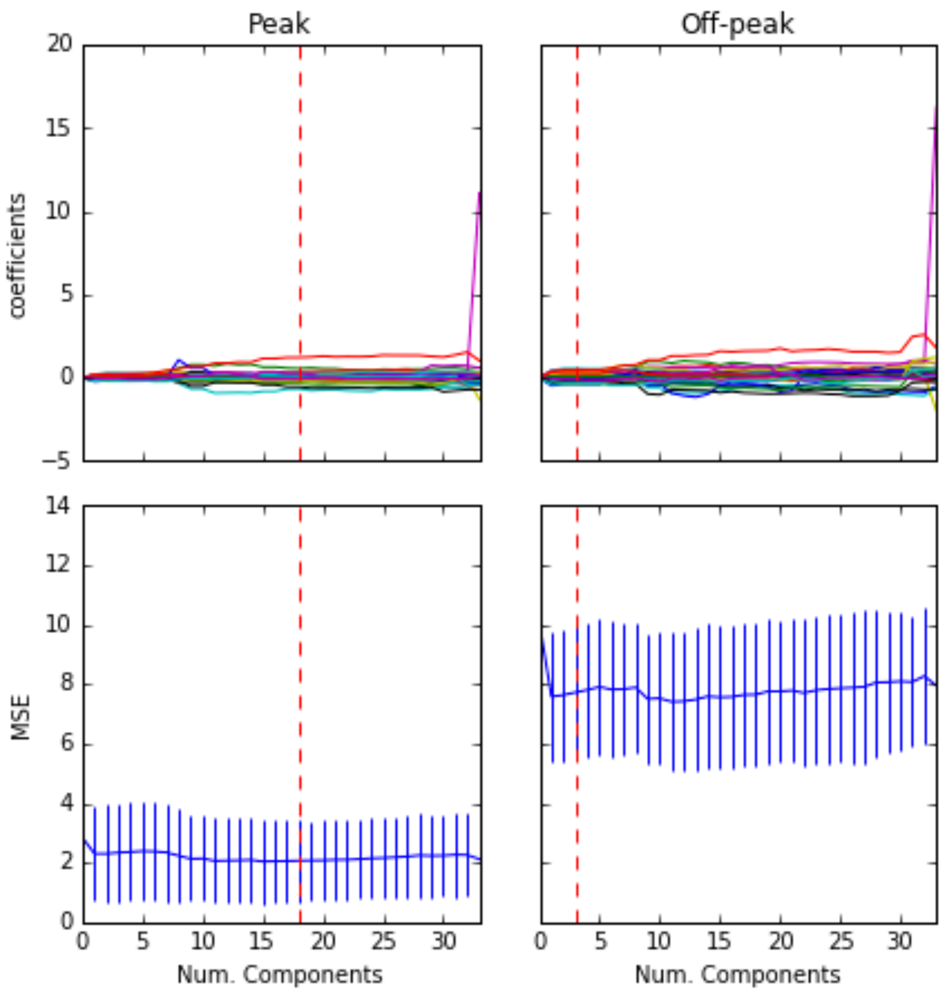

Figure 5-8 Principal Components Regression. Top panel: variation of coefficients with the number of principal components. Bottom panel: variation of mean squared error (MSE) on test data with the number of principal components. The dashed line represents the alpha value with minimum test MSE.

5.3.2.5 Random Forest

Random forests estimate the dependent variable as the mean estimation of a set of regression trees. Figure 5-9 presents an extract of a sample regression tree. The algorithm splits on predictors and assigns values to observations on either side of each split that minimizes the squared error. The split predictors and split points are also determined to minimize squared error. The leaves at the bottom of the tree give estimations of the dependent variable. In random forests, each node split is chosen from a random subset of predictors. This avoids the situation where several dominant predictors are consistently selected at the top of the tree leading to correlation between trees in the forest. We have set the number of candidate predictors at each node to the square root of the total number of predictors, as is common practice [117]. The number of trees in the random forest was set to 30. There is generally no disadvantage to more trees except for the computational cost. The cross-validated MSE stabilizes at fewer than 30 estimators. Each tree is constructed by resampling the training subset with replacement. The random forest model is not split between peak and off-peak periods but run as a single model. The dependent variable is left as log consumption and models are present for peak, off-peak and total demand to permit comparison of MSE between models. Numerical independent variables are untransformed.

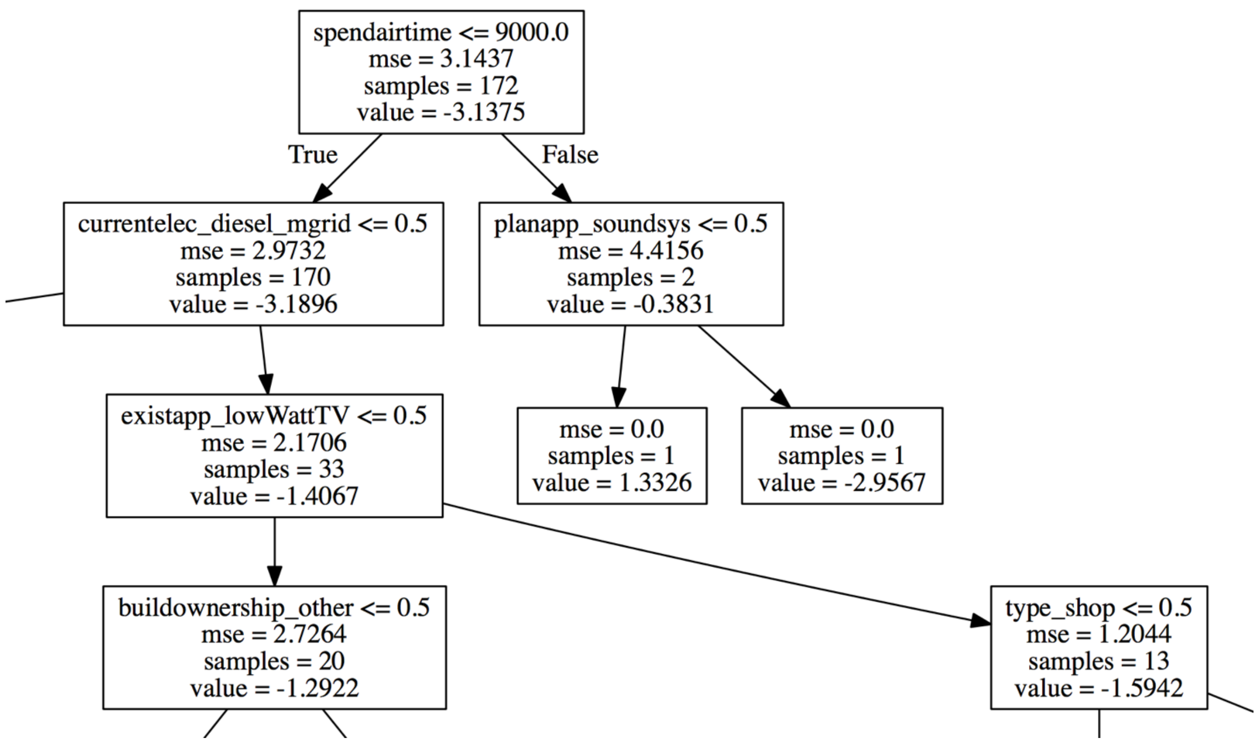

Figure 5-9 Extract from sample regression tree.

5.4 Results

Each model described in section 5.3.2 was trained on a randomly selected training set, consisting of 70% total of observations. This was repeated 1,000 times for different training/test splits. The model coefficients, intercepts, tuning parameters, and training/test MSEs were recorded for each iteration.

5.4.1 MSE

Figure 5-10 presents boxplots of the six models for the mean squared error on test data for 1,000 random train/test splits for peak and off-peak periods. Combined results are the MSE of the sum of peak and off-peak predictions. This sum is computed as $\log\left(e^{\hat{y}_{peak}} + e^{\hat{y}_{off-peak}}\right)$. The results show significant improvement in prediction performance over the intercept only baseline model. The standard OLS model is outperformed by the other candidate models with the exception of the PCR and random forest peak consumption models, which perform similarly.

As seen in Figure 5-10, the LASSO model produced the lowest mean test MSE for all periods, followed by Ridge regression. The PCR and random forest models perform only slightly better than the standard OLS model. In this context, the coefficient shrinkage methods therefore seem to be the best approaches to minimizing the squared error of predictions, suggesting little advantage is obtained in using the non-linear random forest model. The random forest model does, however, do a better job picking out higher consumption customers (at the cost of some loss of accuracy for customers close to the mean) which could mean there are some non-linear effects at extreme values that are not captured by the linear models. Off-peak prediction performs much more poorly than on-peak for all models. Mean daily peak consumption per customer is 129 Wh compared to 52 Wh off-peak. The relatively poor prediction performance of off-peak demand therefore has limited impact on the accuracy of predictions for total daily demand.

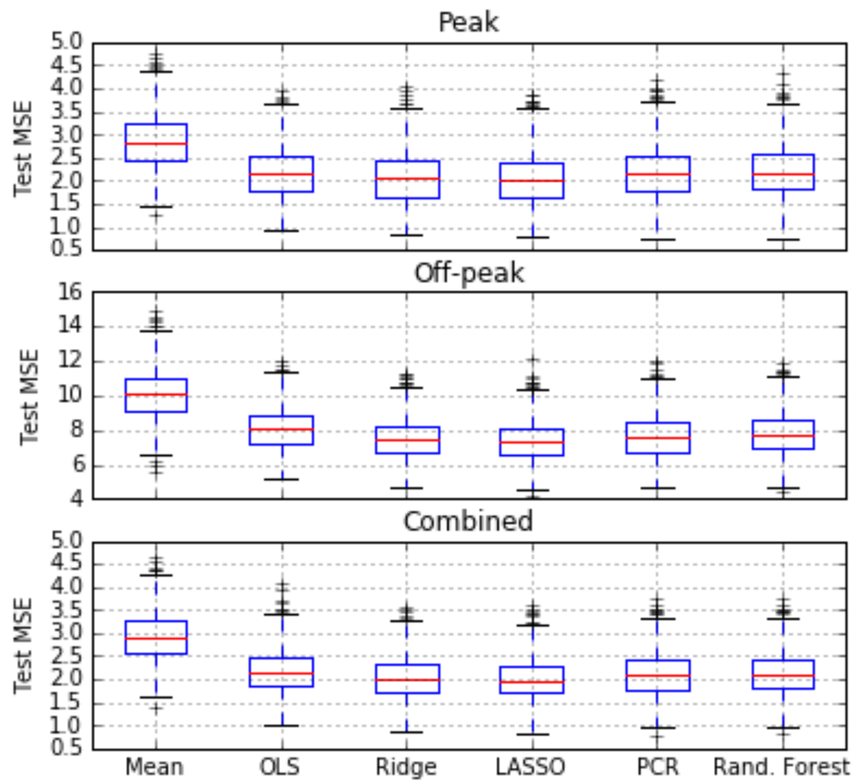

Figure 5-10 Boxplots of test MSEs for 1,000 train/test data splits.

5.4.2 Coefficients

The coefficients for the OLS, Ridge, LASSO, and PCR models trained on the entire dataset are provided in Table 5-5. We evaluated the models by training the model on 1,000 random train/test spits, computing model parameters on the training data, and testing predictive performance on the test data for each split. Table 9-2 in Appendix C contains the mean and standard deviation of the parameters from these iterations. Because the LASSO regression performs variable selection, median values are also reported, as the mean can be misleading when it includes zeros from iterations when a variable was not selected. A non-zero median indicates that a variable is selected more often than not. Figure 5-14 provides further details on LASSO variable selection

Table 5-5 Regression model parameters fit to entire data set

	OLS		Ridge		LASSO		PCR	
	Peak	**Off-peak**	**Peak**	**Off-peak**	**Peak**	**Off-peak**	**Peak**	**Off-peak**
Tuning Parameter			0.575	1.33	0.004	0.010	18.0	3.00
Intercept	-3.53	-9.43	-3.75	-7.57	-4.20	-7.32	-4.06	-7.02
Own Building	-0.038	0.031	-0.021	-0.007			0.017	-0.075
Building Type								
Well Built Concrete	-0.456	0.068	-0.067	0.128			-0.011	0.268
Brick/Mud Brick/Sticks & Mud/Wood	-0.421	0.105	-0.113	-0.178			-0.081	-0.335
Current Light/Electricity Source								
None/Kerosene Lamp	-0.712	-0.249	-0.399	-0.527	-0.284	-0.271	-0.319	-0.216
Solar Lantern	-0.183	0.594	-0.138	-0.076			-0.193	-0.188
Solar < 50W	-0.197	0.316	-0.206	-0.209			-0.253	-0.174
Solar > 50W	0.125	1.235	-0.114	0.188		0.204	-0.130	0.225
Generator/Mini-Grid	1.03	1.79	0.88	1.10	1.508	1.96	0.946	0.483
Other	0.215	0.208	0.103	0.123			0.393	0.189
Existing Appliances								
None	-0.301	0.528	-0.150	0.104			0.003	-0.375
Computer/Refrigerator/Printer/Copier	0.334	0.615	0.235	0.447	0.065	0.119	0.236	0.414
Television	0.591	0.817	0.382	0.440	0.531	0.466	0.271	0.456
Radio	-0.184	-0.235	0.048	0.070			-0.013	0.211
Phone Charger	0.009	-0.038	0.000	-0.020			0.056	0.028
CD-DVD Player/Sound System	-0.011	0.005	-0.015	-0.031			0.091	-0.055
Other	-0.389	-0.690	-0.170	-0.341	-0.040	-0.091	-0.263	0.127
Planned Appliance								
None	-0.379	0.059	0.048	0.137			0.625	0.339
Computer/Refrigerator/Printer/Copier	0.090	0.374	-0.021	0.074			-0.117	0.052
Television	0.311	0.958	0.014	0.122			-0.065	-0.365
Radio	0.323	-0.010	0.190	-0.011	0.194		0.337	-0.356
Phone Charger	0.270	0.230	0.175	0.050	0.186		0.177	-0.248
CD-DVD Player/Sound System	-0.011	0.005	-0.015	-0.031			0.091	-0.055
Lights	0.035	0.295	-0.076	-0.058			-0.055	-0.140
Other	0.168	0.253	0.067	0.148			-0.078	-0.028
Customer Type								
Home	0.330	-0.503	-0.012	-0.430		-0.237	0.012	-0.170
Restaurant/Bar	0.618	0.179	0.411	0.250	0.361		0.890	0.151
Shop/Hair Salon/Guest House	0.181	0.432	0.101	0.351	0.031	0.366	0.173	0.168
Other	-0.309	-0.572	-0.474	-0.463	-0.509	-0.182	-0.714	0.096
Time of Use	11.1	16.2	0.290	0.612	0.540	1.50	0.223	0.403
Numerical Variables								
Log Peak Tariff (TSH/kWh)	-1.30		0.023				0.024	
Log Off-peak Tariff (TSH/kWh)		-1.96		0.067				0.054
Log Airtime Spend (TSH)	-0.070	0.022	-0.015	0.074			-0.021	0.099
Log Electricity Spend (TSH)	0.031	0.065	0.029	0.053	0.013	0.019	0.053	0.042
Log Number of Existing Lights	-0.206	0.195	0.035	0.239		0.259	0.219	0.154

frequency. While the structure of the random forest model does not lend itself to concise summary in Table 5-5, the model is particularly useful for identifying the relative importance of model variables, as we will discuss later in the paper.

5.4.3 Prediction Intervals

Regardless the model employed, there will be some level of uncertainty in the demand forecast. When designing the microgrid and business model, it is important to understand these uncertainties [22], [118]. Figure 5-11 plots model predictions against actual values from the test data with 90% prediction intervals for the models evaluated. We estimated prediction intervals for the OLS, Ridge, LASSO and PCR regression models using a method proposed by Steinberger and Leeb [119]. This technique constructs prediction intervals by taking quantiles of the leave-one-out residuals on the training data. Similarly, prediction intervals for the random forest are constructed using quantile regression forests, as proposed by Meinshausen [120]. The intervals appear to be generally slightly under confident, with 7.4%, 9.9%, 4.9%, 6.2%, and 12.3% of observations falling outside of these prediction intervals for OLS, Ridge, LASSO, PCR and random forest models, respectively. When converted from log values to true values, all the intervals are quite large, indicating a high level of uncertainty in predicted values for individual customers. The level of correlation between customers in a community will determine how customer level uncertainty translates to aggregate community level demand uncertainty. It should be noted that taking the exponential of the expectation of log consumption does not return the expectation on the unlogged scale due to Jensen's Inequality. Because the log is a monotonically increasing function, quantiles are preserved. Assuming the log consumption being estimated is normally distributed, the exponential of the logged expectation is the median value on the unlogged scale in kWh.

