

Udeani, Chukwudi; Jaramillo, Paulina; Williams, Nathaniel J.

Article

A techno-economic and environmental assessment of residential rooftop solar-Battery systems in grid-connected households in Lagos, Nigeria

Development Engineering

Provided in Cooperation with:

Elsevier

Suggested Citation: Udeani, Chukwudi; Jaramillo, Paulina; Williams, Nathaniel J. (2021) : A techno-economic and environmental assessment of residential rooftop solar-Battery systems in grid-connected households in Lagos, Nigeria, Development Engineering, ISSN 2352-7285, Elsevier, Amsterdam, Vol. 6, pp. 1-15, <https://doi.org/10.1016/j.deveng.2021.100069>

This Version is available at:

<https://hdl.handle.net/10419/242326>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by-nc-nd/4.0/>



A techno-economic and environmental assessment of residential rooftop solar - Battery systems in grid-connected households in Lagos, Nigeria

Chukwudi Udeani^a, Paulina Jaramillo^{a,c,*}, Nathaniel J. Williams^{b,c}

^a Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA, USA

^b Golisano Institute for Sustainability, Rochester Institute of Technology, NY, USA

^c Kigali Collaborative Research Center, Kigali, Rwanda

ARTICLE INFO

Keywords:

Residential solar-battery systems
Energy economics
Grid reliability
Air emissions
Nigerian households

ABSTRACT

We developed a techno-economic model to simulate the performance of residential solar-battery systems as a means of reducing the reliance on backup generators in grid connected households in Lagos, Nigeria. We compared the economic and environmental performance of solar-battery systems to the technology options in households that may currently rely on backup generators to supplement unreliable grid service. Our analysis shows that solar-battery systems are economically profitable for households who rely on their backup generators to ensure at least 8-h of reliable service daily. We also show that the solar-battery systems could offer a cost-effective alternative for households intending to increase the level of the electricity services they receive without greater demand from backup generators. Finally, installing the solar-battery system lowers annual air emissions from households by 15%–87%. The paper proposes that policymakers provide access to low interest loans to improve the economic attractiveness of solar-battery systems across all the reliability preference levels.

1. Introduction

The benefits of reliable electricity supply remain elusive for the majority of Nigerian households as a result of unreliable and poor quality grid service (Amadi, 2015; Oseni and Pollitt, 2015). While the peak demand in Nigeria is estimated to be 24 GW, the installed capacity in Nigeria is 10.5 GW and the available on-grid capacity hovers around 5 GW daily (Farquharson et al., 2018a). In response, Nigerian homes and businesses rely on fossil-fuel based backup generators (Akin and O., 2017; “Diesel Power Gener.,” 2014; Oluseyi et al., 2016). Some estimates put Nigeria’s backup generator capacity at approximately 10 GW, which is almost equivalent to the installed grid capacity (Farquharson et al., 2018a; IFC, 2019). Annual electricity generated from backup generators is estimated to be 7–20 Terawatt-hours of electricity annually (Farquharson et al., 2018a; IFC, 2019), which is between 20 and 60% of total on-grid electricity generation in 2015. Generator ownership among Nigerian households is estimated to be 11 million in 2018 (A2EI, 2019). Nigeria imported 3 million generators in 2016, and ranked amongst the top importers of electricity generators in Africa (IFC, 2019; Nwachukwu Clara, 2011).

The unreliable grid service and the resulting high reliance on backup generators, in response, imposes socio-economic and environmental

burdens on Nigerians. Nigerians reportedly consume 10 billion liters of diesel and gasoline fuel annually and spend between US\$1.6 - US\$17 billion annually on backup generation (“Diesel Power Gener.,” 2014; Farquharson et al., 2018a; IFC, 2019; Ley et al., 2014). Despite being among the largest oil producers in the world, Nigeria’s refining capacity is low and refined diesel and gasoline used for backup generation is imported (Ezeoha et al., 2016; Nwachukwu and Chike, 2011). The Nigerian federal government spent N1.5 trillion naira (4.1 billion USD) on fuel subsidies in 2019 (Eboh, 2020). Gasoline subsidies accounted for 3–5% of total government expenditures in 2018 (A2EI, 2019). Even with these subsidies, Nigerian households spend 15–40% of their income on operating backup generators (Akin and O, 2017; Chidebell-Emordi, 2015). Beyond economics, studies link backup generator use to negative health impacts such as respiratory illnesses and loss of life as a result of the emissions of criteria air pollutants from the generators (Ayodele and Ogunjuyigbe, 2015; Oseni, 2017). Similarly, backup generators are a source of greenhouse gases that contribute to climate change. Backup generators in Nigeria account for 7.2 million metric tons of CO₂ emissions, 8.8 thousand metric tons of SO_x emissions, 14 thousand metric tons of PM_{2.5} emissions, and 190 thousand metric tons of NO_x emissions annually (Farquharson et al., 2018a).

