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An investment risk assessment of microgrid utilities for rural electrification using the stochastic techno-economic microgrid model: A case study in Rwanda

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ABSTRACT

Access to electricity is a key enabler of social and economic development. However, 1.2 billion people still do not benefit from reliable electricity services. Microgrids have been proposed as a cost-effective means to accelerate access for communities located far from existing grid infrastructure. Scarcity of capital has been a barrier to both on-grid and off-grid electrification efforts and governments have sought private sector participation in an effort to close this gap. 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. This paper introduces the Stochastic Techno-Economic Microgrid Model (STEMM), which enables assessment of the effect of technical design decisions as well as financial conditions on the financial viability of microgrid projects from an investment perspective. Using STEMM, this paper presents a risk analysis of the key uncertain variables affecting microgrid investments to both debt and equity investors using four technology scenarios as case studies in Rwanda. We find that major contributors to risk are fuel price volatility, uncertain electricity demand, and foreign exchange risk for investments in hard currency. Choice of technology strongly influences the risk profile of microgrids, with solar powered microgrids susceptible to demand uncertainty and diesel-based systems exposed to fuel price volatility. Hybrid solutions provide a middle ground with partial mitigation of both fuel price and demand risk. If electricity tariffs are linked to changes in fuel price, fuel price risk can be effectively passed to consumers.

Introduction

It is widely accepted that electrical energy is an enabler and driver of economic growth and development (International Energy Agency, 2011). Despite this, more than 1.2 billion people in the world today still lack access to reliable electricity services (International Energy Agency, 2015). The regions most affected are also the least urbanized in the world (United Nations, Department of Economic and Social Affairs, Population Division, 2014) and the cost of reaching rural populations with a centralized grid is high (Parshall et al., 2009). 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 (Szabó et al., 2011; Blum et al., 2013). One such decentralized solution is microgrids, community-scale electricity networks with local, often renewable, power generation. However, a barrier for both centralized and decentralized electrification programs has been a scarcity of capital from public sources and the donor community. As a result, the pace of progress towards meeting ambitious energy access goals has been slow. Governments have looked to the private sector for investment, but high perceived risk has been a deterrent to investors' participation in improving energy access via microgrids (Williams et al., 2015). While a range of organizations – including development aid agencies (African Development Bank; Deutsche Gesellschaft für Internationale Zusammenarbeit), private foundations (Rockefeller Foundation), private capital facilities (Microgrid Investment Accelerator (MIA)), and private enterprises (Odyssey Energy Solutions) – are investing large sums in developing microgrid business models and best practices, investor risk remains largely unquantified.

The need for increased investment and high perceived investment risk has been noted in the literature. Gujba et al. (2012) surveyed potential sources of finance to fund energy access using low carbon technologies in Africa. Risks identified include poor investment climate and uncertain fiscal policy, political risk and fuel price volatility for biomass. Schmidt et al. (2013) identified four board categories of risk facing investors in energy access in Indonesia: energy market risk, institutional/licensing risk, technology risk and financial risk. Using a survey based approach, Wagemann and Manetsgruber (2016) identified political risk, payment risk and energy resource price variability as major drivers

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of operational risk for rural microgrids. Hazelton et al. (2015) breaks project risk down into performance, commercial and pragmatic risks. While a number of authors have qualitatively assessed risks faced by investors in microgrid projects, there has been little work to quantify these risks and assess their relative importance.

We seek to address this critical gap; in this paper, we develop the Stochastic Techno-Economic Microgrid Model (STEMM) to quantitatively compare the drivers of risk in microgrid utilities. With particular consideration of the uncertainty inherent in many critical microgrid inputs, STEMM enables examination of how different business models and technologies affect the potential for these projects to attract finance and scale up deployment. The primary contributions of this paper are threefold:

- Description of the Stochastic Techno-Economic Microgrid Model (STEMM), which enables assessment of the effect of technical design decisions as well as financial conditions on the financial viability of a project from an investment perspective.
- Identification of key drivers of risk in microgrid investments and their relative weight.
- Quantitative comparison of the effects of business model and technology decisions on risk to both debt and equity investors. In particular, we consider a range of scenarios including different electricity supply technologies and tariffs independent of and linked to diesel prices.

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 internally generated 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 the project meets or exceeds the target return or cost of equity.