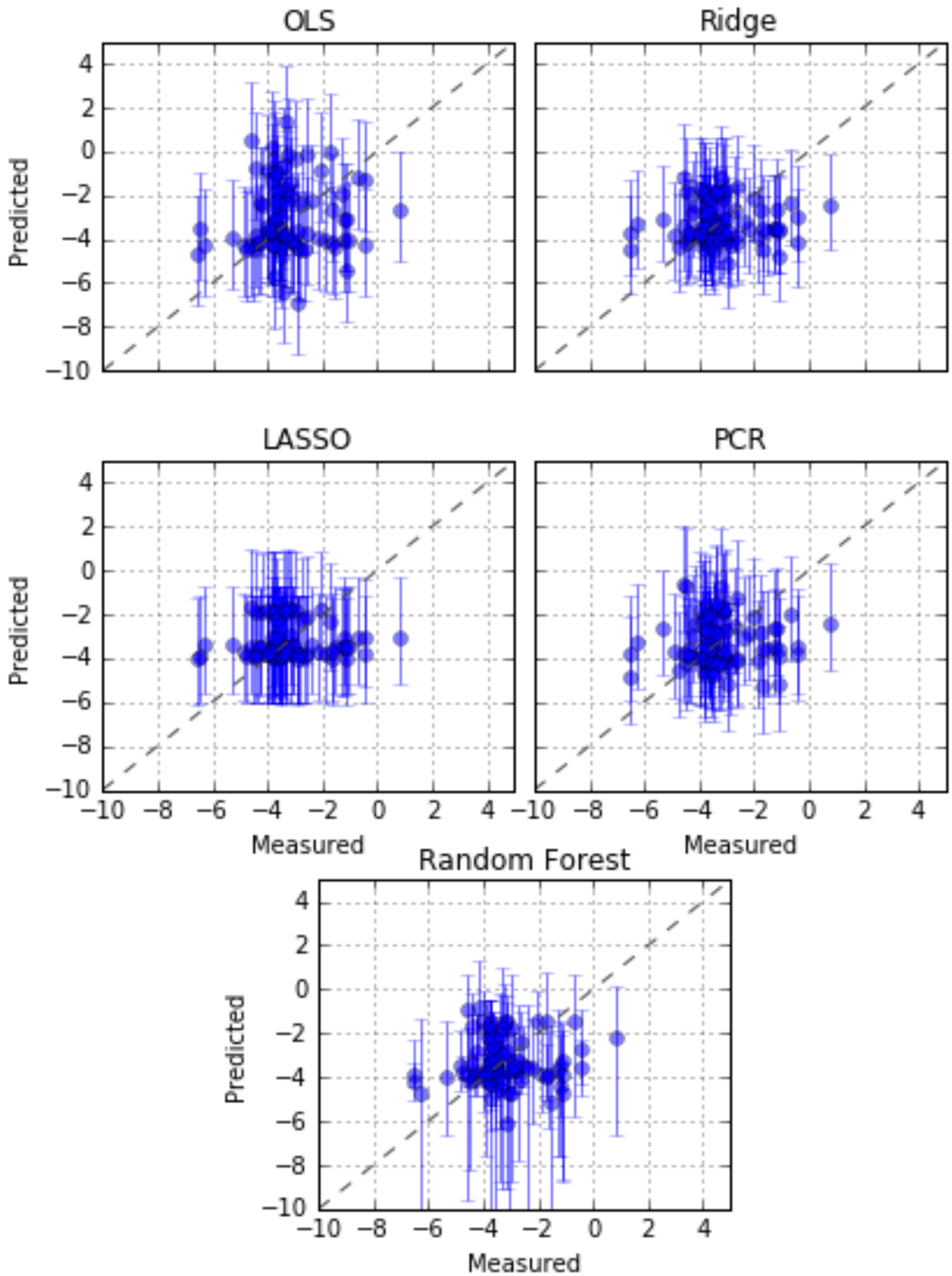

Figure 5-11 90% prediction intervals of test data predictions for OLS, Ridge, LASSO, PCR, and Random Forest models plotted against actual values of log(daily consumption).

5.4.4 Classification accuracy

Microgrid operators with multiple tariff tiers typically offer lower tariffs to customers that consume more electricity. Low use customers require the same grid infrastructure to deliver power but attract less revenue to recover these costs. One application of the models developed in this paper is then to place customers into tariff groups by level of consumption. Figure 5-12 uses each model to class customers in the test data into low (less than 250Wh/day), medium (between 250Wh and 500Wh/day), and high use (more than 500Wh/day) tiers and compares them to the observed consumption (left column). Overall classification accuracy among the models is 84.0%, 81.5%, 82.7%, 84.0% and 85.2% for OLS, Ridge, LASSO, PCR, and random forest, respectively. The LASSO model classifies all customers as low users while Ridge classifies only two customers as medium and the rest as low. The random forest model performs relatively poorly on MSE but has the highest classification accuracy, doing a better job of picking out higher use customers. These customers are fewer in number but of high interest to microgrid operators. OLS and PCR also pick out more medium and high use customers, many inaccurately. These diverging results suggest that there may be some trade off in selecting models. LASSO and Ridge perform well in minimizing MSE but fail to identify customers far from the mean level of consumption. The random forest model is able to pick out some of the higher use customers at the cost of some inaccuracy for customers closer to the mean. This can be seen in the wider distribution of customers towards the center of the prediction versus measured consumption plots in Figure 5-11 for the random forest compared to LASSO and Ridge. The heat map on the right in Figure 5-12 provides another visualization of prediction accuracy on an analog scale. Again, the Ridge and LASSO models greatly underestimate consumption of high use customers.

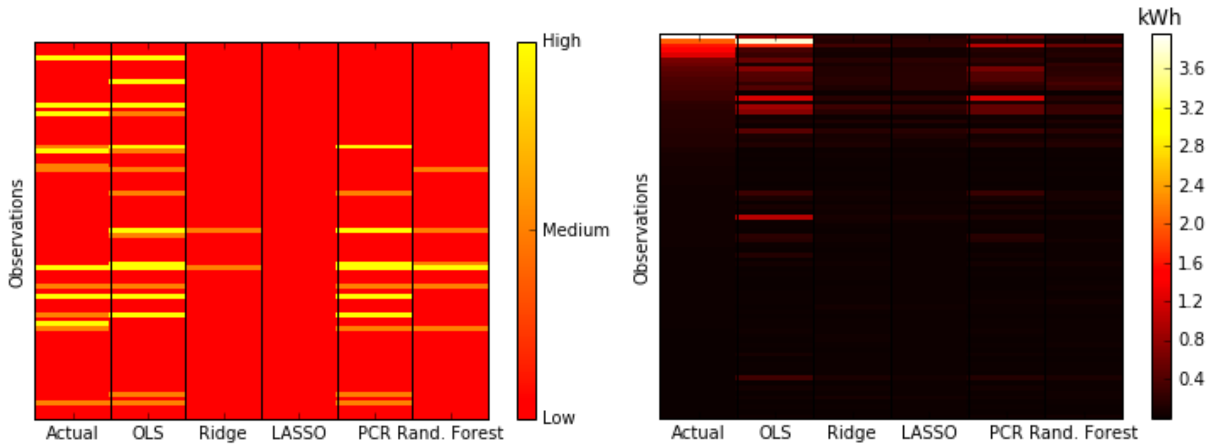

Figure 5-12 (Left) Classification of customers into low (< 250Wh/day), medium (< 500Wh/day), and high (≥ 500Wh/day) consumption groups compared to observed consumption (left column) for each model applied to test data. (Right) Heat map of estimated median daily consumption for each model with observed consumption on left.

5.4.5 Important Predictors

Figure 5-13 shows the relative importance of predictors in the random forest model. The figure provides the top 10 predictors for both peak and off-peak periods. These rankings are derived from the reduction of variance resulting from a split on that predictor, weighted by the proportion of observations passing through the node, averaged over all trees in the forest [121]. The most important predictors are spending on electricity (pre-connection to the PowerGen microgrid), electricity tariffs, the number of existing lights, spending on airtime, and whether or not the customer is already using a generator or grid-based source of electricity. The spending predictors appear to be good proxies for the spending power of customers. The importance of having access to high capacity sources of electricity like a diesel generator or pre-existing microgrid suggest that prior exposure to electricity has a significant effect on demand. While long-term data are not yet available, it may be the case that long-term exposure to electricity results in increased consumption, perhaps after users have acquired a larger set of electrical appliances. Planned electrical appliance acquisitions do not feature strongly but that may be because after only 30 days of access, customers have not yet had the opportunity to obtain new appliances.

Unsurprisingly, the price per kWh charged to the customer is also an important determinant of electricity consumption. The tariff coefficients for the OLS model in Table 5-5 indicate a high level of price elasticity suggesting that customers are very sensitive to price.

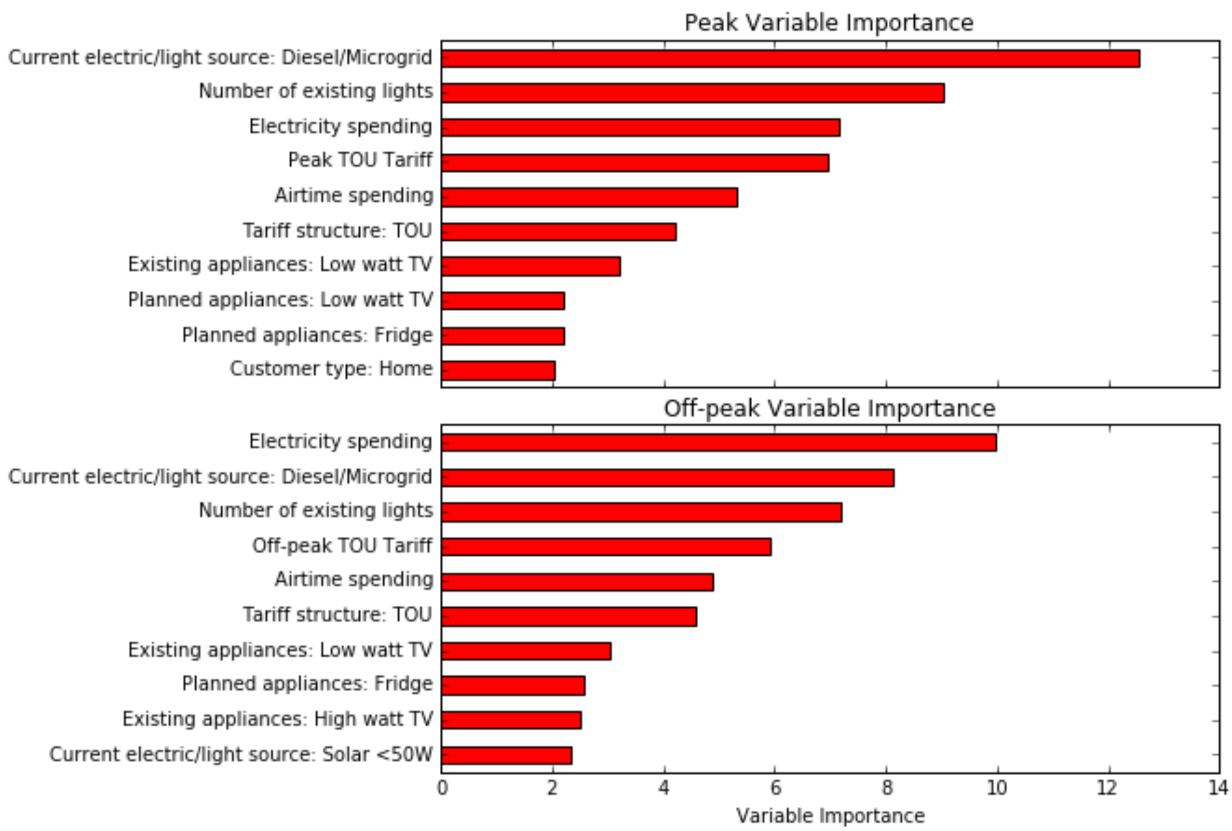

Figure 5-13 Top 10 ranked predictor variable importance from random forest model for peak and off-peak periods.

Another indicator of predictor importance is the subset of predictors selected by the LASSO model. Figure 5-14 shows the percentage of train/test splits in which each predictor is selected by the LASSO model over the 1,000 splits for both the peak and off-peak models. Surprisingly, the tariff rates are not frequently selected in the LASSO models. Whether or not a customer is on a TOU tariff rather than a bundled plan, however, is selected in almost all iterations with TOU customers consuming more than bundle customers. Prior use of a generator or microgrid and having a television are both frequently selected predictors associated with higher consumption levels both on and off-peak. Customers without any access to electricity or using kerosene lamps for lighting are frequently selected in both models and have a lower demand for electricity. This supports the argument that prior exposure to electricity supports higher demand. Spending on airtime and electricity does not feature as strongly as in the random forest case with electricity spending being selected about 50% of the time in both periods.

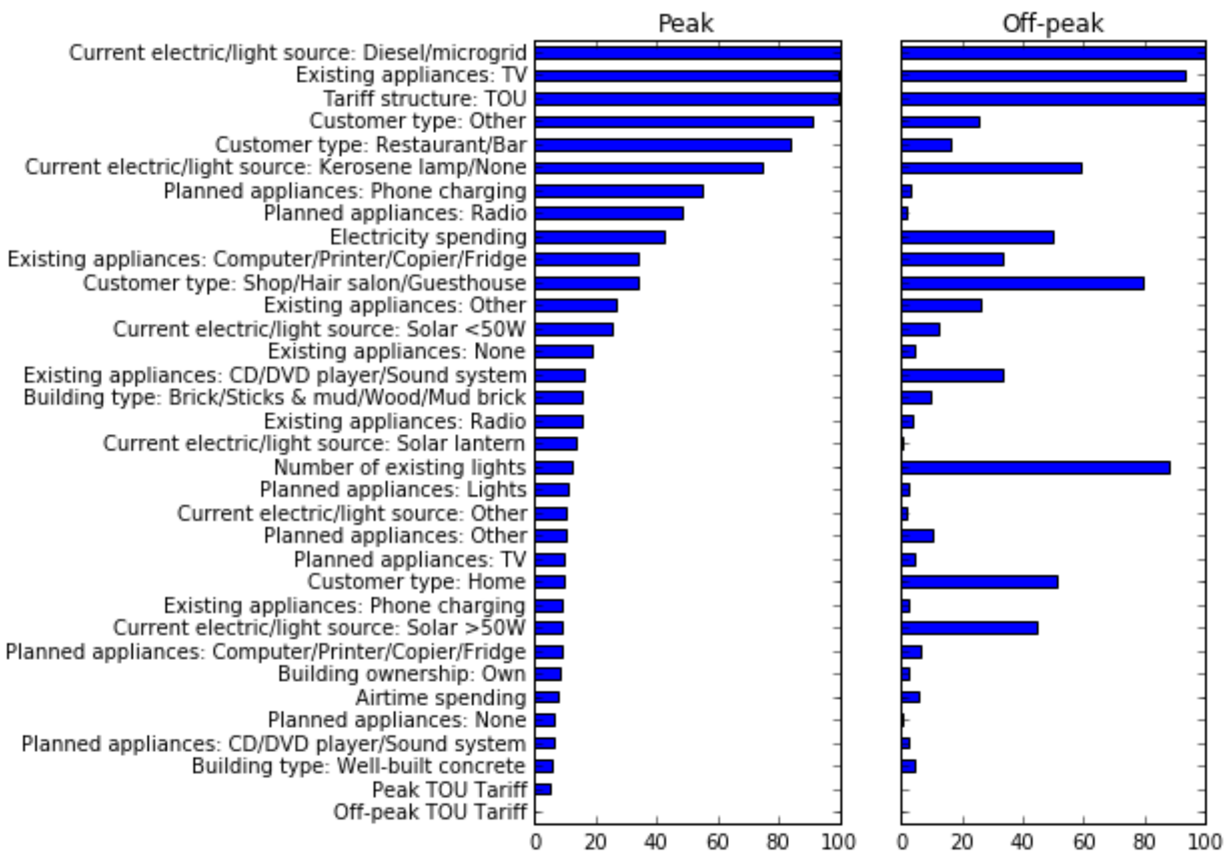

Figure 5-14 LASSO variable selection frequency over 1,000 train/test data splits reported as percent.

Predictor selection frequency diverges between peak and off-peak periods in many cases. Curiously, having a large number of lights tends to have a strong positive influence on consumption during off-peak periods but not on-peak, when it is dark. The reason for this is not clear. The bars and restaurants dummy is frequently selected for the peak model but not the off-peak model. The peak model coefficient is positive and the frequency of selection is almost certainly due to the fact that most of their business occurs in the evenings during the peak period. Shops, hair salons and guesthouses use more electricity during the day (during the off-peak period) and are frequently selected by the LASSO model during this period. Overall, the LASSO model tends to select predictors relating to customer type, tariff structure and source of electricity and lighting, and, to a lesser extent, current electricity appliances.