Alternative technologies such as residential solar PV systems have

* Corresponding author. Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA, USA.

E-mail address: paulina@cmu.edu (P. Jaramillo).

<https://doi.org/10.1016/j.deveng.2021.100069>

Received 5 February 2021; Received in revised form 9 July 2021; Accepted 28 July 2021

Available online 4 August 2021

2352-7285/© 2021 Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

been found to be economically and environmentally beneficial in developed countries, where households enjoy reliable grid service (Coria et al., 2018; Hagerman et al., 2016; La Monaca and Ryan, 2017). However, studies investigating the economic and environmental benefits of residential solar battery systems in households that experience unreliable service like Nigeria has been limited. Most of the existing studies of urban households examine the solar-battery systems as standalone backup options and conclude that the solar-battery systems can be cheaper alternative to backup generators as standalone options (Adaramola and Paul, 2016; Enongene et al., 2019; Okoye et al., 2016). These prior studies did not consider that solar-battery systems could work in tandem with the grid and backup generators. Furthermore, existing studies for grid-connected households do not quantify the effects of grid outages on the economic attractiveness of the solar-battery systems (Adaramola and Paul, 2016; Enongene et al., 2019).

In this paper we develop a techno-economic model to simulate the technical performance of residential solar-battery systems as part of a household's electricity supply portfolio, which includes backup generators and unreliable grid supply. Specifically, we compare the economic and environmental performance for three backup system set-ups. In the status quo set-up, households rely solely on backup generators to provide power during grid outages. In the GD-PB set-up, households install a solar-battery systems to operate in conjunction with existing backup generator. Finally, in the G-PB set-up, households fully replace the backup generators with solar-battery systems.

2. Methods

We examine the economic and environmental implications of installing solar-battery systems in grid-connected households in Nigeria using a techno-economic model of multi-source household electricity systems. The technical analysis uses an hourly time resolution to capture temporal variability in household load, grid availability, backup generator availability, and renewable energy generation. Estimates of electricity and fuel consumption from the technical model serve as input to an economic model to estimate the total lifetime household costs and an emissions model to estimate the greenhouse gas emissions and criteria air emissions associated with meeting household electricity demand.

2.1. Technical simulation model

We relied on the Stochastic Techno-Economic Microgrid Model (STEMM), previously developed to simulate the techno-economic performance of off-grid energy systems or microgrids using a multi-source generation model to meet end-user load and battery charging demands (Williams et al., 2018). We selected STEMM because unlike other existing modeling tools like HOMER, the code for STEMM is openly available and transparent. Furthermore, our analyses required full control of the time of day the dispatchable sources can be used, as determined by the household preferences for reliable electricity services (discussed later). Finally, our analysis includes assumption for grid improvement, which to the best of our knowledge is not yet available in HOMER.

We relied on STEMM's mathematical formulations of multi-generator systems described by (Williams et al., 2018). For PV, we used equations that estimate the PV module fill factor, which assumes that the PV array operates at the maximum power point (MPP). The battery storage model simulates the performance of a battery bank using a modified version of the Kinetic Battery Model (KiBaM) (Manwell and McGowan, 1993; Williams et al., 2018), and a capacity fade model to estimate the lifetime of the battery and the capacity degradation (Hitinger et al., 2015). For this paper, we adapted STEMM in two ways to include a binary constraint on dispatchable sources and to include a grid module to account for unreliable grid supply in Nigerian households, as described below.