The model is implemented in Analytica (Lumina Decision Systems, 2015), 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 a few inputs, including fuel price, exchange rates, electricity demand, and solar resource as uncertain. The model propagates uncertainties using Monte Carlo simulation. In this paper, we use a 10-year model horizon, based on the assumption of a 10-year debt tenor and that equity investors will take a relatively short view, given long-term risks that are more difficult to quantify such as grid encroachment. While the lifetime of the microgrid itself will exceed this period, it is unlikely investors will take such a long-term view when evaluating these projects.

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. Fig. 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.

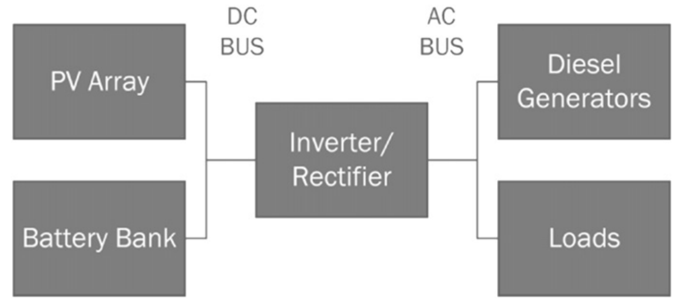

Fig. 1. General microgrid technical configuration in STEMM.

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 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 model results from uncertainty in meteorological data 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 the Supplementary Information (SI). 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) (Manwell and McGowan, 1993) and a capacity fade model to estimate battery lifetime and capacity degradation (Hittinger et al., 2015), also described in more detail in the SI.

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 the SI. In addition, STEMM can model tariffs changing in real terms over time (for example, if tariffs move with the price of diesel fuel), 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 paper, however, only includes case studies in which there is a single aggregate load without prioritization between customers and without demand growth. The paper 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. Fig. 2 provides an overview of the data flows between other technical models and the dispatch model. The details of the dispatch algorithm are available in the SI. 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.

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. Fig. 3 illustrates the load-shed algorithms available in STEMM. For this paper we use the shed by load algorithm with a single load.

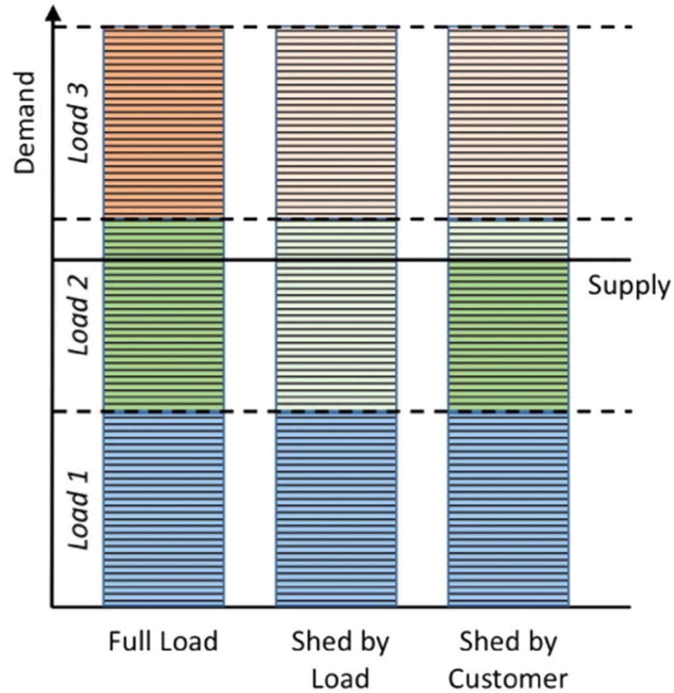

Fig. 3. Comparison of load shedding algorithms. In the shed by load scenario, any load that cannot be met completely is shed; while in the shed by customer scenario, partially loads can be supplied. The lighter colors in the figure represent loads shed.

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 the SI) 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. Microgrid assets can have different lifetimes. To account for this, STEMM models not only initial capital costs but also calculates timings for replacement of capital assets through the relevant time horizon (in this case, 10 years). The SI includes a detailed description of the methods used to account for such replacement costs. We also note that the model currently assumes there is no salvage value to the assets. There are two reasons for this assumption: 1. The period used for the financial analysis from the investor's point of view (in this case, 10 years) is shorter than the life of the microgrid; 2. Salvage values for these assets are likely to be negligible compared to the cost of accessing and transporting equipment from typically remote sites. Operating costs, also described in more detail in the SI, 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 (Wilkie, 1993). 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 the SI. In this paper, we rely on fuel price volatility from a long term study of US oil prices (Pindyck, 1999). 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.