5.5 Discussion

The ability to forecast demand for electricity in newly electrified communities is of critical importance to microgrid developers for both system design and financial modeling. Anecdotal evidence from energy access entrepreneurs suggests that current techniques practiced in the field often lead to wildly inaccurate predictions. With a number of companies like PowerGen Renewable Energy pioneering the microgrid space in East Africa and collecting high-resolution data on electricity consumption and customer profiles, it is now possible to take a more data driven approach.

Significant reductions in MSE over the baseline intercept model are possible by implementing statistical learning techniques. The LASSO and Ridge models perform the best in minimizing prediction MSE but fair poorly in identifying higher use customers. In this regard, the random forest model performs a slightly better in classing customers into tariff groups using the basic decision model described in 5.4.4. The OLS and PCR models also identify more large-use customers, but with many false positives. Running multiple models can be used to identify cases where estimates diverge. These cases can be investigated further to identify unique customer characteristics that are not fully captured by the models. Users of the model are restricted to tariff structures used by PowerGen. These include TOU tariffs with two periods, one from 10am to 4pm and a second from 4pm to 10am. A single period is also possible by making tariffs for both periods equal. Bundled tariffs are also modeled however, due to the sensitivity of specific price points and the way that these tariffs are structured, the bundled tariff feature is not useable by third parties.

Data availability presents several limitations. At the time this analysis was performed, only about 35 days of data were available for two of the four microgrids. This limited the time horizon that could be assessed. Furthermore, the sample size of 269 connections is relatively small compared to the number of predictors available. This can make estimating coefficients challenging. The PCR and LASSO regression techniques address this challenge by reducing the number of variables used. As more sites are installed, these data can be incorporated into the training data to improve model performance and overcome sample size limitations. Furthermore, new consumption data is continuously being collected which will permit analysis of consumption at different intervals after first connection.

The initial consumption during the first 30 days is also a good starting point for developing time series models to forecast changes in consumption patterns over time. As seen in Figure 5-4, initial data on demand growth do not show consistent patterns across sites and requires further investigation. Understanding how customer-level predictions can be aggregated to create prediction intervals for communities is also the subject of future work. A key component of this will be understanding how site level characteristics affect demand that may lead customers on some microgrids with similar individual characteristics to have more or less demand for electricity than others. This can be achieved by collecting site level data that can be incorporated into these models.

Through this work, I have also been able to identify predictors that are important in estimating the electricity consumption of newly connected customers. These include tariff structures and prices, pre-connection sources electricity and lighting, levels of spending on electricity services and airtime, and pre-connection appliance ownership. Prior exposure to electricity, disposable income, and price are dominant factors in estimating demand. This information can be used as a guide for practitioners in developing pre-deployment surveys and demand forecasts.

Despite the improvements in prediction accuracy, uncertainty in individual customer forecasts remains high. Users of the model should consider their objectives when selecting a model. If the goal is to estimate demand for system sizing purposes or to project revenues in financial models, the LASSO and Ridge regression models produce the smallest overall prediction error. The models presented here are limited in their usefulness for revenue forecasting and system sizing however, because of the short time horizon considered. Time series models to understand how demand changes over time should be developed to overcome these limitations. It may also be the case that these models are used to screen customers and identify potentially high consumption customers. LASSO and Ridge perform poorly here compared to the random forest, PCR, and OLS regression. The development of classification models merits investigation as a way of better identifying high consumption customers. With all of the models, uncertainty in demand predictions for individual customers remains high. When aggregated, the overall relative uncertainty should be reduced but more work is required to quantify this. Other future work should focus on refining demand models, exploring other potentially significant predictors of demand, understanding how and what impacts the evolution of demand over time, and building bottom up aggregate models for load profiles at the community scale based on customer demographics.

6 Conclusions

Expanding access to electricity is central to social and economic development in East Africa. Achieving universal access within the next one or two decades will require massive increases in investment. Public and donor sources of capital are unlikely to be able to fill this gap. Private sector participation in electrification is therefore essential to meeting electricity access targets [21]. Policymakers have also acknowledged that extension of the central electricity grid to homes and businesses in remote rural areas is often not as cost effective as decentralized alternatives such as microgrids and solar home systems [84]. Increasingly, microgrids are being recognized as essential components of rural electrification efforts.

With grid-based power dominated by highly regulated and subsidized state owned utilities, the off-grid sector offers space for innovative private sector entrepreneurs and developers to contribute to electrification efforts without competing directly with subsidized and highly politicized state-owned actors. A number of privately owned companies have entered this space to offer electricity services in rural areas using solar home system and microgrid technologies on a commercial basis. While the solar home system space has grown quickly, microgrids have lagged behind. This is due in part to challenges in raising capital for a business model that is perceived to be risky. Where solar home systems receive fixed payments for use of the system regardless of how much energy is used, microgrids are a shared resource for which payments usually relate directly to consumption. Furthermore, solar home system customers that default on their payments can have their systems repossessed and redeployed. This is not the case for microgrids. Despite the higher levels of risk, microgrids offer a level of service that solar home systems cannot provide that enables productive and income generating use of power. There is thus a need to overcome these challenges to enable microgrids to raise capital and scale up deployment. This thesis aims to identify and quantify the primary sources of investment risk in microgrid utilities and study ways in which these risks can be mitigated to make these businesses more viable.

Through this thesis work, I have identified that the most important sources of risk for microgrid developers include fuel prices, foreign exchange rates, price elasticity of demand, and the level of demand for electricity. The relative importance of these sources is technology dependent. While solar powered microgrids are not exposed to fuel price risks, they are more sensitive to uncertainty about electricity demand than diesel powered systems. Assuming finance is obtained in hard currency and revenue is collected in local currency, capital intense solar/battery powered microgrids are slightly more sensitive to foreign exchange rates. Diesel powered systems however, are still sensitive to foreign exchange through fuel prices that are set on global markets in dollars. Debt providers, who use different metrics than equity investors to assess projects, are exposed to more risk in diesel-powered scenarios than solar/battery scenarios. Attracting debt finance is therefore more feasible for solar/battery microgrids or high solar penetration hybrid systems. System-sizing decisions can, to a certain degree, mitigate risks. However, there is a tradeoff between mitigating risk and maximizing expected returns. Furthermore, high solar penetration scenarios are more attractive to lenders, allowing equity to leverage lower cost debt to increase returns on equity. From a policy perspective, governments and donors can both promote the use of clean solar power in microgrids and de-risk projects by reducing exposure of fuel prices by offering low cost concessional debt to microgrid utilities.

Demand for electricity in rural microgrids is a key uncertainty that drives financial risk for these systems. Predictive demand models that make use of data that can be collected before deploying the systems could help mitigate some of this risk. Using customer demographic data collected prior to connection as part of the PowerGen customer application process, I developed predictive models of electricity consumption for individual customers during the first 30 days after connection to the microgrid. Significant predictive performance gains were achieved over the status quo that assumes all customers consume the same amount of electricity based on historical averages. However, uncertainty at the customer level remains high. Model selection should consider user objectives. While LASSO and Ridge regression produces the lowest overall prediction error, they also perform poorly in identifying high consumption users. LASSO and Ridge regression may therefore be more appropriate when the goal is to estimate aggregate demand from individual customer characteristics for system sizing or revenue projections. When screening customers to identify potential high use customers, the random forest, PCR, and OLS models may be more suitable. Model performance should improve over time as more data becomes available from new installations. At present, the small sample size is a limitation.

Through these models, I was also able to identify predictors that are important in estimating the electricity consumption of newly connected customers. These include tariff structures and prices, pre-connection sources electricity and lighting, levels of spending on electricity services and airtime, and pre-connection appliance ownership. Prior exposure to electricity, disposable income, and price are dominant factors in estimating demand. This information can be used as a guide for practitioners in developing pre-deployment surveys and demand forecasts.

This thesis is a step forward in addressing the challenges to expanding access to electricity with microgrids in East Africa, but much work remains to be done. There are numerous opportunities to enhance STEMM and address current limitations. For example, new technologies can be added such as small hydro and wind. Currently, STEMM assumes microgrids are sized before deployment but several companies are looking at ways to mitigate demand risk by deploying generation capacity over time once demand patterns have been observed. Adding a capacity expansion feature that makes decisions on deploying new generating capacity is the subject of future work. Some risks are simply difficult to quantify, for example, political and policy risks and the risk of grid encroachment.

The predictive demand model presented in this thesis is only a first step. Work is already underway in the field to collect a broader set of data on microgrid customers to explore whether other indicators may be important predictors of demand that can improve prediction accuracy. Beyond initial demand, it is important to understand how electricity consumption patterns change over time. Another important area of future work is developing time series models to model demand growth. These new models of demand should then be integrated into STEMM to improve STEMM's currently rudimentary load model.

Beyond the research finding described above, major outputs of this thesis are a set of tools that are designed to assist microgrid developers and investors make more informed design and investment decisions. It is my hope that STEMM will develop into a tool that can be used by developers to design microgrid utilities that are more financially robust and by investors to evaluate investment opportunities in an unbiased and comprehensive manner. The electricity demand modeling work is an on-going project that will enable microgrid developers to make more informed site selection and system design decisions, in concert with STEMM. The demand model is already being integrated into PowerGen's planning and design processes and therefore already having an impact on the ground. Plans are as well in place to pilot the use of STEMM in a real world setting with PowerGen and the German development agency, the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ).

7 Appendix A: STEMM Documentation

7.1 Model Structure

STEMM models microgrid utilities as individual corporate entities. The model consists of two primary components: a technical model and a financial model. These models are linked to simulate connections between technical design and performance and financial outcomes. STEMM is designed from an investor's perspective; therefore the financial model only includes costs and revenues accruing to the microgrid.

The model assumes each project starts operation on January 1st of the model start year with initial capital costs being incurred December 31st of the previous year. The model time horizon used will depend on the modeler's objectives. For example, if the goal is to understand the bankability of a project, the model horizon should be at least as long as the initial debt tenor. When studying the attractiveness of a project to equity investors, the target period for achieving a minimum equity return should be used. The technical model uses a temporal resolution of one hour, whereas the financial model aggregates cash flows on a monthly basis. As the model is implemented in the modeling software Analytica [88], any input can be modeled as uncertain (as a distribution) or deterministic (as a point value). This provides the user flexibility in determining which uncertainties to model explicitly as distributions or parametrically. A few inputs, including fuel price, demand, and solar resource, are structured explicitly in the model as uncertain.

7.2 Technical Model

The technical model simulates microgrid performance at an hourly resolution over the model horizon. It is currently capable of modeling multiple AC loads, a solar photovoltaic generator, multiple diesel generators, and battery-based energy storage. Figure 7-1 depicts the general system configuration of STEMM. Key outputs of the technical model that feed into the financial model include satisfied and unsatisfied customer demand, fuel consumption, and microgrid component runtimes.

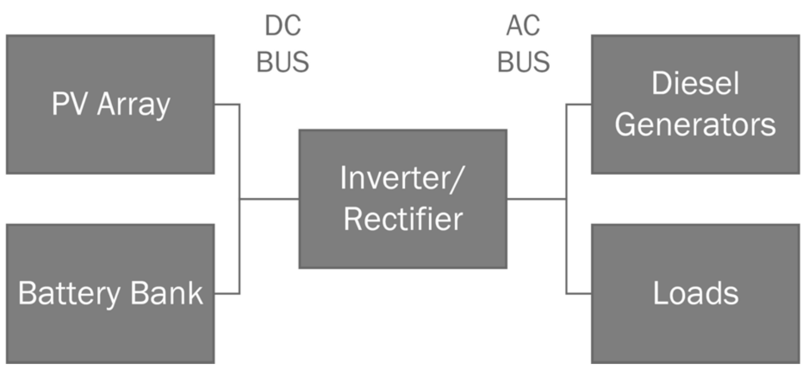

Figure 7-1 General microgrid technical configuration in STEMM.

7.2.1 Meteorological Model

STEMM requires local meteorological data in order to simulate the technical performance of the PV array including local solar irradiation and ambient temperature.

7.2.2 Solar Resource

Solar irradiation data is input into STEMM as hourly global horizontal and array tilt irradiation over a year. STEMM generally relies on data for a "typical meteorological year" (TMY). Where long-term data are available, it is possible to input solar data over the entire model horizon. STEMM accounts for uncertainty associated with solar resources by modeling total annual solar resource measurement bias and hourly irradiation values as normal distributions. The uncertainty of hourly measurements is modeled as independent with mean zero and a user-defined relative standard deviation. These values are scaled using the solar resource bias expressed as

$$G_i = G_{i,meas} \cdot N\left(0, G_{i,meas} \cdot \sigma_{meas}\right) \cdot \left(1 - N(\mu_{bias}, \sigma_{bias})\right)$$

where G_i is the modeled irradiation at hour i, $G_{i,meas}$ is the measured or TMY input, σ_{meas} is the relative measurement error, μ_{bias} is the mean bias of the irradiation data and σ_{bias} is the standard deviation of the measurement bias of the database from which the data is drawn. This accounts both for bias and measurement uncertainty of solar resource data. TMY data does not account for inter annual variation of solar resource. This could result in an underestimate of annual extreme values such as the minimum DSCR. This effect is not generally expected to be significant but could become important in undersized systems that are heavily reliant on PV generation.

7.2.3 Temperature

Obtaining hourly temperature profiles can be difficult for remote sites. NASA's Surface meteorology and Solar Energy (SSE) database provides daily maximum and minimum ambient temperatures globally over 22 years (1983-2005) [101].

7.2.3.1 Ambient

STEMM models ambient temperature profiles based on daily maximum and minimum temperatures from this database when user-provided hourly profiles are not available. These maximum and minimum temperatures are modeled as normal distributions with root mean squared errors (RMSE) from validation studies used as the standard deviation [122]. Hourly temperature profiles are derived using the solar irradiation profiles and a model used in the meteorological software package Meteonorm [123]. This model, described in the Meteonorm 7 Theory Handbook [123], assumes that temperature changes are proportional to the 'ground to extraterrestrial irradiation ratio' defined as

$$kx(t) = \frac{\int_{sunrise}^{t} GHI(t)dt}{\int_{sunrise}^{t} G_0 dt}$$

where GHI is the global horizontal irradiation and G_0 is the solar constant. The maximum daily temperature occurs when kx is at its maximum value, kx_{max}. The slope of the temperature profile before kx_{max} is

$$slp_b = \frac{Ta_{d,max} - Ta_{d,min}}{kx_{max}}$$

and the slope after kx_{max} is

$$slp_a = 1.7 \cdot slp_b$$

where $Ta_{d,max}$ is the maximum daily ambient temperature and $Ta_{d,min}$ is the minimum daily ambient temperature. These minimum and maximum daily ambient temperatures for remote locations around the world are available through NASA's Surface meteorology and Solar Energy (SSE) database [101].

Hourly temperatures between sunrise and kx_{max} are then given by

$$Ta(t) = Ta(t_{sunrise}) + slp_b \cdot kx(t)$$

and temperatures between kx_{max} and sunset are given by

$$Ta(t) = Ta(t_{max}) + slp_a \cdot (kx_{\max} - kx(t))$$

where $Ta(t_{max})$ is the maximum daily temperature. Night time temperatures are assumed to decrease linearly from the temperature at sunset to the daily minimum temperature the following day at sunrise [123]. Uncertainty of maximum and minimum temperatures and solar irradiation are reflected in the hourly temperature profiles the model generates.

7.2.3.2 Solar Cell

The solar module cell temperature is estimated from the ambient temperature and incident solar irradiation as

$$T_{cell} = T_a + \left(\frac{NOCT - 20}{0.8\ kW}\right) \cdot G$$

where T_a is the ambient temperature and $NOCT$ is the normal operating conditions temperature from the manufacturer's data sheet [124].

7.2.3.3 Battery

Currently, STEMM assumes that batteries operate at either ambient temperature or a constant temperature if temperature control is available.

7.2.4 Generation Model

STEMM currently includes diesel and photovoltaic generators. The model allows the use of multiple diesel generators while aggregating all photovoltaic generation into a single array.

7.2.4.1 Diesel Generators

Diesel generators are dispatchable generators assumed to be available to supply power at any time within a range of load factors. The low end of this range is user-defined and the upper end is assumed to be 100%. Therefore, a diesel generator with a rated capacity of 10kW and a minimum load factor of 30% could supply anywhere from 3kW to 10kW in any time step. STEMM assumes the diesel generator's fuel consumption curve is linearly related to electrical output with a non-zero no-load fuel consumption of the form

$$F_{tot} = F_{marg} \cdot P_{gen} + F_{nl}$$

where F_{tot} is the total fuel consumption at each time step, F_{marg} is the marginal fuel consumption per kW of generator output (P_{gen}), and F_{nl} is the no load fuel consumption which is consumed regardless of output level. STEMM users can derive these parameters by fitting linear curves to manufacturer-supplied fuel consumption data.