2.1.1. Grid module

Any analysis of grid connected systems needs to capture the unreliable nature of the grid service from the distribution utility (Enongene et al., 2019). We captured this unreliable nature of grid service using a stochastic two-state model, as shown in Fig. 1. The stochastic assumption comes with its shortcomings as it conflates planned outages (i.e. scheduled maintenance practices) with unplanned outages that can be caused by mismatched grid demand and supply or infrastructure vandalism (Oseni, 2011). Unfortunately, households are not effectively informed prior to a planned outage and cannot plan for such events, which in turn leads them to perceive all outages, including load shedding events, as erratic and operate their residential energy systems accordingly. Our grid model assumes the binary state of the grid in a given hour when grid electricity can either be on ($G[h] = 1$) or off ($G[h] = 0$). We modeled the grid as a single generator delivering unreliable service using stochastic durations of grid service and grid outage based on similar studies in the literature (Givler and Lilienthal, 2005; Murphy et al., 2014). We assumed an upper limit of 10 kW for grid capacity since pole-mounted transformers for residential end-users are typically up to 25 kV A, much higher than reported residential peak loads in Nigeria.

The duration (H), in hours, in each state (on or off) is determined by sampling from an exponential distribution defined by a rate parameter (λ), which is the stochastic process used in studies that assess component reliability (Murphy et al., 2014). After the duration in each state has elapsed, the model toggles to the opposite state and the duration in that state is determined in a similar fashion. The toggling process continues until the hourly grid schedule is populated for a year. Each year, over a 15-year horizon, the model parameters are updated to account for the yearly grid improvements using a grid improvement factor (ω). Each new year, the duration of grid service event increases by this exponential improvement factor (ω) and the duration of the grid outage event decreases by an exponential decay factor ($-\omega$) as shown in Equations (1) and (2). This process is repeated until an hourly grid schedule is populated over the model horizon (15 years). The inputs required to populate the grid schedule are the rate parameters for both exponential distributions in the grid ON and Grid OFF states. Where rate parameters are unavailable, we used the inverse of average durations of uninterrupted grid service (T_{ON}) and individual grid outages (T_{OFF}) reported in the literature as shown in Equations (1) and (2).

$$\lambda_{ON}[y] = \lambda_{ON} \cdot e^{\omega(y)} = \frac{1}{(T_{ON})} e^{\omega(y)} \quad (1)$$

$$\lambda_{OFF}[y] = \lambda_{OFF} \cdot e^{-\omega(y)} = \frac{1}{(T_{OFF})} e^{-\omega(y)} \quad (2)$$

2.1.2. Dispatch with binary constraints on dispatchable sources

Studies show that urban Nigerian households have their backup generators available for 6 h per day (3.1 h are available between 6PM and 10PM) despite receiving grid service for only 10–12 h daily (Akin and O, 2017; Babajide and Brito, 2021; Oseni, 2016). This behavior inherently suggests a preference in the hours in which the household's backup generators will be available for dispatch during an outage. We capture this preference by including a binary constraint for the availability of dispatchable sources. The binary constraint determines whether the household's load in a given hour is a priority (must be met) or not (can go unmet). If the load at a given hour is priority ($r[h] = 1$), all dispatchable electricity sources (backup generators & battery storage) will be available for dispatch (with priority given to battery storage over backup generators). Otherwise ($r[h] = 0$), the dispatchable sources will be unavailable for dispatch, and the household's load could go unmet if there are no other sources available. As a result, there are three scenarios in any given hour that guides our dispatch algorithm, as summarized in Table 1. Based on these scenarios, our dispatch algorithm uses a merit order dispatch that prioritizes electricity generated from the solar-battery systems over backup generators during outages to control