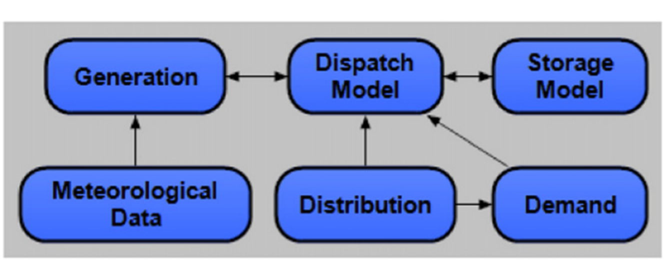

Fig. 2. Technical model influence diagram.

STEMM accounts for three different types of revenue: energy consumption-based tariffs, fixed monthly service charges, and connection fees. The case studies in this paper 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 the SI. 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.

Risk assessment methods and case study inputs

The risk assessment presented in this paper relies on two different sensitivity analysis methods to analyze the relative importance of key

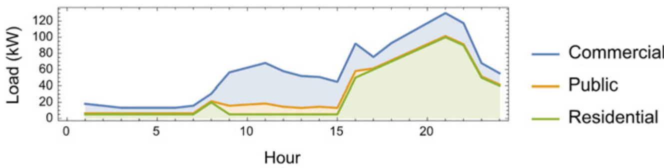

Fig. 4. Average load profile for a typical load center from REG electricity master plan.

uncertain inputs. In the first sensitivity analysis, we hold all variables but one at their expected value; we 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. We 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 variable at its expected value for each uncertain input. This provides an estimation of how much the uncertainty of outputs could be reduced by eliminating the uncertainty of an individual variable. We refer to this as a probabilistic sensitivity analysis.

For the sensitivity analyses in this paper, we 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 Fig. 4. Empirical data of load profiles for newly electrified rural customers are sparse and were not available for this study. Such data could be used in STEMM when available. While not ideal, the load data we used has been used for system planning in Rwanda and is thus representative for the kind of a priori data that are available to developers when performing feasibility studies. Finally, we included a price elasticity of demand, as described in the SI, to account for the price effects on demand for electricity.

To model the supply-side of the system, we built four generation scenarios (described in Table 1). Such scenarios allow us to compare financial outcome sensitivity to different technologies. The SI provides a detailed description of the process we used to determine the generator sizings of each scenario. We also determined an initial tariff for each generation scenario such that equity NPV is approximately zero when the model is run deterministically.

In addition to the generation technology scenarios, we also evaluate cases with tariffs fixed in real terms and tariffs that are linked to diesel prices. In the fixed tariffs case, we include an annual escalation factor, equal to inflation, to the initial tariffs in Table 1. In the linked tariffs case, only a portion of the tariff is escalated in addition to inflation. This additional escalation rate is the same rate that real fuel prices have increased/decreased in the preceding year. 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 grid, many countries have fixed national tariffs. Kenya includes a fuel surcharge in their tariffs that link electricity prices to the cost of fuel. Table 2 summarizes the uncertain inputs considered in the sensitivity analysis. The SI provides a more detailed list of inputs. Finally, Table 3 summarizes the finance structure assumptions.

Table 1
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)	1137	1137	1219	1665
Diesel weight	1	0.69	0.46	0
Initial capex (k$)	432.1	607.9	790.4	1297

1 USD is approx. 800 RWF.

Table 2
Uncertain inputs considered in sensitivity analysis.

Input	Distribution	Parameters
Mean daily demand (kWh)	Normal	Mean: REG profile Rel. std. dev.: 10%
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: 20,000 h Mode: 25,000 h Max: 30,000 h
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[a]	XA: 0.89 XV: 0.00038

[a] See Supplemental information for further details.

Results

Figs. 5 and 6 present the results of the deterministic sensitivity analysis. Fig. 5 presents the case with tariffs fixed in real terms while Fig. 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 with the corresponding variable set to its 5th percentile value based on the distributions in Table 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 we allowed to vary randomly around the median load profile. The baseline value is the indicator value with all variables fixed to their median values with the aforementioned exception.

Figs. 5 and 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 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

Table 3
Financing assumptions.