7.2.4.2 Photovoltaic Array

The solar PV model in STEMM relies on the fill factor of the PV module. Fill factor is defined as the ratio of maximum power point power to the product of open-circuit voltage and closed-circuit current,

$$FF = \frac{P_{MPP}}{V_{oc} \cdot I_{sc}}$$

where FF is the module fill factor, P_{MPP} is the module power output at maximum power point, V_{oc} is the module open-circuit voltage, and I_{sc} is the module short-circuit current. Solving for P_{MPP}, the module power at MPP can be found using expressions for FF, V_{oc}, and I_{sc}.

Fill factor can be expressed in terms of the normalized open-circuit voltage,

$$FF_0 = \frac{v_{oc} - \ln(v_{oc} + 0.72)}{v_{oc} + 1}$$

where v_{oc}, the normalized open-circuit voltage, is defined as

$$v_{oc} = \frac{q}{nkT} V_{oc},$$

n is the module ideality factor, k is the Boltzmann constant, and T is the PV module cell temperature [125]. For crystalline silicon PV modules, the ideality factor is typically between 1 and 1.3, but Carerro et al. [126] notes that assuming an ideality factor of one is acceptable for most modeling applications. For simplicity, STEMM also adopts this assumption. Correcting for module series resistance, this expression becomes

$$FF_s = FF_0 \left(1 - \frac{R_s}{V_{oc}/I_{sc}}\right)$$

where R_s is the module series resistance. A further correction is applied for the module shunt resistance

$$FF = FF_s \left(1 - \frac{(v_{oc} + 0.7)}{v_{oc}} \frac{FF_s}{\left({R_{sh}}/{(V_{oc}/I_{sc})}\right)}\right)$$

where R_{sh} is the module shunt resistance.

The parasitic resistances, R_s and R_{sh}, can be estimated using methods proposed by Carrero et al. [126]. Shunt resistance can be found by solving the following equation for R_s

$$R_s = \frac{1}{I_{MPP}} \cdot \left(V_{oc0} - V_{MPP} - n \cdot V_{th} \cdot \ln\left(\frac{V_{MPP} + n \cdot V_{th} - I_{MPP} \cdot R_s}{n \cdot V_{th}}\right)\right)$$

where V_{MPP} and I_{MPP} are the module voltage and current at maximum power point under standard test conditions as reported on manufacturer data sheets, and V_{th} is the module thermal voltage defined as $V_{th} = nkT/q$ where q is the electron charge.

Because this equation cannot be solved explicitly for R_s, an iterative approach is taken, assuming that $R_s = 0$ in the right side of the equation for the initial iteration and substituting the new value in subsequent calculations. STEMM iterates this value until the difference between iterations is less than 0.001Ω. Carrero et al. [126] express the module shunt resistance as

$$R_{sh} = \frac{(V_{MPP} - n \cdot V_{th}) \cdot (V_{MPP} - I_{MPP} \cdot R_s)}{(I_{sc0} - I_{MPP}) \cdot (V_{MPP} - I_{MPP} \cdot R_s) - I_{MPP} \cdot n \cdot V_{th}}.$$

The module open-circuit voltage is dependent on the incident solar irradiation and can be expressed as

$$V_{oc} = \frac{V_{oc0}}{\left(1 + \delta \cdot \ln\left(\frac{G_0}{G}\right)\right)}$$

where V_{oc0} is the open circuit voltage at the standard test conditions irradiation, G, 1kW/m^2 as reported on manufacturer data sheets [127]. The parameter δ is dimensionless and depends on the technology used. This is the only parameter in the PV model that cannot be found or derived from information commonly found on PV module manufacturer datasheets. The value adopted in the STEMM is that found by Zhou et al. [128], 0.058 for mono-crystalline silicon modules. Other values are reported in the literature; for example, van Dyk et al. [129] use a value of 0.085, also for monocrystalline silicon technology.

Module voltage is also dependent on PV cell temperature. Many manufacturers report module voltage and current temperature coefficients separately in addition to an aggregated power temperature coefficient. Because STEMM assumes operation at MPP and does not model system voltage explicitly, a single temperature correction of the module power is applied rather than modeling the temperature effects on voltage and current individually (although this functionality is available).

The module short-circuit voltage is effectively proportional to incident solar irradiation [124]

$$I_{sc} = I_{sc0} \cdot \frac{G}{G_0}$$

where I_{sc0} is the short circuit voltage at standard test conditions irradiation as reported on manufacturer datasheets.

Returning to the equation for the fill factor, the PV module output at maximum power point can then be expressed as a function of irradiation and temperature as

$$P_{MPP}(G, T_{cell}) = FF \cdot V_{oc} \cdot I_{sc} = FF \cdot \frac{V_{oc0}}{\left(1 + \delta \cdot \ln\left(\frac{G_0}{G}\right)\right)} \cdot \left(I_{sc0} \cdot \frac{G}{G_0}\right) \cdot \left(1 - \gamma \cdot (T_{cell} - 25°\mathrm{C})\right)$$

where T_{cell} is the module cell temperature and γ is the module power temperature coefficient provided on the module manufacturer's data sheet.

The PV module power output can then be scaled up proportionally to the total array size with loss factors for DC cabling losses ($\alpha_{dc,cable}$), losses due to module soiling (α_{soil}) and other user specified DC losses (α_{other}) to find the total DC power at the inverter terminals,

$$P_{PVdc} = \frac{P_{array}}{V_{MPP} \cdot I_{MPP}} \cdot P_{MPP}(G, T_{cell}) \cdot (1 - \alpha_{dc,cable}) \cdot (1 - \alpha_{soil}) \cdot (1 - \alpha_{other})$$

where P_{array} is the rated DC capacity of the PV array.

Further losses will be incurred in inversion before delivery to the microgrid. The net AC PV power is calculated as

$$P_{PVac} = \min\,(P_{\boxtimes dc} \cdot \eta_{inv}, P_{inv,maxac})$$

where η_{inv} is the inverter efficiency and $P_{inv,maxac}$ is the maximum AC inverter capacity. This is the total PV power available to power AC loads on the microgrid. Excess capacity or capacity clipped because of inverter limitations can be used as DC current to charge a battery bank if present.

7.2.4.3 Inverter and Rectifier

The current version of STEMM assumes a constant inverter and rectifier efficiency. Future versions of STEMM may incorporate efficiency curves as a function of inverter/rectifier output.

7.2.5 Storage Model

The storage model simulates the performance of a lead-acid battery bank using a version of the kinetic battery model (KiBaM) [89] and either a simple amp hour throughput model or a capacity fade model [90]. KiBaM is derived from chemical kinetics processes to dynamically simulate maximum charge and discharge current, and update the battery state of charge.

7.2.5.1 Operating Model

The KiBaM model can be conceptualized as a battery with two separate tanks connected with a fixed conductance. The first tank is available charge and the second tank is bound charge that is not immediately available. To be discharged, the bound charge must be transferred to the available charge tank. Mathematically, this model can be expressed by the following differential equations:

$$\frac{dq_1}{dt} = -I - k(1-c)q_1 + kcq_2$$

$$\frac{dq_2}{dt} = k(1-c)q_1 - kcq_2$$

where q_1 is the available charge, q_2 is the bound charge, k is a rate constant related to the conductance between the tanks, and c is the ratio of available charge to total charge when both tanks are full. Solving these equations gives the following expressions for available and bound charge per battery:

$$q_{1,i} = q_{1,i-1}e^{-kt} + \frac{(q_{i-1}kc - I)(1-e^{-kt})}{k} - \frac{Ic(kt-1+e^{-kt})}{k}$$

$$q_{2,i} = q_{2,i-1}e^{-kt} + q_{i-1}(1-c)(1-e^{-kt}) - \frac{I(1-c)(kt-1+e^{-kt})}{k}$$

where $q = q_1 + q_2$, t is the model timestep, and I is the current flowing into and out of the battery, negative flows being charge and positive flows being discharge.

The maximum charge and discharge current is given by

$$I_{d,max,i} = \frac{kq_{1,i-1}e^{-kt} + q_{i-1}kc(1-e^{-kt})}{1-e^{-kt}+c(kt-1+e^{-kt})}$$

$$I_{c,max,i} = \frac{-kcq_{max} + kq_{1,i-1}e^{-kt} + q_{i-1}kc(1-e^{-kt})}{1-e^{-kt}+c(kt-1+e^{(-kt)})}$$

where q_{max} is the maximum battery capacity.

Model constants can be derived from manufacturer data sheets. Using data on Ah capacity at different discharge rates, the constants c and k can be extracted by fitting the data to the following function:

$$\frac{q_{T=t_1}}{q_{T=t_2}} = \frac{t_1}{t_2}\left(\frac{(1-e^{-kt_2})(1-c)+kct_2}{(1-e^{-kt_1})(1-c)+kct_1}\right)$$

where $q_{T=t_i}$ is the total Ah capacity of the battery discharged over t_i hours. These are the same constants used in the HOMER battery model [99]. The HOMER battery database can therefore also be used to find battery parameters.

The maximum battery capacity with a slow discharge rate, q_{max}, can be found using the constants c and k,

$$q_{max} = \frac{q_{T=t}((1 - e^{-kt})(1 - c) + kct)}{kct}$$

using $q_{T=t}$ for a long discharge time t.

The constant c is assumed to be fixed but k varies as a function of temperature. This accounts for the variation in battery capacity at different temperatures. The functional form of the relation is assumed to be

$$k = A \cdot e^{\left(\frac{-B}{T_{bat}+273.15-C}\right)}$$

where T_{bat} is the battery temperature, which is similar in form to the Arrhenius rate equation. The model constants were derived by taking data on relative battery capacity as a function of temperature and discharge rate and solving the KiBAM equations for the value of k. The model was then fit to the battery temperature and k data as in Figure 7-2. The three points at each temperature level represent different discharge/charge rates.

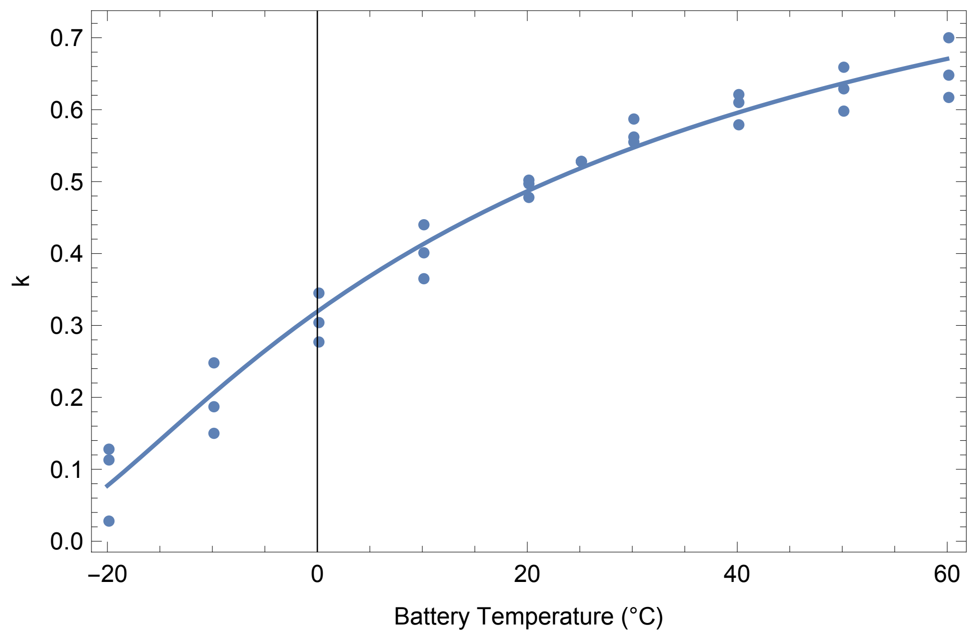

Figure 7-2 KiBAM constant k as a function of battery temperature.

The above model simulates the performance of the battery bank on the level of an individual battery. STEMM users can also specify the number of batteries in a string and the number of strings in the battery bank. The nominal battery bank voltage is the product of the nominal battery voltage and the number of batteries in a string. The total current from the battery bank is then the current into or out of an individual battery multiplied by the number of strings. The total battery DC power flow is therefore

$$P_{bat} = I_b \cdot V_{b,i} \cdot N_{per\ string} \cdot N_{strings}$$

where I_b is the current from a single battery, $V_{b,i}$ is the battery voltage, $N_{per\ string}$ is the number of strings per battery, and $N_{strings}$ is the number of strings in the battery bank. The battery voltage, $V_{b,i}$, depends on whether or not the battery is charging or discharging

$$V_{b,i} = \begin{cases} \dfrac{V_b}{\sqrt{A \cdot \ln\left(-I_b/I_{rate}\right) + B}}, & i = charge \\ V_b\sqrt{A \cdot \ln\left(I_b/I_{rate}\right) + B}, & i = discharge \end{cases}$$

where V_b is the nominal battery voltage, I_{rate} is the nominal 20h battery capacity in Ah, and A and B are empirical constants that relate battery efficiency to discharge rate. When dispatched to power loads, the DC power is multiplied by the inverter efficiency. The constants for the battery efficiency model were derived from data used by Hittinger et al. [90] as seen in Figure 7-3.

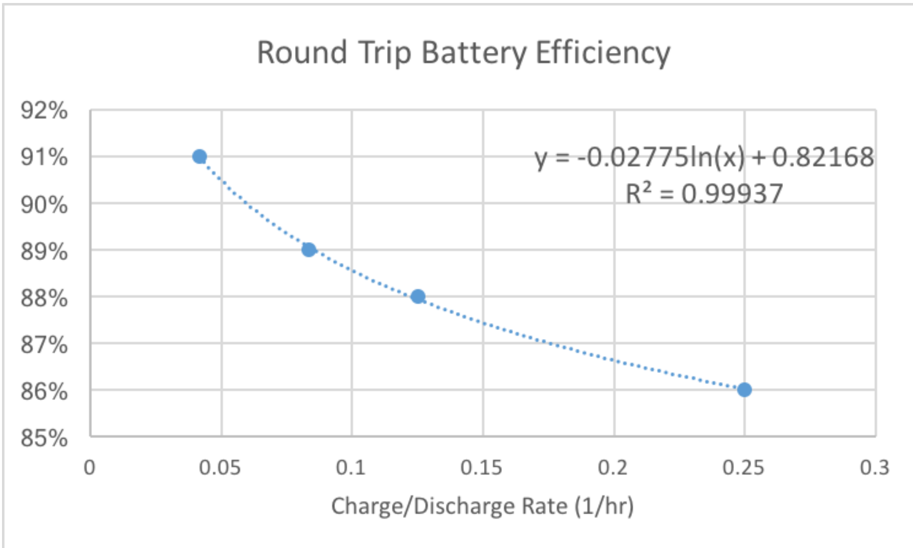

Figure 7-3 Battery efficiency curve as a function of discharge/charge rate.

7.2.5.2 Lifetime

Users have the option to choose between a simple Ah throughput model or a capacity fade model to estimate battery lifetime.

7.2.5.2.1 Ah throughput model

In the throughput model, lifetime Ah throughput is specified by the user. The battery reached its end of life when the total number of Ah charging and discharging the battery reaches the lifetime throughput. Lifetime throughput can be estimated from manufacturer data by

$$Ah_{lifetime} = C_{bat} \cdot DOD \cdot Cycles_{DOD}$$

where C_{bat} is the nominal battery capacity, DOD is the average depth of discharge, and $Cycles_{DOD}$ is the number of cycles to failure with a depth of discharge DOD. This method is particularly appropriate for a cycle charging battery dispatch scenario. In a load following scenario where the depth of discharge is not consistent, it may be more appropriate to average the lifetime throughput for a range of depths of discharge between the 0% and the specified maximum depth of discharge [130].

7.2.5.2.2 Capacity fade model

The capacity fade model estimates the loss of battery capacity over time as a function of battery throughput and temperature with batteries being replaced after reaching a specified cumulative level of capacity fade, usually when the battery reaches 80% of original capacity [90]. The capacity fade rate is specified as a percentage of capacity losses relative to original capacity her full cycle equivalent. At each one-hour time step, the capacity fade is therefore

$$C_{fade} = \frac{|I_{string}|}{2 \cdot C_{bat}} \cdot R_{fade}$$

where R_{fade} is the capacity fade rate. The capacity fade is cumulated over time to adjust the battery capacity and resets when it reaches 80% of original capacity.