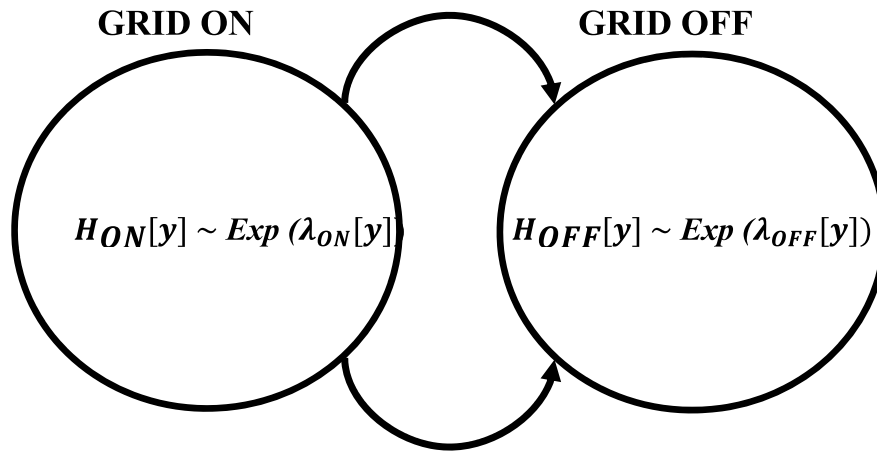


Fig. 1. Two-State Stochastic Grid Model with Exponentially Distributed holding times.

Table 1

Description of scenarios that guide Dispatch Algorithm.

Grid Status G[h]	Priority load status r[h]	Description of Dispatch
Grid is OFF (G[h] = 0)	load IS NOT priority (r[h] = 0)	<ul style="list-style-type: none"> Charge battery with solar-PV Use excess solar PV to meet load if sufficient, Else, load as unmet
Grid is OFF (G[h] = 0)	load IS priority (r[h] = 1)	<ul style="list-style-type: none"> Check if solar-battery system can meet load If yes, meet load with solar-battery system If no, meet load with backup generator (if available) charge battery storage with solar PV (if available)
Grid is ON (G[h] = 1)	Priority designation is irrelevant (r[h] can be 0 or 1)	<ul style="list-style-type: none"> Use the grid to meet the net demand (difference between electricity supplied by the solar PV and the total electricity demand from load and battery charge). Grid demand is zero if PV is sufficient to meet total electricity demand even though it is available for consumption.

how electricity supply assets are used to meet the household’s electricity demand. A graphical representation of the dispatch flow algorithm is shown in Fig. 2.

For each hour the backup generator is dispatched, we calculated the fuel consumption using Equation (3)

$$Fuel_{D-L}[h] = (F_{NL} \cdot Cap_D) + F_L \cdot Q_{D-L}[h] \quad (3)$$

where the intercept F_{NL} is the no-load fuel use. No-load fuel use is the fuel used when the generator is available even if it isn’t actively generating electricity; F_L is the generator fuel slope or the marginal consumption in liters per kilowatt-hour (l/kWh/hour); $Q_{D-L}[h]$ is the generator output at time h, and Cap_D is the installed capacity of the backup generator.

Our model allows for multiple backup generator replacements within the model horizon, depending on duration of use. We assumed that the backup generators are already in use, starting at half their lifetime. For battery storage replacement, we adopted a capacity fade model to estimate battery lifetime and capacity degradation, similarly used in (Hit-

2.2. Economic model

The economic model aggregates the hourly outputs from the technical model to an annual resolution to perform an annual cash flow analysis. We used two economic metrics: annualized household costs of electricity (Naira/year) and unit cost of backup electricity (Naira/kWh). We used the local currency in Nigeria (Naira, N) since all the associated costs incurred by the household are in local currency. We assume that the solar-battery system is wholly bought and owned by the household without any debt financing or any public incentives, as is currently the case in Nigeria.

2.2.1. Annualized household costs (N/year)

We use a discounted nominal cash flow analysis to measure the present value of all the associated costs of household power supply, which we then convert from present value of the costs to a uniform annual cost value as summarized in Equation (4). The total present cost is then given by:

$$PC = \delta_{sys} \cdot IniCap + \sum_{y=1}^T \frac{1}{(1+d)^y} \sum_{h=1}^{8760} \left[\begin{aligned} & (Q_{G-T}[h,y]) \cdot g[y] \\ & + \left(\begin{aligned} & Feul_{D-L}[h,y] \cdot f + D[h,y] \cdot om + Repl_D[y] \cdot \\ & CapEx_D + \delta_{sys} \cdot Repl_{Inv}[y] \cdot CapEx_{Inv} + \delta_{sys} \cdot \\ & Repl_B[y] \cdot CapEx_B \end{aligned} \right) \cdot (1+i)^y \end{aligned} \right] \quad (4)$$

tinger et al., 2015; Williams et al., 2018). If the capacity fade of the battery exceeds the maximum allowable capacity fade, the battery is replaced in the year it occurred i.e. $Repl_B[y] = 1$.