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

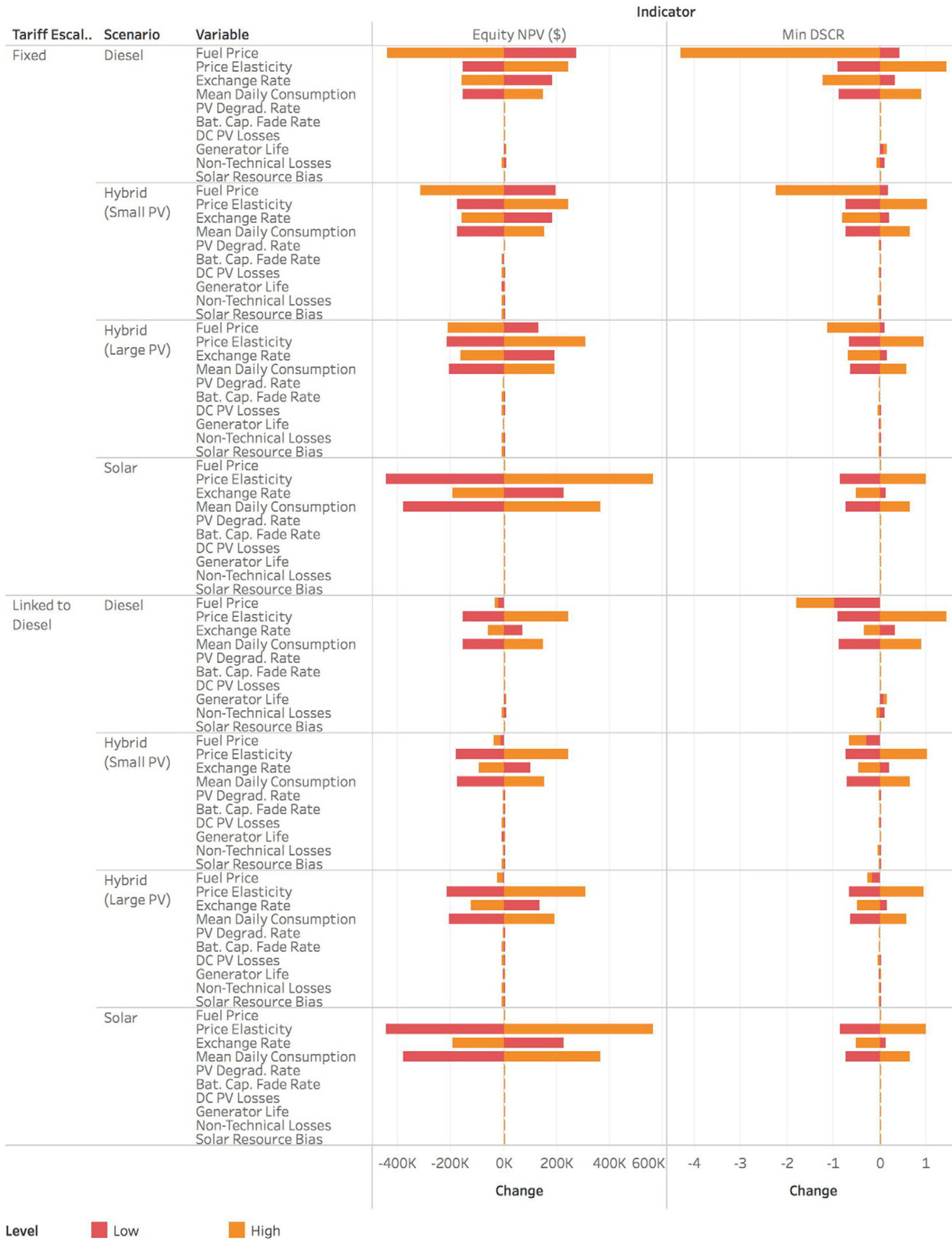

Fig. 5. Deterministic sensitivity analysis results with fixed tariffs.

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.

Fig. 6. Deterministic sensitivity analysis results with tariffs linked to diesel price.