The capacity fade rate varies as a function of temperature. For every 10˚C above 25˚C the battery operates, the capacity fade rate doubles and for every 10˚C below 25˚C, the rate halves. This is implemented as

$$R_{fade} = R_{25} \cdot 2^{\left(\frac{T_{bat}-25}{10}\right)}$$

where R_{25} is the nominal capacity fade rate at 25˚C.

7.2.6 Demand Model

Demand on the microgrid can be modeled as a single load or as multiple loads that can be controlled independently. This allows the STEMM user to prioritize certain loads over others in the case of a shortfall in supply, and/or to implement different tariff structures for each load. It is further possible to specify penalties for failing to meet demand for all or specific loads. Currently, the model allows only AC loads. Expected load profiles are user-defined on an hourly basis for each month of the year. Because electricity demand is usually a key uncertainty for microgrids, STEMM accounts for uncertainty in the load profiles.

When tariffs are modeled as changing in real terms over time (for example, if tariffs move with the price of diesel), a price elasticity can be defined to adjust demand based on a constant price elasticity of demand model. The user inputs demand growth over time as an annual growth rate. Users input load profiles as hourly, expected mean demand. This can be entered on a monthly basis to account for seasonal changes in demand.

STEMM models mean hourly load profiles with two separate uncertain parameters. The first uncertainty relates to the relative demand between hourly time steps. This is modeled as independent normal distributions, truncated at zero, at each time step with the user input values as means and a user defined relative standard deviation. Truncated distributions assign probability density for negative demand as probability mass at zero, which leads to a finite, though usually very small, probability that there is no load at all during that time step. To account for correlation between demand at each time step, the mean total daily demand is also modeled with a truncated normal distribution. The mean demand at each time step in the load profile is then scaled up or down so that the sum over time steps is equal to this total demand. Mathematical, the mean demand at time step i can be expressed as

$$L_{i,mean} = N_{trunc}(L_{i,input}, c_{v,hr} \cdot L_{i,input}) \cdot \frac{L_{day,mean}}{\sum L_{i,input}}$$

where $L_{day,mean} = N_{truc}\left(\sum L_{i,input}, c_{v,day}\right)$, $L_{i,input}$ is the user input expected demand at time step i, $c_{v,hr}$ is the relative standard deviation from the user input expected demand at each time step, $c_{v,day}$ is the relative standard deviation from the expected total daily demand, and N_{truc} is defined as

$$N_{trunc}(\mu, \sigma) = \begin{cases} 0 & if\ N(\mu, \sigma) < 0 \\ N(\mu, \sigma) & if\ N(\mu, \sigma) \geq 0 \end{cases}$$

with $N(\mu, \sigma)$ being a normal distribution with mean μ and standard deviation σ.

To account for variation around this mean, demand at each hour of operation is modeled as

$$L_j = N_{trunc}\left(L_{mod(j,24),mean}, c_{v,var} \cdot L_{mod(j,24),mean}\right)$$

where $c_{v,var}$ is the variation of demand at each time step about the mean.

When tariffs are modeled as changing in real terms over time (for example, if tariffs move with the price of diesel), a price elasticity can be defined to adjust demand based on a constant price elasticity of demand model. Demand growth over time is input by the user as an annual growth rate.

7.2.7 Distribution Model

STEMM models the distribution system as having losses equal to a user-specified percentage of the total energy delivered on the system. The user can specify these losses by individual load and input them separately as technical and non-technical losses. Non-technical losses are not strictly speaking losses due to the distribution system, as they represent electricity theft and customer non-payment; however, both losses represent load that does not generate revenue.

7.2.8 Dispatch Model

The dispatch model determines how dispatchable generation resources operate to meet demand and charge the battery bank. In the case of a shortfall in generation capacity, it also determines which loads to serve and which loads to shed. Figure 7-4 provides an overview of the data flows between other technical modules and the dispatch module.

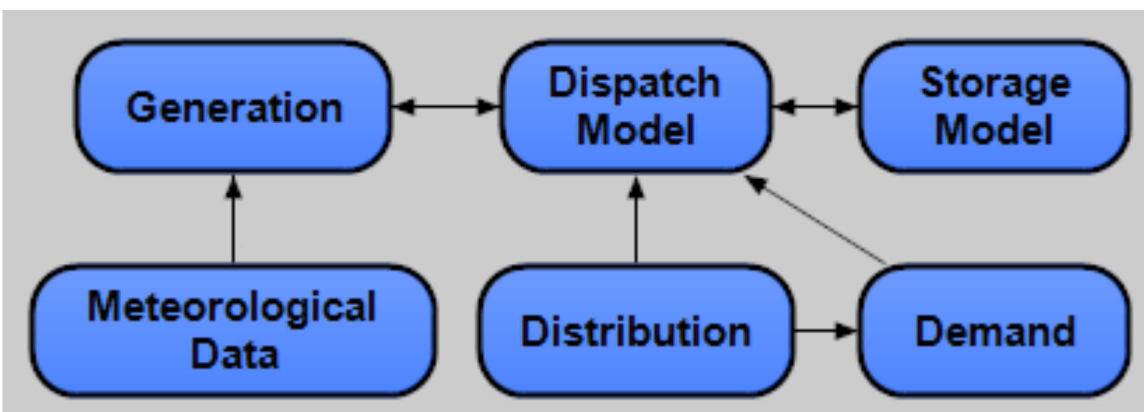

Figure 7-4 Technical model influence diagram.

In a system using PV and diesel generators, STEMM first assigns load to the PV generator and then to the diesel generators. The diesel generator dispatch algorithm seeks to dispatch generators so that they operate efficiently at high load factors. Dispatch is subject to constraints on minimum diesel generator load factor.

In a PV/battery configuration (without diesel generators), loads are supplied directly by the PV array when possible. Any excess PV generation is used to charge the battery bank. When the PV array cannot satisfy demand, the battery bank supplies the balance of power so long as the battery bank is maintained above the minimum specified state of charge.

The dispatch algorithm is more complicated when a battery bank enables energy storage and generation includes diesel generators. Different algorithms are possible to determine when the battery bank should be charged or discharged in this configuration. STEMM adopts two simple algorithms, similar to those found in HOMER [130], called load following and cycle charging. The load following algorithm uses only excess PV generation to charge the battery bank, whereas the cycle charging algorithm uses excess diesel generator capacity to charge batteries.

In a system using PV and diesel generators, STEMM first assigns load to the PV generator and then to the diesel generators. The diesel generator dispatch algorithm first searches for the generator that meets or exceeds the remaining demand by the smallest margin. If no single generator can supply the demand, the largest generator is dispatched and the algorithm starts again with the remaining generators. This continues until all demand is satisfied or all generators are dispatched. While not an optimization, this algorithm attempts to operate generators efficiently at high load factor. Dispatch is subject to constraints on minimum diesel generator load factor. For example, if the total demand is 10kW and available generating capacity includes a 10kW generator with a minimum load factor of 30% and a PV array generating 9kW, 2kW of

PV generation would be curtailed in order to operate the diesel generator at the minimum 3kW output. This curtailed solar power would be used to charge batteries if they are not full.

In a PV/battery configuration (without diesel), the PV array directly supplies loads when possible. Any excess PV generation is used to charge the battery bank. When the PV array cannot satisfy demand, the battery bank supplies the balance of power, so long as the battery bank is maintained above the minimum specified state of charge.

The dispatch algorithm is more complicated when a battery bank enables energy storage and generation includes solar and diesel sources. Different algorithms are possible to determine when the battery bank should be charged or discharged in this configuration. STEMM adopts two simple algorithms, similar to those found in HOMER [130], called load following and cycle charging. Figure 7-5 illustrates these cases. The load following algorithm uses only excess PV generation to charge the battery bank. The battery dispatch priority in this case falls after the diesel generators and therefore is used to meet peak demand, subject to the minimum state of charge constraint. In this algorithm, diesel fuel never charges the battery bank.

In addition to using excess PV to charge the batteries when available, the cycle charging algorithm uses the excess capacity from the diesel generators to charge batteries. This ensures that diesel generators operate more efficiently at high load factor (but it also consumes extra diesel fuel). To ensure that batteries are not maintained in a low state of charge, once the battery bank reaches a certain minimum state of charge, they cannot be discharged again until they reach an upper set point state of charge. Such battery cycling batteries improves battery life, whereas maintaining batteries in a low state of charge can result in permanent capacity loss. During cycle charging, the battery bank is prioritized after the PV generator and before the diesel generators. Therefore, whenever the battery bank is available for dispatch, the batteries supply the loads while the diesel generators remain idle.

The algorithm that performs the best economically will depend on the technical design of the microgrid and the loads on the system. Load following may result in less load shedding as batteries are dispatched last and are therefore kept in a higher state of charge to serve peaks. On the other hand, the battery bank may then be underused. STEMM can simultaneously run load following and cycle charging scenarios to determine which strategy performs best in a particular case.

STEMM currently provides two load-shedding algorithm options for cases when supply is not sufficient to satisfy demand. The algorithms depend on the level of control the grid operator can exert on demand. In the simplest case, the operator is only able to shed entire circuits on the grid, represented in the model as loads. If generation is not sufficient to meet the entire demand on the system, load shedding occurs based on user specified priority order until generation is sufficient to supply the remaining loads. Deployment of smart meters can enable microgrid operators to control demand on a finer scale. In the case where operators are able to disconnect individual customers, STEMM assumes that the demand of all customers in the load is equal. Loads are shed until there is sufficient generation capacity to partially meet the demand of the lowest priority load. Higher priority loads are met in full. Generation capacity is assigned to the partially fulfilled load in increments equal to the total demand from that load divided by the number of customers in the load. Unmet demand is calculated and, if specified by the user, a financial penalty is assigned per kWh shortfall in the financial model. Figure 7-6 illustrates the load shed algorithms available in STEMM.

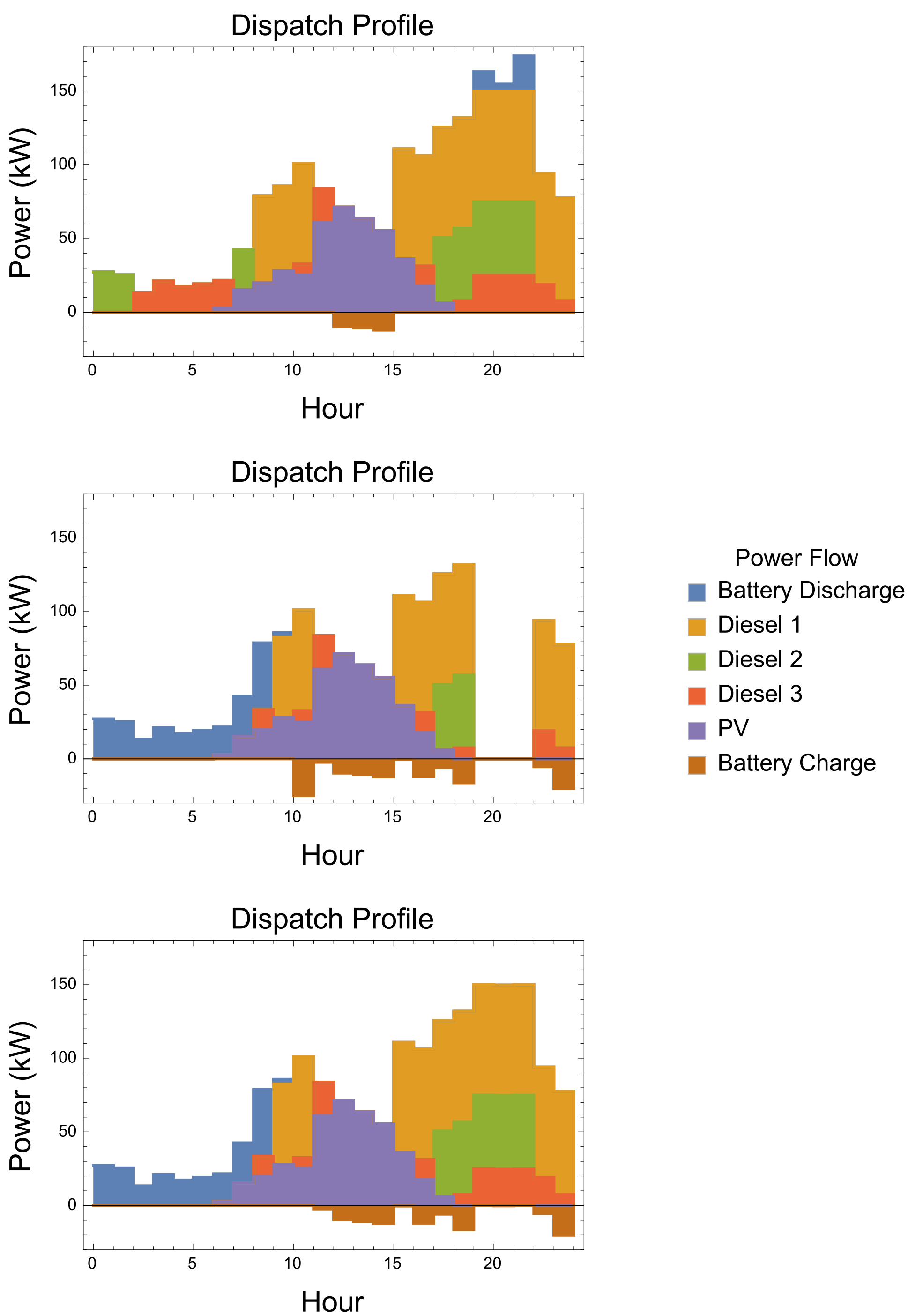

Figure 7-5 Examples of battery dispatch and load shedding strategies: Load Following (top), Charge Cycling with load shedding by load (center), and Charge Cycling with load shedding by customer (bottom).

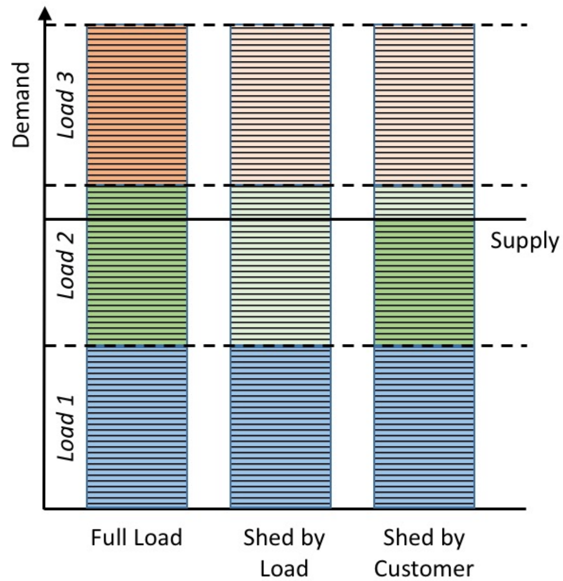

Figure 7-6 Comparison of load shedding algorithms. In the shed by load scenario, any load that cannot be met completely is shed; while in the shed by customer scenario, partially loads can be supplied. The lighter colors in the figure represent loads shed.

7.3 Financial Model

The STEMM financial model simulates cash flows over the model horizon, on a monthly resolution, using technical model outputs and user inputs. These cash flows are then used to generate the financial indicators, equity NPV, DSCR, and LCOE. Cash flows in STEMM include capital costs, operating costs, revenues, corporate income tax, and debt payments. The model supports two currencies, typical one hard currency and one local currency, and uses the Wilkie Investment model to stochastically simulate consumer price indices in both currencies and the exchange rate [131]. With the exception of fuel costs, the current assumption is that costs are constant in real terms. Similarly, because most of the financial parameters are decision variables, STEMM currently treats these input parameters (with the exception of fuel costs) as deterministic values. It is however possible to model these probabilistically if desired.

7.3.1 Capital Expenditure

STEMM models not only initial capital costs but also calculates timings for replacement of capital assets at end of life. Diesel generator lifetimes are calculated in hours of runtime and battery lifetimes are determined by total Ah throughput or capacity fade as described in 7.2.5.2. Other capital assets like the PV array, inverters, distribution equipment, and meters are assumed to have fixed lifetimes specified in years. These inputs are subject to uncertainty and can be entered either as point values or distributions. Initial capital costs are assumed to occur December 31st of the year prior to the model start year. Replacement costs are incurred on the last day of the month in which the asset life is exhausted. Replacement costs for capital assets are fixed in real terms. Technology costs for equipment like solar panels are fall rapidly however the lifetimes of these assets are often longer than the model horizon. Future versions of STEMM may incorporate learning curves to account for technology price evolution over time.