where y is the year; h is the hour of each year; T is the model horizon; d is the annual discount rate; δ_{sys} is a dummy variable (1 when the household uses a solar-battery system; zero otherwise) for initial capital cost of system (IniCap); Q_{G-T} is the total hourly grid electricity consumed by

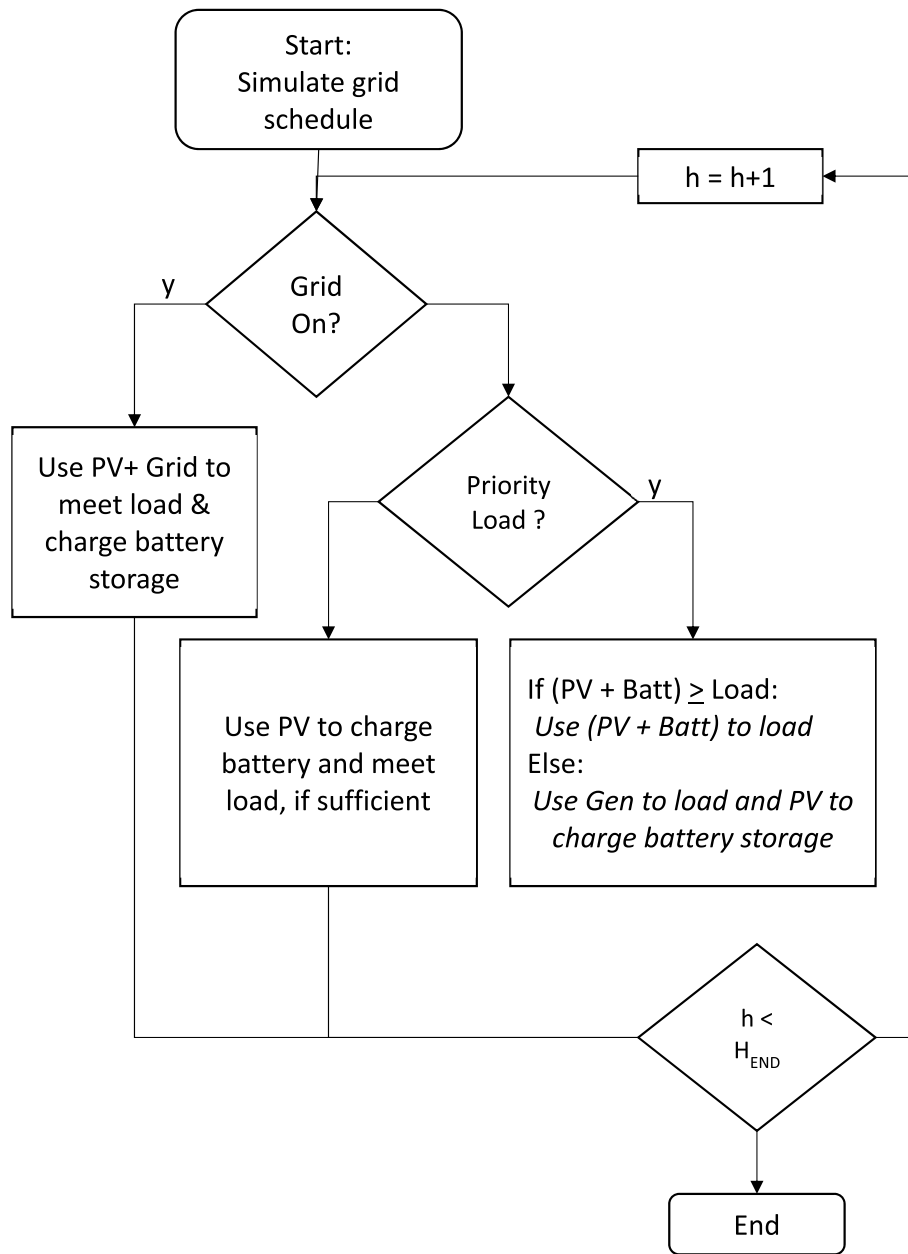


Fig. 2. Flowchart of hourly dispatch algorithm; PV is from solar PV; Batt is battery storage; Gen is backup generator; HEND is the last hour in the model horizon.