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

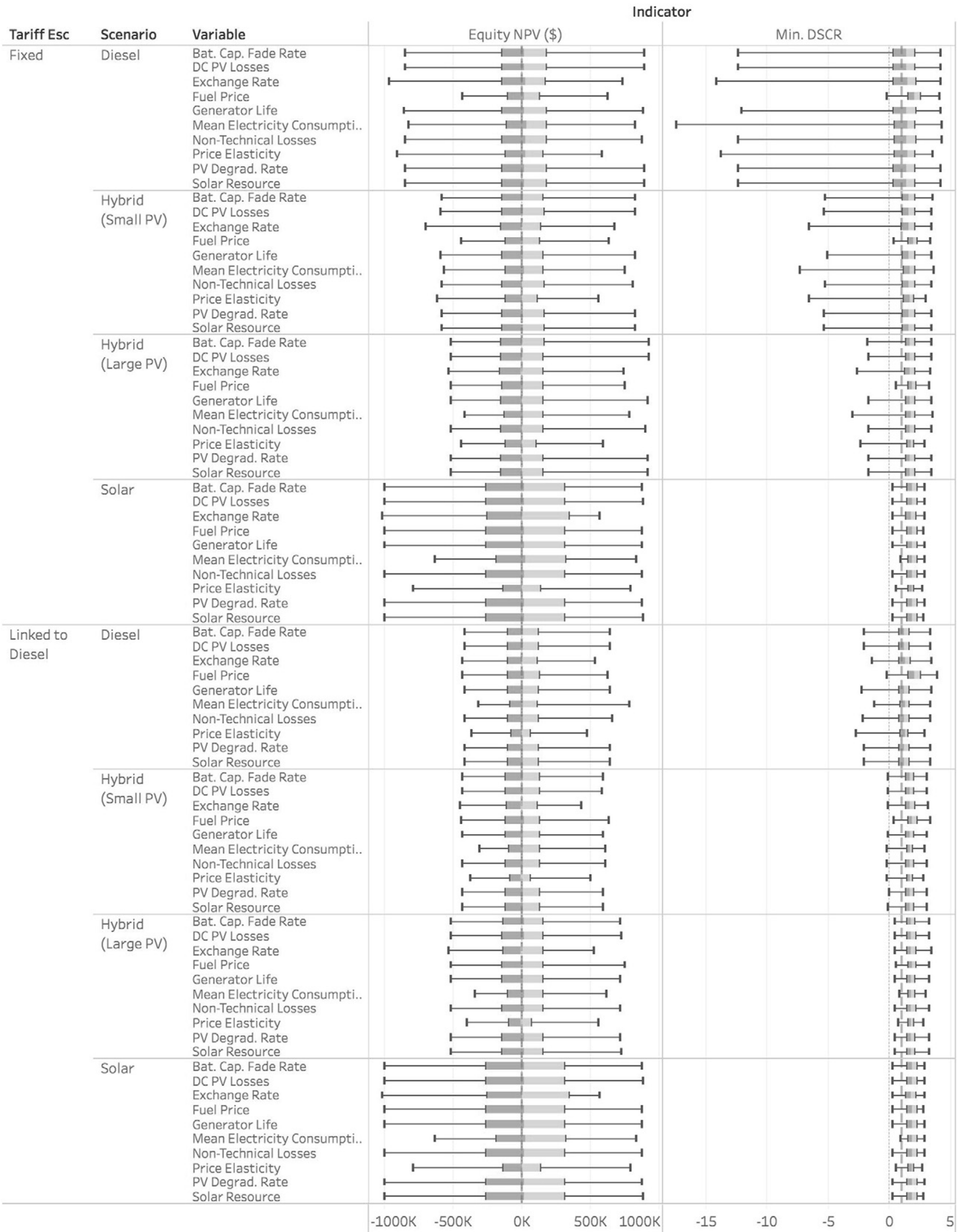

Fig. 7. Probabilistic sensitivity analysis results with fixed tariffs.

costs of solar panels and batteries, which may remain unused if demand falls short of expectations.