7.3.2 Operating Expenditure

Operating costs can be broken down in many ways. STEMM splits operating costs into the following categories: fixed operating costs, fuel costs, PV operation and maintenance (O&M), battery O&M, diesel generator O&M, and unmet demand penalties. Fixed operating costs are general overhead and maintenance costs that are roughly constant on a monthly basis. This could include costs like operator salaries and general distribution system maintenance. Fuel costs, unlike other costs, are modeled as changing in real terms. Fuel price uncertainty is a key driver of risk in microgrids with significant amounts of fossil fuel-based generation. This uncertainty is modeled using a geometric Brownian motion (GBM) model.

7.3.2.1 Fuel Price

The GBM model requires an initial fuel price, annual volatility, and an annual price drift in order to project future diesel prices:

$$P_{fuel,i} = P_{fuel,i-1} \cdot \left(1 + \frac{D_{fuel}}{12}\right) + P_{fuel,i-1} \cdot V_{fuel} \cdot \sqrt{\frac{1}{12}} \cdot N(0,1)$$

where fuel price, $P_{fuel,i}$, is indexed by month, D_{fuel} is the annual percent fuel price drift representing the mean long term real price progression, and V_{fuel} is the annual fuel price volatility [132]. Figure 7-7 shows ten samples of simulated fuel prices using the GBM model.

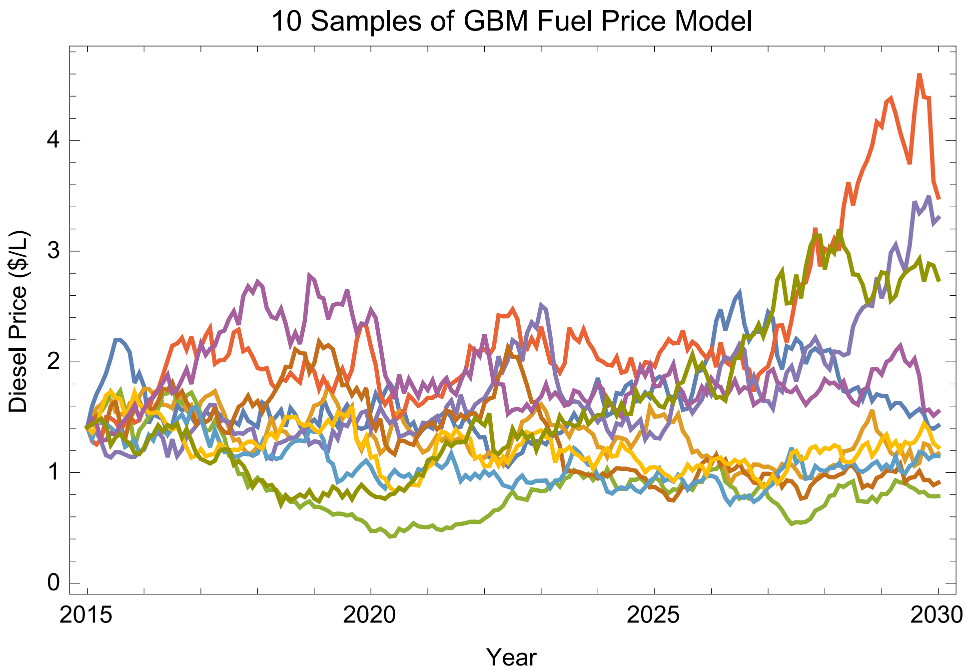

Figure 7-7 Samples of simulated real fuel price time series using Geometric Brownian Motion model.

7.3.2.2 Fuel Transport Cost

Most microgrid sites are located in remote areas. The cost of transporting fuel to these sites can therefore be significant. STEMM uses the transport cost model found in Szabó et al. [26]. The transport cost per liter is calculated as

$$P_{trans} = \frac{2 \cdot P_{fuel} \cdot c_{fuel} \cdot t_{fuel}}{V_{fuel}}$$

where c_{fuel} is the diesel fuel consumption per hour in transit, t_{fuel} is the transit time, and V_{fuel} is the volume of fuel transported in one delivery.

7.3.3 Revenue

STEMM accounts for three different types of revenue: energy consumption-based tariffs, fixed monthly service charges, and connection fees. Consumption-based tariffs are specified in local currency units per kWh of billable demand. Different tariff levels can be set for different loads. Fixed monthly service charges are specified in local currency units per customer. Connection charges are charged on a per customer basis for the period immediately preceding connection. In its current form, STEMM does not model the addition of new customers so in practice, all collection charges are received during the first model time step.

7.3.4 Foreign Exchange Model

Foreign exchange rates and consumer price indices are modeled using the Wilkie Investment Model. This model assumes exchange rates vary as a function of the ratio of price indices for each currency and a scale factor that varies around a static mean value over time. Inflation rates are modeled as a first order autoregressive time series denoted AR(1) from which consumer price indices are derived. Inflation in period i is computed as

$$I_i = I_\mu + QA \cdot I_{i-1} + QSD \cdot N(0,1)$$

where I_i is the inflation rate in period i, QA is an autoregressive constant, QSD is a constant and $N(0,1)$ is a normal distribution with mean zero and standard deviation one.

Exchange rates are modeled using a purchase parity model of form

$$XR_{jk} = XK \cdot \frac{CPI_k}{CPI_j}$$

where XR_{jk} is the units of currency i exchanged for one unit of currency j, CPI_k is the consumer price index for currency k, and XK is a scale factor. XK is modeled as

$$\ln(XK) = X_\mu + XN$$

where X_μ is a constant and XN is an AR(1) variable calculated as

$$XN_i = XA \cdot XN_{i-1} + XSD \cdot N(0,1)$$

where XN_i is the value of XN at time step i, XA is an autoregressive constant and XSD is a constant.

7.3.5 Finance Model

STEMM assumes that microgrid capital costs are financed with a combination of debt and equity. Key inputs include the percentage of capital financed by debt, the interest rate, and the debt tenor. These parameters are fixed for all capital expenses. Loan repayments are calculated based on a constant monthly payment method. Interest rates can be specified in real or nominal terms. If interest rates are specified in real terms, the current inflation rate, calculated from the simulated consumer price index, is added to the interest rate to obtain a nominal value in each period.

7.3.6 Tax and Depreciation Model

STEMM accounts for corporate income taxes payable on microgrid profits. The tax model assumes straight-line depreciation of capital assets relying on user-defined depreciation periods. Users can specify in which currency assets are depreciated. The model also assumes that financial losses can be carried over indefinitely. The tax payments are calculated on a monthly basis. Taxable income per period is calculated as

$$Taxable\ Income = Revenue - Opex - Depreciation - Interest - Carried\ Loss.$$

The tax paid is equal to

$$Tax = \begin{cases} Taxable\ Income \times Tax\ Rate, & Taxable\ Income > 0 \\ 0, & Taxable\ Income \leq 0 \end{cases}.$$

When taxable income is less than zero, this loss is carried over to the following year.

7.3.7 Subsidy Model

Various forms of subsidy can be modeled using STEMM, including both capital and operating subsidies. Capital subsidies can be specified as a percentage of capital cost and can be applied for only initial capital expenses or for ongoing capital costs. The tax model treats this subsidy as reduction of the book value of the asset, thereby reducing the depreciation value of the asset [133]. Other subsidies are treated as standard revenues. These include initial cash grants, tariff subsidies, fuel subsidies, and operating subsidies based on the number of customers served. Tariff subsidies are specified on a kWh basis and are provided directly to the microgrid operator. Fuel subsidies are input as a percentage of the unsubsidized price.

7.4 Model Outputs

The primary model outputs are financial indicators meant to shed light on the attractiveness of the microgrid as an investment opportunity to equity and lenders. The core strength of STEMM is its ability to compute these metrics probabilistically so as to account for risk and uncertainty. Debt Service Coverage Ratio (DSCR) measures the "bankability" of the project, while the net present value (NPV) of projected equity cash flows measures the attractiveness of the project to equity investors. In addition to equity NPV and DSCR, STEMM also computes a levelized cost of energy (LCOE).

7.4.1 Equity Net Present Value

The equity NPV is the net present value of equity cash flows discounted by a user-defined target return on equity. This cost of equity can be defined in nominal or real terms. If defined in real terms, the nominal rate is calculated each period by adding the real cost of equity to the annual inflation rate in that period. Equity cash flows are calculated as

$$\begin{aligned} &Equity\ Cash\ Flow \\ &\quad = Revenue - OPEX - CAPEX \cdot \left(1 - R_{D/E}\right) - Interest - Principal - Tax \end{aligned}$$

where $R_{D/E}$ is the percent of capital funded by debt. The CDF of the equity NPV gives an indication of the probability that the project will meet or exceed the benchmark return.

7.4.2 Debt Service Coverage Ratio

Lenders use the DSCR to determine whether or not the cash flows generated by a project will be sufficient to make loan payments. DSCR is the ratio of cash available to repay debt to the debt payment owed in a period. STEMM computes this indicator on a monthly basis as

$$DSCR = \frac{Revenue — OPEX - Tax}{Interest + Principal}.$$

A DSCR less than one indicates that the project cannot pay its debt from project revenues. Lenders typically want to have DSCRs in excess of at least 1.2 [134]. Examining the cumulative distribution function (CDF) of the minimum DSCR provides an estimation of the probability a project will miss payments or default on loans.

7.4.3 Levelized Cost of Energy

LCOE provides a measure of the "per unit cost" of generating and delivering electricity on the microgrid. It is defined as the sum of operating costs and annualized capital costs, divided by the number of kWh consumed. The capital recovery factor used to annualize capital costs uses a user-specified discount rate.

STEMM calculates the levelized cost of energy for electricity generated and delivered on the microgrid for each model year. This is because factors like demand, load factor and fuel cost are modeled as changing over time. The average LCOE is calculated as the average LCOE over model years weighted by kWh consumption. The general formulation is

$$LCOE = \frac{Annualized\ Capex + Annual\ Opex}{Total\ kWh\ consumed}$$

where 'opex' includes all operating expenses but not tax and financing costs. An annualized capital cost is computed for each capital asset by applying a capital recovery factor

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1}$$

where i is the discount rate and n is the lifetime of the asset. For capital assets with lifetimes defined as a number of years of useful life, n is equal to this lifetime. For generators and batteries, whose lives are defined in terms of hours of runtime and Ah throughput, respectively, n is calculated by taking the total lifetime runtime/throughput divided by the total runtime/throughput during the year for which the LCOE is being calculated. The total annualized capital cost is then obtained by computing the sum of annualized capital costs for all capital assets, $\sum_{assets} CRF \times Capex$.

8 Appendix B: STEMM Sensitivity Analysis model inputs

STEMM requires a large number of inputs. This section of the supplemental information documents the inputs and assumptions used in the case studies presented in this paper.

8.1 Financial Inputs

8.1.1 Cost Inputs

Costs are divided into capital costs and operating costs which are treated differently in the tax model. Capital costs are capitalized and depreciated while operating costs directly offset taxable income.

8.1.1.1 Capital Costs

The capital costs used are deterministic and presented in **Table 8-1**.

Table 8-1 Summary of capital cost assumptions.

Input	Value	Units	Description	Source
PV Array	2700	USD/kWp	Capital cost of PV array inclusive of mounting and cabling	[135]
Inverters	500	USD/kW	Capital cost of AC/DC power inverters	[136]
Meters	40	USD/unit	Capital cost of customer electricity meters	[75]
LV Distribution	26.4	USD/m	Capital cost of low voltage distribution network	[98]
LV network per Customer	22	m	Average low voltage network length per customer	[98]
Connection Cost	92	USD/unit	Capital cost to connect a customer to the low voltage network	[98]
Number of Customers	521	Unit	Total number of customers on grid	[98]
Battery Cost	1320	USD/unit	Capital cost per battery in battery bank	[136]

8.1.1.2 Asset Lifetimes

Asset lifetimes are used to determine when capital assets must be replaced. The assets in Table 8-2 are set in years and, in these case studies, modeled deterministically. Batteries and diesel generator lifetimes are calculated as a function of cumulative capacity fade and runtime, respectively, using the parameters in Table 8-3.

Table 8-2 Summary of asset lifetimes for asset lives set in year.

Asset	Value	Units	Source
Distribution Network	30	yr	[137]
Meters	10	yr	[138]
Solar Array	25	yr	[139]
Inverters	15	yr	[140]

Table 8-3 Summary of probabilistic asset lifetimes.

Asset	Distribution	Parameters	Units	Source
Diesel Generators	Triangular	Min: 20,000 Mode: 25,000 Max: 30,000	hours runtime	
Batteries	Triangular	Min: 0.0119 Mode: 0.0121 Max: 0.0196	%/full cycle equivalent	[99]

8.1.1.3 Operating Costs

Except for fuel price, operating costs are modeled deterministically. Table 8-4 summarizes the inputs used in the cases.

Table 8-4 Operating cost inputs.

Input	Value	Units	Description	Source
Initial Fuel Price	1.07	USD/L	Retail price per liter of diesel fuel	[141]
Fuel Price Drift	0	%/yr	Annual fuel price drift parameter in Geometric Brownian Motion model	[92]
Fuel Price Volatility	20	%/yr	Annual fuel price volatility parameter in Geometric Brownian Motion model	[92]
Fuel Transport Burn Rate	12	L/h	Fuel burn of fuel delivery vehicle	[26]
Fuel Delivery Transit Time	1	h	One way transit time for fuel delivery from retail source	[26]
Fuel Delivery Volume	300	L	Liters of fuel in one delivery	[26]
Generator O&M	120	RWF/h	Diesel generator O&M cost per hour of	[142]

			generator runtime	
PV O&M	6500	RWF/kWp/yr	PV array and battery bank maintenance cost	[136]

8.1.2 Financing Inputs

The financing structure assumes a 50:50 debt equity ratio with a ten-year debt tenor. Other assumptions are summarized in Table 8-5.

Table 8-5 Summary of financing inputs.

Input	Value	Units	Description
Cost of Debt	10	%/yr	Real cost of debt
Leverage	50	%	Percent of capital cost financed by debt
Loan Currency	USD		Currency in which debt finance is acquired
Debt Tenor	10	yr	Debt repayment period
Accounting Currency	RWF		Currency in which assets are depreciated
Cost of Equity	15	%/yr	Real cost of equity

8.1.3 Tax/Depreciation Inputs

The tax rate used is the Rwandan corporate tax rate of 30% [143]. Assets are depreciated in local currency, converted from the currency it was acquired in on the acquisition date, over the period in Table 8-6.

Table 8-6 Depreciation periods of capital assets.

Asset	Value	Units
Distribution Network	30	yr
Meters	10	yr
Solar Array	25	yr
Inverters	15	yr
Batteries	5	yr
Diesel Generators	5	yr

8.1.4 CPI and Foreign Exchange Inputs

The parameters of the consumer price index (CPI) and foreign exchange models described in section 7.3.4 where estimated using monthly time series data of Rwanda and US CPI data and Rwandan Franc (RWF) and US Dollar (USD) exchange rate data from February 2009 to July 2016. These time series are plotted in Figure 8-1 and Figure 8-2. The parameters of the AR(1) series described in section 7.3.4 obtained by fitting the Wilkie Investment model to these data are summarized in Table 8-7.

Table 8-7 AR(1) parameters for CPI and foreign exchange models.

Series	Initial Value	Constant	Autoregressive Coefficient	Variance
Rwanda CPI	7.5%	$2{,}430\times10^{-6}$	0.350	195×10^{-6}
US CPI	1.0%	755×10^{-6}	0.466	7.68×10^{-6}
XN (RWF/USD)	806.4	0	0.8913	375×10^{-6}

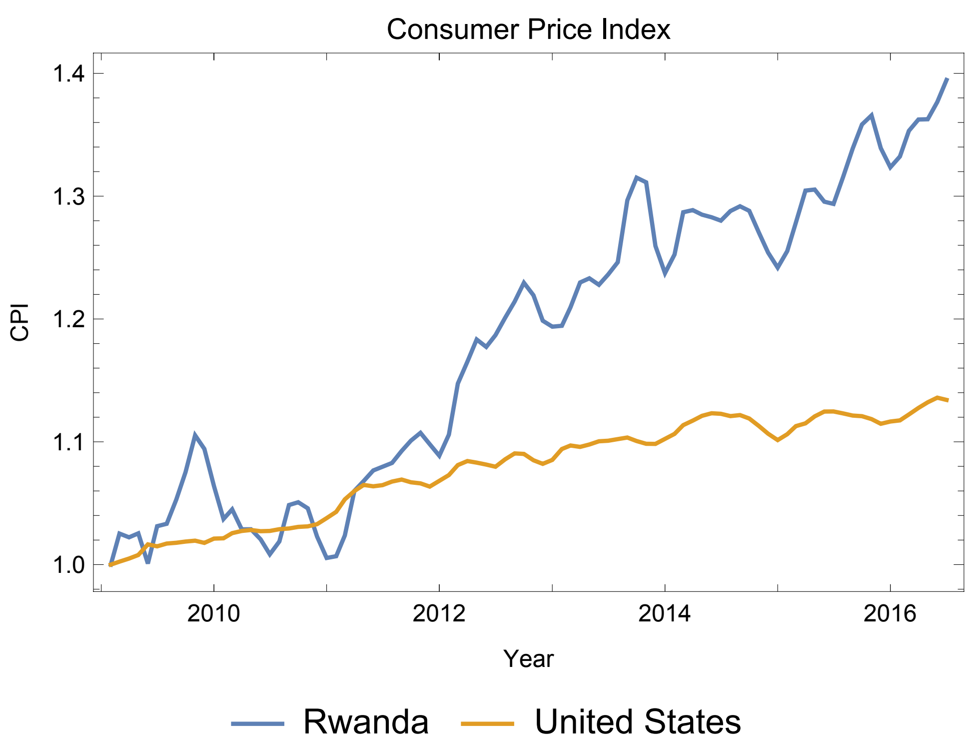

Figure 8-1 Time series plot of consumer price index data used to fit inflation model parameters.