the households; $g[y]$ is the electricity tariff for year y ; $Fuel_{D-L}$ is the hourly fuel consumption from running backup generators (from Equation (3)); f is the cost of fuel in (N/liter); i is the inflation rate; D is a binary variable which indicates whether the generator is on; om is the cost of operations and maintenance in Naira per hour of generator runtime (N/Hour); $Repl_D$ is a binary variable which indicates the replacement year of the diesel generator; $Repl_{Inv}$ is a binary variable that indicates the replacement year of the inverter; $Repl_B$ is a binary variable that indicates the replacement year of the battery storage; and finally $CapEx_B$ and $CapEx_{inv}$ are the capital costs of the battery storage and inverter respectively. After obtaining the total present cost, we calculate a uniform annual cost (UAC) using the capital recovery factor as shown in Equation (5):

$$UAC = PC \frac{d}{1 - (1 + d)^{-y}} \quad (5)$$

2.2.2. Cost of backup electricity (N/kWh)

Finally, we also calculate the average cost of backup electricity (Naira/kWh), which we computed as the total costs associated with providing backup power i.e. excluding the cost of grid consumption to meet the load. To estimate the present value of the costs of the backup system, PC_{Backup} , we replaced Q_{G-T} in Equation (4) by parameter Q_{G-B} , which is the grid electricity consumed to charge the batteries. We then divided this present value of the costs by the amount of electricity provided by the backup system over the life of the project, as shown in Equation (6)

$$COE_{Backup} = \frac{PC_{Backup}}{\sum_{y=0}^T \frac{1}{(1+d)^y} \sum_{h=1}^{8,760} Q_{D-L}[h,y] + \delta_{sys} \cdot (Q_{PV-L}[h,y] + Q_{B-L}[h,y])} \quad (6)$$

where Q_{D-L} is the electricity supplied by the backup generators; Q_{B-L} is the electricity supplied by the battery; and Q_{PV-L} is the electricity supplied by the solar PV to meet the household's load.

2.3. Emissions model

We assess the emissions reductions of two different categories of air pollutants namely: criteria air pollutants and greenhouse gases. The supporting information shows the system boundaries we used for estimating the criteria air pollutants and greenhouse gases (GHG) emissions. For GHG, we included CO₂ and methane emissions from crude oil production, refining, transport, and combustion, as well as emissions from power generation in Nigeria. Previous work suggests that solar PV and battery manufacturing can contribute to the life cycle GHG emissions of residential systems (Ren et al., 2020), so we also included GHG emissions from these sources. Table 2 shows the equations used to estimate the GHG emission from the different stages, the sum of which are the total lifetime emissions from the systems.

For criteria air pollutants, we include emissions from on-site diesel combustion and emissions from on-grid power generation. We do not include criteria air emissions from upstream fuel production and transportation, or system component manufacturing as such data are not widely available. Furthermore, the human health impacts of criteria air emissions in different locations are not additive and the most significant impacts come from emissions at the combustion sites (power plants or diesel generators). Equation (7) shows the formulation for total lifetime criteria air emissions when the backup generator is on, and grid electricity is consumed

$$Pol_p = \zeta_{PD} \cdot \sum_{y=1}^T \sum_{h=1}^{8,760} F_{D-L}[h, y] + \zeta_{PG} \cdot \sum_{y=1}^T \sum_{h=1}^{8,760} Q_{G-T}[h, y] \quad (7)$$

where Pol_p is the total emissions of pollutant p; ζ_{PD} (kg-pollutant/liter) and ζ_{PG} (kg-pollutant/kWh) are the emissions factors for pollutant p from the backup generators and the grid respectively, Fuel_{D-L} is the amount of diesel used by the generator (from Eq. (3)), and Q_{G-T} is grid electricity used.