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

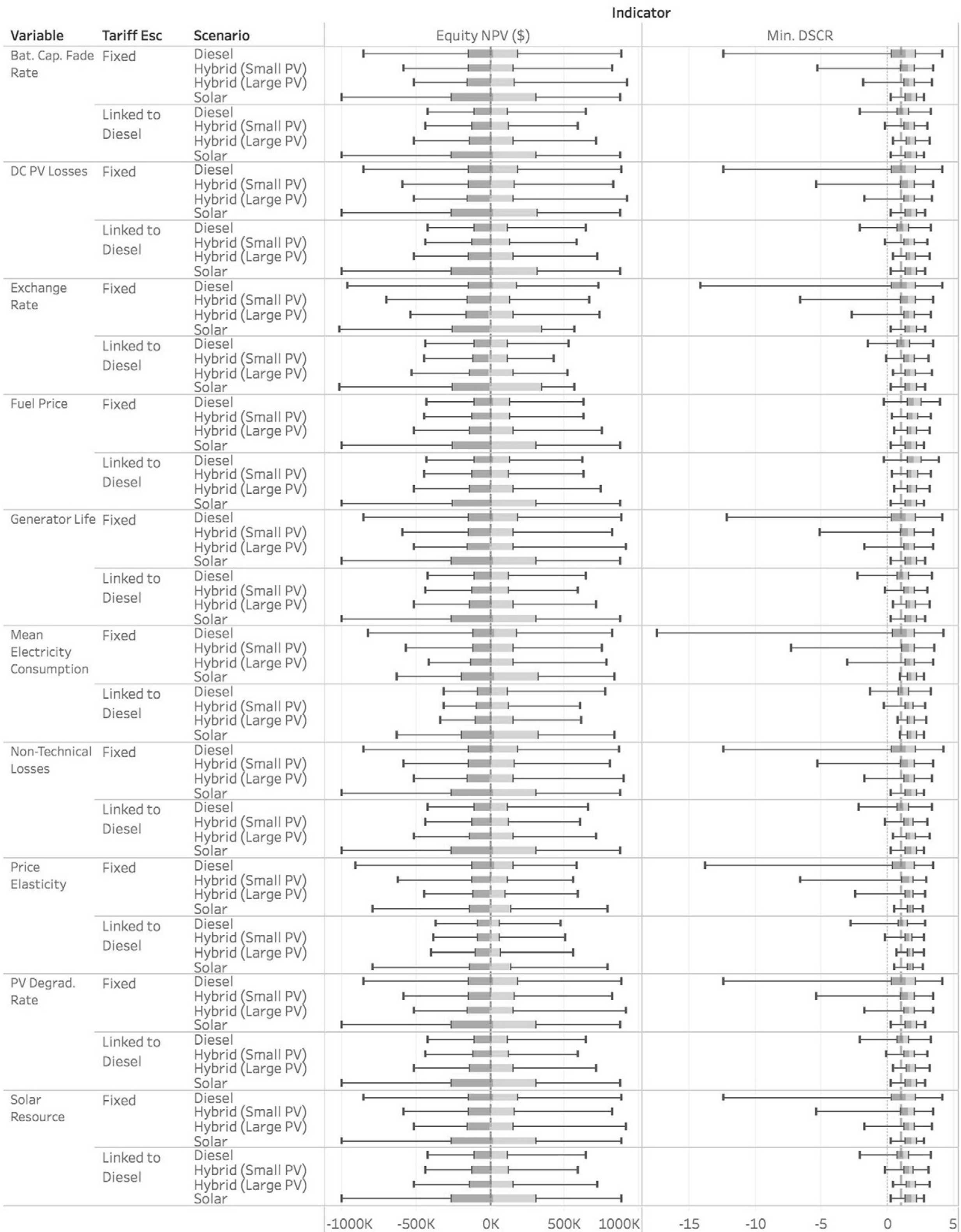

Fig. 8. Probabilistic sensitivity analysis results with tariffs linked to diesel price.

fuel prices reduce cash flows 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 the 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.

Figs. 7 and 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 min. 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 Figs. 7 and 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.

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.

Contrary the equity NPV, lenders face greater risk in diesel heavy scenarios as seen in the DSCR results in the right panel of Figs. 7 and 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.

Discussion and conclusion

Microgrid utilities hold great potential to accelerate the roll-out of electricity services to rural areas in sub-Saharan Africa. If this potential is to be realized, barriers need to be overcome to unlock the capital required to scale up deployment. Due to the risk associated with these projects, it is important to understand the sources of these risks and how to mitigate them. The risk assessment presented in this paper 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 (Whitley and van der Burg, 2015). Introducing or increasing solar penetration into diesel powered microgrids is effective in mitigating fuel price risk exposure (Williams et al., 2016). Securing reliable anchor customers could reduce uncertainty of electricity demand and price elasticity (Williams et al., 2015). Further research is also needed to better understand consumer behavior in these settings. The case studies presented in this paper 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.

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Supplementary information. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esd.2017.09.012.

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