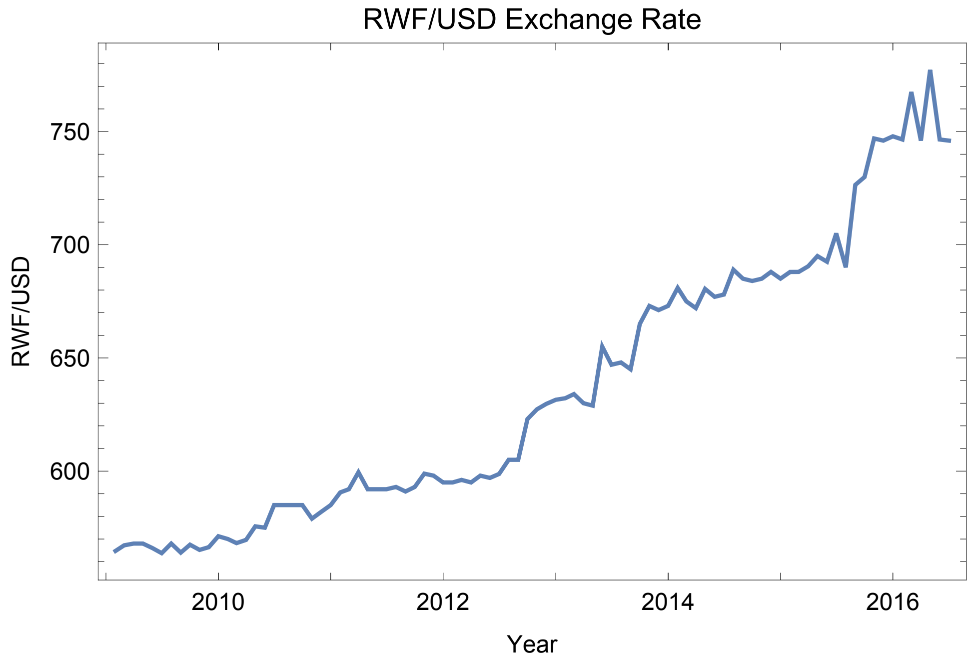

Figure 8-2 Time series plot of monthly exchange rate data used to fit foreign exchange model parameters.

8.2 Technical Inputs

8.2.1 Scenario Generator Sizing Method

The generator sizings for the technology scenarios used in this paper are presented in Table 8-8. The scenarios were constructed using an iterative approach with HOMER [99] and STEMM. Initial sizing was fixed using HOMER and the load profile provided by REG found in Figure 8-3 [98]. Tariffs where then set by finding the value in STEMM (in deterministic mode using median values of uncertain inputs) that provides an equity NPV approximately equal to zero to the nearest Rwandan franc. Because I rely on the load profile from the grid electricity supplier, I assume that such demand is representative of demand at the grid tariffs. STEMM adjusts the demand on the microgrid as a function of the energy tariff using a constant price elasticity of demand model. The level of demand at the tariff level determined in STEMM is then adjusted in HOMER and the optimization is re-run. The new configuration is then entered into STEMM and a new tariff is determined. This process was repeated until the optimal generator sizing converged. Table 8-8 includes information about the tariffs used.

Table 8-8 Summary of generation technology scenarios.

Scenario	Diesel	Hybrid (small PV)	Hybrid (large PV)	Solar/Battery
Diesel Gen 1 (kW)	50	50	50	
Diesel Gen 2 (kW)	25	25	25	
Diesel Gen 3 (kW)	25	25	25	
PV Array (kWp)		50	100	200
Inverter (kW)		50	50	75
Battery Strings		1	4	22
Tariff (RWF/kWh)	1,137	1,137	1,219	1,665
Diesel Weight	1	0.69	0.46	0
Initial Capex (k$)	432.1	607.9	790.4	1,297

1 USD is approx. 800 RWF

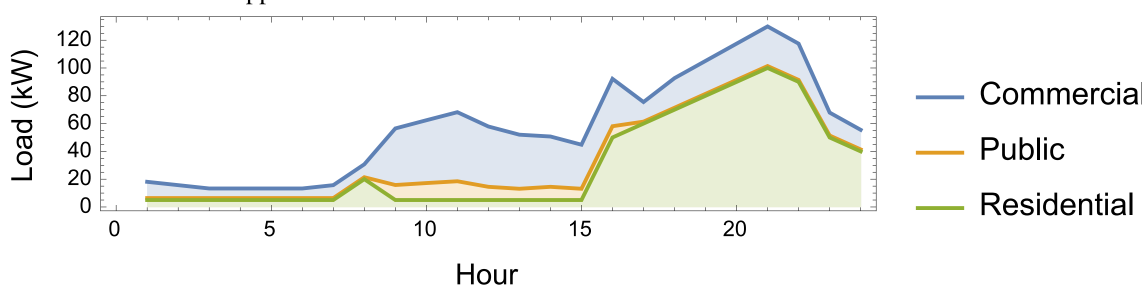

Figure 8-3 Average load profile for a typical load center from REG electricity master plan.

8.2.2 Meteorological Inputs

Solar Resource Data

Solar resource data is drawn from the HelioClim-3 v5 database for the period from February 1, 2004 to January 31, 2005 for the coordinates 2° S, 30° E located in central Rwanda [100]. I assumed a north-facing array with latitude tilt. Ideally, a longer time series would be available to account for inter-annual variability. Lacking this, a typical meteorological year would be appropriate to ensure the use of data that represents the long-term average solar resource. However, because the only available hourly time series for the location was a single year of measured data, I relied on such data for the case studies.

Solar Resource Uncertainty

The uncertainty model for solar resource relies on validation studies of the HelioClim-3 database that compare the satellite derived data with ground based measurements from 65 sites around Europe, Africa, and South America [102]-[105]. The relative bias values from these sites fit a normal distribution as in Figure 8-4 and the relative standard deviation values fit to a lognormal distribution as in Figure 8-5. Distribution parameters are found in Table 8-9.

Table 8-9 Solar resource uncertainty parameters.

Input	Distribution	Parameters	Units	Description	Source
Hourly Solar Resource Measurement Error	LogNormal	μ: 20.1 σ: 5.04	%	Measurement uncertainty of hourly solar resource	[102]-[105]
Solar Resource Bias	Normal	μ: 0.592 σ: 2.63	%	Bias of annual solar resource measurement	[102]-[105]

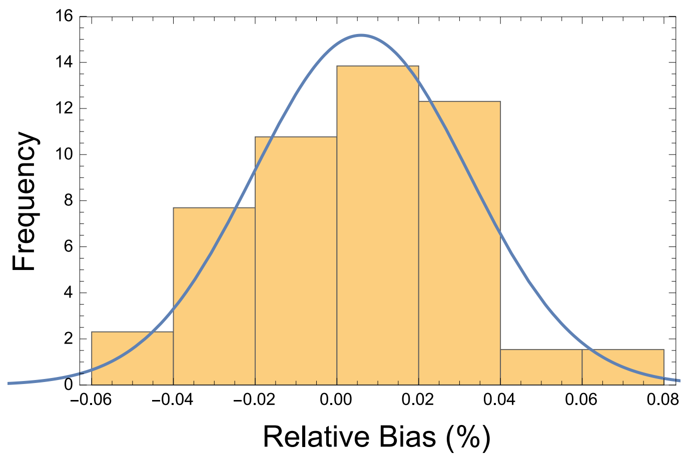

Figure 8-4 Distribution of relative bias of HelioClim-3 v5 data from 65 ground measurement sites.

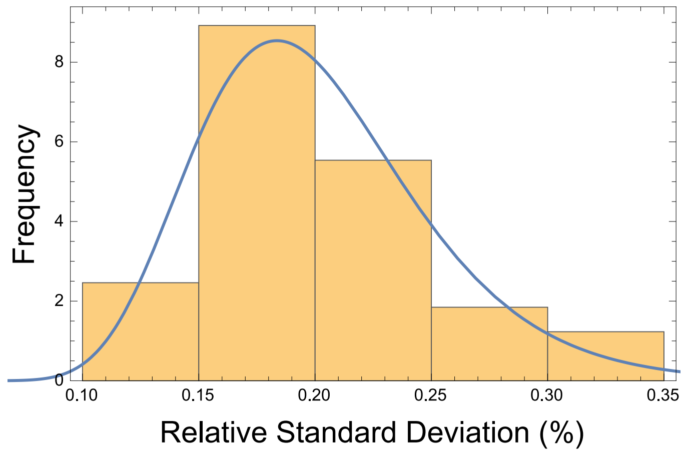

Figure 8-5 Distribution of relative standard deviation of HelioClim-3 v5 data from 65 ground measurement sites.

Temperature Data

Daily maximum and minimum temperatures used in the model are from the NASA SSE database [101]. This time series is from the same coordinates and time period as the solar irradiation data. Figure 8-6 shows the profiles of total daily solar insolation, and daily maximum and minimum ambient temperatures used in the case studies. Uncertainty parameters are in Table 8-10.

Table 8-10 Temperature uncertainty parameters.

Input	**Value**	**Units**	**Description**	**Source**
Ta_{max} Uncertainty	3.1	˚C	Standard deviation of distribution of daily maximum ambient temperature	[122]
Ta_{min} Uncertainty	2.5	˚C	Standard deviation of distribution of daily minimum ambient temperature	[122]

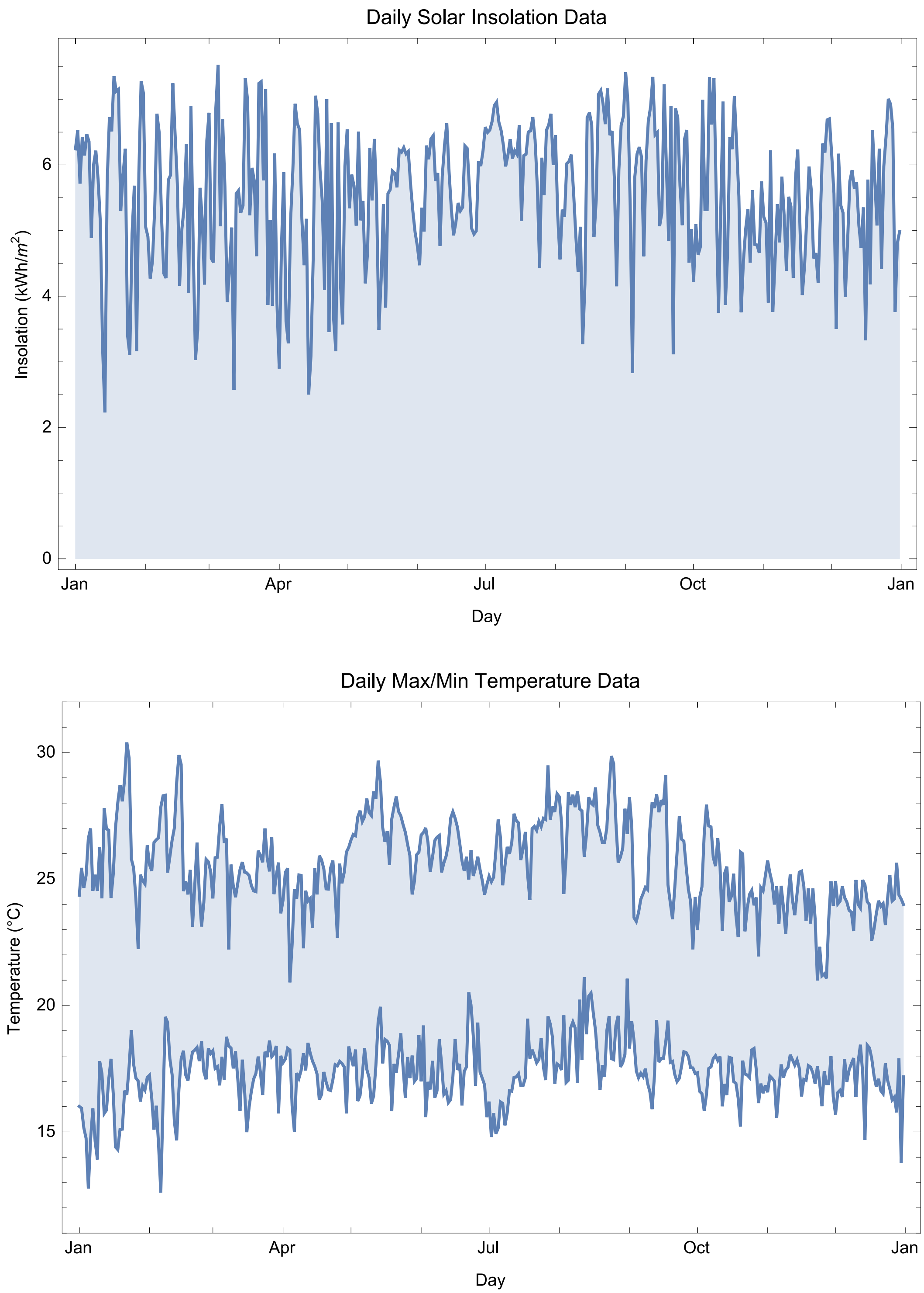

Figure 8-6 Daily solar and temperature profiles used in case studies.

8.2.3 Solar Inputs

Solar array and inverter inputs were taken primarily from data sheets for Trina solar modules and Fronius inverters, respectively. These inputs are found in Table 8-11. PV array output degradation and system losses are modeled probabilistically using the inputs in Table 8-12.

Table 8-11 Deterministic solar array inputs.

Input	Value	Units	Description	Source
V_{mpp}	30.3	V	Maximum power point voltage of PV modules at STC	[139]
I_{mpp}	8.27	A	Maximum power point current of PV modules at STC	[139]
V_{oc0}	38	V	Open circuit voltage of PV modules at STC	[139]
I_{sc0}	8.79	A	Closed circuit current of PV modules at STC	[139]
NOCT	44	˚C	Normal operating cell temperture	[139]
Power Temperature Coefficient	0.41	%/˚C/yr	Temperature dependence coefficient of PV model power output	[139]
Inverter Efficiency	96.5	%	DC to AC conversion efficiency of inverters	[144]

Table 8-12 Probabilistic solar array inputs.

Input	Distribution	Parameters	Units	Description	Source
Annual PV Degradation	Triangular	Min: 0.2 Mode: 0.5 Max: 0.8	%/yr	Annual power output degradation of PV modules	[111]
DC PV Losses	Beta	α: 12.8 β: 96.7	%	Energy losses in PV system from array to inverters	[110]

8.2.4 Diesel inputs table

Diesel generator inputs are summarized in Table 8-13.

Table 8-13 Diesel generator inputs.

Input	Value	Units	Description	Source
No Load Fuel Consumption	0.0911 × Gen. Capacity	L/h	Generator fuel consumption per hour regardless of electric output	[142]
Marginal Fuel Consumption	0.264	L/kWh	Generator fuel consumption in addition to no load fuel consumption per kWh generated	[142]
Minimum Load Factor	30	%	Minimum generator output while operating as percent of rated capacity	[145]

8.2.5 Load/distribution inputs table

Load profile and distribution loss model inputs are found in Table 8-14 and Table 8-15.

Table 8-14 Load and distribution inputs

Input	Value	Units	Description	Source
Expected Load Tariff	182	RWF/kWh	Tariff assumption in constructing load profile	[146]
Demand Uncertainty	20	%	Relative standard deviation of mean daily electricity consumption	Based on author experience
Load Profile Uncertainty	10	%	Relative standard deviation of mean hourly electricity demand	
Timestep Variability	8	%	Relative standard deviation of hourly demand distributed around mean profile	[147]
Technical Losses	5	%	Technical losses incurred in distribution of electricity	[148]

Table 8-15 Load and distribution input distributions.

Input	Distribution	Parameters	Units	Description	Source
Price Elasticity of Demand	Triangular	Min: -0.82 Mode: -0.5 Max: -0.17		Price elasticity of demand for electricity	[149], [150]
Non-Technical Losses	Triangular	Min: 0 Mode: 2 Max: 4	%	Non-technical losses due to non-payment and theft	[109]

8.2.6 Battery Inputs

Battery model inputs are summarized in Table 8-16.

Table 8-16 Battery inputs.

Input	Value	Units	Description	Source
c (KiBaM)	0.254		Constant in KiBam model described in section 7.2.5.1	[99]
A_k	1.058		Constant in model for KiBaM reaction rate described in section 7.2.5.1	
B_k	44.16		Constant in model for KiBaM reaction rate described in section 7.2.5.1	
C_k	236.3		Constant in model for KiBaM reaction rate described in section 7.2.5.1	
20hr Capacity	1350	Ah	Capacity of battery at standard conditions at 20-hour discharge rate	[99]
Nominal Voltage	4	V	Nominal voltage of each battery	[99]
Batteries per String	12		Number of batteries connected (in series) in a string	
A_η	-0.0278		Constant in model of battery efficiency described in section 7.2.5.1	
B_η	0.822		Constant in model of battery efficiency described in section 7.2.5.1	
Min. SOC	40	%	Minimum battery state of charge	
Battery Setpoint SOC	90	%	Battery state of charge when battery bank becomes available for discharge after reaching minimum SOC	Typical value
Rectifier Efficiency	90	%	AC to DC conversion rate of rectifier for battery charging	[151]

8.2.6.1 Capacity fade distribution

The distribution for the battery capacity fade constant is derived from cycle life data in the HOMER database [99]. Table 8-17 shows the cycle life of the battery modeled at different depths of discharge. These cycles are then converted to full cycle equivalents and the capacity fade rate is calculated assuming the batteries reach end of life at the conventional 80% of original capacity. A triangular distribution is constructed using the maximum and minimum values with the distribution mode equal to the fade rate at the minimum depth of discharge being modeled.

There are limitations to this approach. For example, this does not account for variation in quality of manufacturing. However, due to a lack of data, this method has been used to approximate the uncertainty associated with battery capacity fade.

Table 8-17 Implied capacity fade rate of Surrette 4kS25P battery from HOMER database [99].

Surrette 4KS25P Cycle Life Data				
DOD	**Cycles**	**Full Cycles**	**Fade**	**Fade Rate**
20	5,100	1,020	20%	0.0196%
30	4,220	1,266	20%	0.0158%
40	3,580	1,432	20%	0.0140%
50	3,170	1,585	20%	0.0126%
60	2,750	1,650	20%	0.0121%
70	2,400	1,680	20%	0.0119%
80	2,000	1,600	20%	0.0125%
90	1,750	1,575	20%	0.0127%
100	1,500	1,500	20%	0.0133%

9 Appendix C: Demand model supplemental information

Table 9-1 Summary of train and test MSEs on 1,000 train/test data splits

		Combined		**Peak**		**Off-peak**	
		Train MSE	*Test MSE*	*Train MSE*	*Test MSE*	*Train MSE*	*Test MSE*
OLS	Mean	1.45	2.17	1.45	2.19	5.51	8.13
	Std Err.	0.16	0.43	0.19	0.52	0.39	1.19
Ridge	Mean	1.68	2.05	1.70	2.11	6.31	7.50
	Std Err.	0.17	0.43	0.20	0.55	0.42	1.14
LASSO	Mean	1.73	2.01	1.76	2.06	6.53	7.39
	Std Err.	0.21	0.43	0.25	0.54	0.50	1.15
PCR	Mean	1.72	2.11	1.75	2.19	6.68	7.65
	Std Err.	0.22	0.45	0.27	0.56	0.59	1.16
Mean	Mean	2.91	2.93	2.82	2.85	9.98	10.09
	Std Err.	0.22	0.51	0.24	0.57	0.60	1.41
Rand. Forest	Mean	0.31	2.14				
	Std Err.	0.04	0.45				

Table 9-2 Summary of model MSEs, tuning parameters, and coefficients for 1,000 train/test splits

	OLS				Ridge			
	Peak		Off-peak		Peak		Off-peak	
Tuning parameter					alpha		alpha	
					0.575	0.000	0.874	0.000
Intercept	-3.419	0.796	-9.303	1.559	-3.686	0.432	-7.498	0.654
Own Building	-0.050	0.179	0.008	0.427	-0.025	0.093	-0.015	0.179
Building Type								
Well Built Concrete	-0.459	0.220	0.062	0.504	-0.065	0.050	0.128	0.090
Brick/Mud Brick/Sticks & Mud/Wood	-0.425	0.223	0.104	0.627	-0.114	0.045	-0.181	0.102
Current Light/Electricity Source								
None/Kerosene Lamp	-0.733	0.249	-0.266	0.510	-0.397	0.088	-0.525	0.166
Solar Lantern	-0.187	0.186	0.617	0.369	-0.136	0.065	-0.070	0.118
Solar < 50W	-0.220	0.240	0.320	0.375	-0.213	0.076	-0.214	0.118
Solar > 50W	0.115	0.284	1.261	0.473	-0.113	0.085	0.188	0.107
Generator/Mini-Grid	1.007	0.309	1.782	0.436	0.868	0.095	1.082	0.100
Other	0.210	0.197	0.208	0.385	0.104	0.077	0.126	0.135
Existing Appliances								
None	-0.305	0.246	0.494	0.527	-0.150	0.083	0.094	0.143
Computer/Refrigerator/Printer/Copier	0.333	0.372	0.621	0.557	0.237	0.229	0.445	0.261
Television	0.576	0.202	0.792	0.377	0.377	0.067	0.436	0.096
Radio	-0.184	0.182	-0.250	0.338	0.047	0.071	0.067	0.111
Phone Charger	0.014	0.183	-0.044	0.299	0.000	0.072	-0.018	0.107
CD-DVD Player/Sound System	-0.401	0.304	-0.198	0.445	0.100	0.127	0.369	0.135
Other	-0.387	0.199	-0.691	0.433	-0.167	0.101	-0.339	0.188
Planned Appliance								
None	-0.356	0.396	0.072	0.565	0.050	0.187	0.127	0.336
Computer/Refrigerator/Printer/Copier	0.092	0.147	0.379	0.278	-0.023	0.071	0.070	0.109
Television	0.301	0.157	0.942	0.382	0.010	0.067	0.112	0.119
Radio	0.336	0.164	0.008	0.311	0.189	0.070	-0.007	0.112
Phone Charger	0.271	0.163	0.228	0.302	0.173	0.072	0.048	0.114
CD-DVD Player/Sound System	-0.003	0.131	0.006	0.275	-0.013	0.067	-0.031	0.121
Lights	0.039	0.153	0.293	0.299	-0.074	0.073	-0.063	0.116
Other	0.156	0.169	0.228	0.295	0.059	0.083	0.137	0.121
Customer Type								
Home	0.342	0.206	-0.486	0.354	-0.006	0.093	-0.419	0.106
Restaurant/Bar	0.624	0.183	0.189	0.401	0.410	0.096	0.253	0.173
Shop/Hair Salon/Guest House	0.179	0.168	0.431	0.304	0.102	0.092	0.349	0.121
Other	-0.298	0.308	-0.571	0.538	-0.463	0.157	-0.456	0.205
Time of Use	10.998	2.061	16.297	3.101	0.286	0.057	0.606	0.081
Numerical Variables								
Log Peak Tariff (TSH/kWh)	-1.292	0.253			0.023	0.007		
Log Off-peak Tariff (TSH/kWh)			-1.974	0.421			0.067	0.012
Log Airtime Spend (TSH)	-0.083	0.087	0.010	0.161	-0.022	0.050	0.067	0.077
Log Electricity Spend (TSH)	0.033	0.025	0.067	0.044	0.029	0.009	0.052	0.013
Log Number of Existing Lights	-0.203	0.132	0.190	0.274	0.037	0.042	0.238	0.072

Table 9-2 Summary of model MSEs, tuning parameters, and coefficients for 1,000 train/test splits cont'd

	LASSO						PCR			
	Peak			Off-peak			Peak		Off-peak	
Tuning parameter	alpha			alpha			Num. Comp.		Num. Comp.	
	0.008	0.008	0.003	0.019	0.019	0.005	15.20	7.01	8.34	4.59
Intercept	-3.997	-4.007	0.249	-7.274	-7.294	0.374	-4.314	0.781	-8.032	0.959
Own Building		0.000	0.032		-0.002	0.041	0.095	0.200	0.052	0.233
Building Type										
Well Built Concrete		-0.013	0.073		0.006	0.037	-0.050	0.169	0.273	0.117
Brick/Mud Brick/Sticks & Mud/Wood		-0.023	0.087		-0.017	0.076	-0.110	0.146	-0.344	0.101
Current Light/Electricity Source										
None/Kerosene Lamp	-0.151	-0.202	0.217	-0.103	-0.232	0.280	-0.354	0.229	-0.559	0.274
Solar Lantern		-0.013	0.063		0.002	0.028	-0.137	0.099	-0.158	0.146
Solar < 50W		-0.045	0.111		-0.019	0.069	-0.223	0.170	-0.324	0.232
Solar > 50W		0.002	0.069		0.148	0.228	-0.148	0.169	0.068	0.183
Generator/Mini-Grid	1.387	1.375	0.231	1.820	1.820	0.273	0.876	0.250	0.940	0.350
Other		0.009	0.048		0.005	0.043	0.094	0.179	0.211	0.189
Existing Appliances										
None		-0.026	0.086		0.024	0.117	-0.076	0.141	-0.006	0.282
Computer/Refrigerator/Printer/Copier		0.122	0.229		0.157	0.298	0.304	0.332	0.550	0.330
Television	0.414	0.414	0.155	0.392	0.402	0.252	0.287	0.155	0.307	0.108
Radio		0.005	0.052		-0.001	0.056	0.046	0.142	0.063	0.175
Phone Charger		0.006	0.048		-0.005	0.042	0.001	0.106	0.003	0.133
CD-DVD Player/Sound System		0.006	0.090		0.092	0.178	0.097	0.258	0.404	0.150
Other		-0.045	0.115		-0.099	0.210	0.094	0.179	-0.245	0.317
Planned Appliance										
None		-0.006	0.069		-0.001	0.046	0.276	0.453	-0.089	0.569
Computer/Refrigerator/Printer/Copier		0.006	0.044		0.011	0.059	-0.093	0.152	-0.074	0.152
Television		0.017	0.070		0.028	0.129	-0.012	0.154	-0.069	0.183
Radio		0.096	0.130		0.003	0.042	0.248	0.144	0.043	0.272
Phone Charger	0.037	0.089	0.110		0.010	0.056	0.125	0.178	-0.195	0.156
CD-DVD Player/Sound System		-0.001	0.032		-0.002	0.030	-0.019	0.124	-0.033	0.158
Lights		0.002	0.046		0.004	0.048	-0.049	0.115	-0.170	0.143
Other		0.006	0.041		0.021	0.080	0.011	0.139	0.092	0.178
Customer Type										
Home		0.017	0.093	-0.034	-0.146	0.204	0.020	0.181	-0.333	0.167
Restaurant/Bar	0.231	0.236	0.186		0.039	0.116	0.664	0.210	0.567	0.395
Shop/Hair Salon/Guest House		0.043	0.090	0.229	0.257	0.221	0.245	0.176	0.639	0.316
Other	-0.378	-0.364	0.250		-0.145	0.297	-0.698	0.292	-0.496	0.433
Time of Use	0.462	0.869	2.052	1.413	1.450	0.877	1.513	3.785	0.564	0.703
Numerical Variables										
Log Peak Tariff (TSH/kWh)		-0.052	0.254				-0.124	0.466		
Log Off-peak Tariff (TSH/kWh)					-0.005	0.115			0.068	0.089
Log Airtime Spend (TSH)		-0.004	0.026		0.004	0.028	0.022	0.097	0.161	0.095
Log Electricity Spend (TSH)		0.010	0.017	0.001	0.018	0.026	0.040	0.012	0.057	0.017
Log Number of Existing Lights		-0.001	0.038	0.208	0.216	0.165	0.114	0.121	0.286	0.103

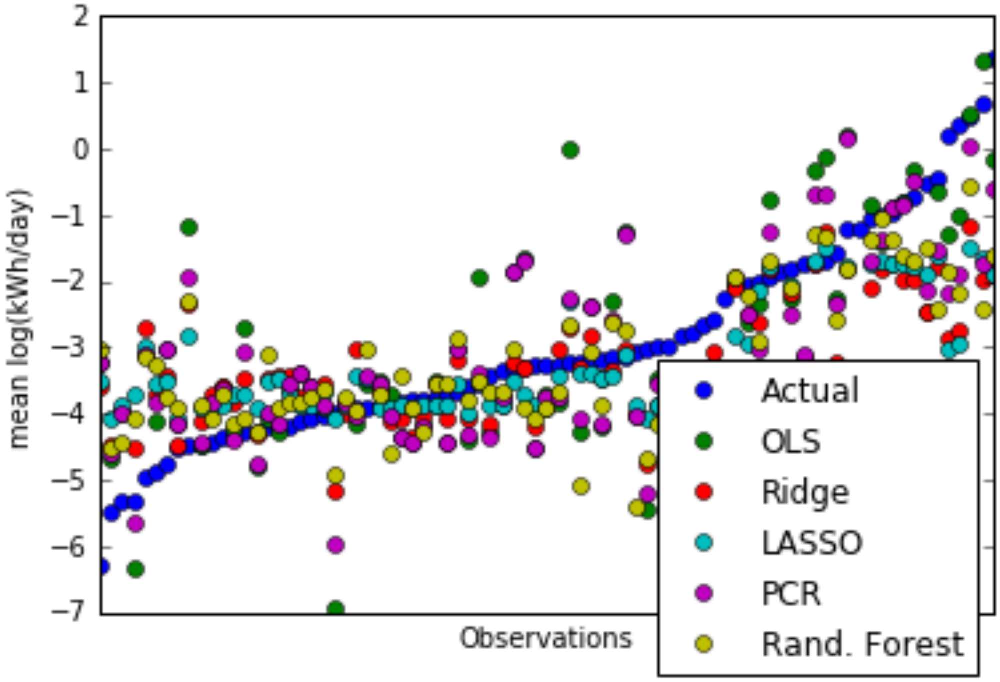

Figure 9-1 Model estimates of log consumption plotted against observed values in the test data.

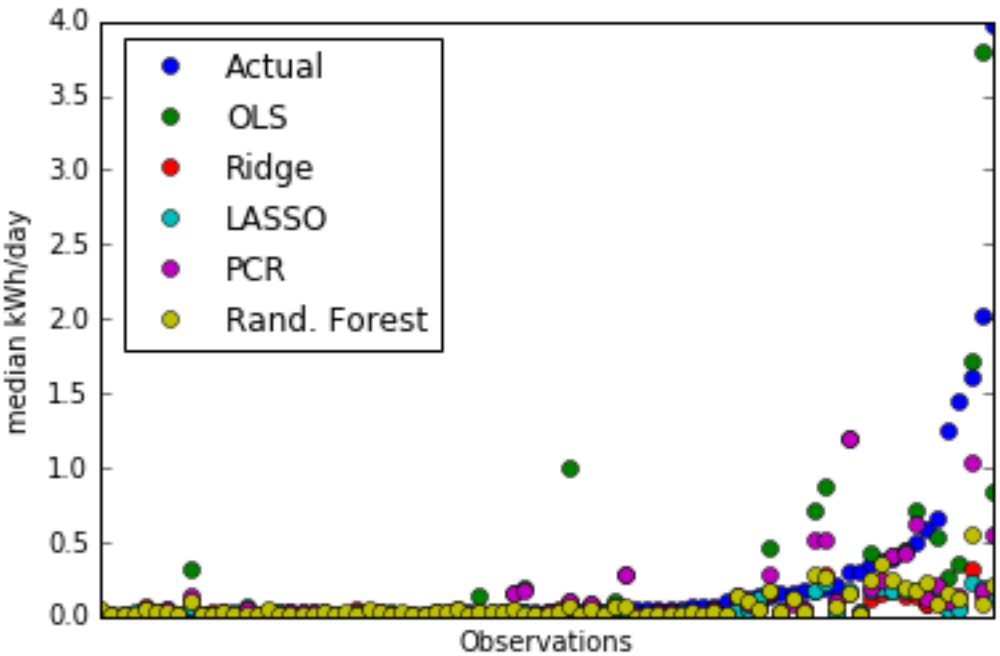

Figure 9-2 Model estimates of median consumption plotted against observed values in the test data.

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