2.4. Model inputs

2.4.1. Load profiles for Lagos households

We focus our analysis on grid-connected households in the state of Lagos because it has a population of 20 million with the highest proportion of grid connected households (99 %) (Akpan, 2015). Our assumptions about hourly household electricity demand and grid service rely on measured data from Lagos reported in the End-use Metering Campaign for Residential Houses (ECN, 2013). This study measured and reported the average hourly household electricity consumption for a representative sample of households in Lagos when the grid was

available, as shown in Fig. 3. According to this study, grid connected households in Lagos consume 7,816 kWh/year (or 21.4 kWh/day). We therefore assumed that this load profile also represents latent demand i. e. what the households would consume if they had reliable grid service during those hours. For hourly solar resource and ambient temperature data for Lagos, we rely on the publicly available HelioClim-3 v5 database (Lagos coordinates: 6.5°N, 3.3°W) from February 1, 2005, to January 31, 2006 (SoDa, 2005). These data are used to compute PV array and battery performance as used in (Williams et al., 2018). Table 3 summarizes the economic assumptions used in the model.

2.4.2. System sizes

Our analysis focuses on using solar-battery systems to meet the household's minimum reliability preferences while a) reducing backup generator reliance (backup generators is an option) and b) completely replacing backup generators (backup generators are not an option). As a result, we run the techno-economic analysis across multiple combinations of PV size and battery storage (as described in more detail in the SI). Table 4 summarizes the technical input values of the unit components considered in our analysis obtained from available retailers of solar-battery systems in Nigeria. We assumed an equator-facing array with latitude tilt.

2.4.3. Grid availability and grid tariffs

The End-use Metering Campaign for Residential Houses also measured the durations grid service and outage experienced by each household investigated (ECN, 2013). Based on these data, we assume a baseline grid service duration and baseline grid outage duration of 4 h, which correspond to a base grid availability of 50 %. We assumed an annual grid improvement factor (ω) of 0.1 %/year to account for the historically slow grid improvements in Nigeria. The Nigerian electricity regulators set residential tariffs in Nigeria from 2020 to 2025 (NERC, 2020). Since our model horizon extends beyond 2025, we calculated the future prices using the inflation rate (10 %) in Table 5.

2.4.4. Reliability preference levels

Since the reliability preferences of customers in Lagos are poorly understood, we account for varying preferences by constructing six reliability preference scenarios using increasing blocks of 4 h. We assumed that household preferences range from 4 h/day to 24 h/day as summarized in Table 6. This implies that households could have between 4 h and 24 h of priority load each day, whereby all dispatchable electricity generating sources will be available for use should an outage occur in those hours. We selected the priority hours by ranking the household load in descending order according to Fig. 3. For example, in

Table 2
Equations for estimating the lifetime GHG emissions from different system components.

Component	Equation	Variable Definitions
Solar PV Manufacturing	$GHG_{PV} = \left(\frac{PV_Size}{PV_Rate} \right) \times Mod_Area \times \xi_{PV}$	PV_size is the peak solar-PV panel output (kWp); PV_Rate is the Rating of a single module (kWp/module); Mod_Area is the area of a single solar module; and ξ _{PV} is the greenhouse emissions factor associated with manufacturing of solar (kgCO ₂ eq/m ²).
Battery Manufacturing	$GHG_{Batt} = \left(1 + \sum_y Repl_B[y] \right) \times No_{Batt} \times \xi_{Batt}$	No _{Batt} is the number of batteries used in the system; Repl _B is a binary variable that indicates the replacement year of the batteries, summed over the model horizon; ξ _{Batt} is the greenhouse emissions factor associated with manufacturing of battery (kgCO ₂ eq/kg)
Inverter Manufacturing	$GHG_{Inv} = \left(1 + \sum_y Repl_{Inv}[y] \right) \times \xi_{Inv}$	Repl _{Inv} is a binary variable that indicates the replacement year of the inverter, summed over the model horizon; ξ _{Inv} is the greenhouse emissions factor associated with manufacturing of the inverter (kgCO ₂ eq/unit)
Diesel (including oil production, refining, transport, and combustion)	$GHG_D = \xi_{gen} \times \epsilon \times \sum_{y=1}^T \sum_{h=1}^{8,760} Fuel_{D-L}[h, y]$	ξ _{gen} is the life cycle emissions factor for diesel fuel (kgCO ₂ eq/MJ); ε is the energy content of diesel (MJ/liter); Fuel _{D-L} is the hourly fuel consumption from backup generators (from Eq. (3)) summed over the life of the project.
Grid-based electricity	$GHG_G = \zeta_{GHG-Gr} \times \sum_{y=1}^T \sum_{h=1}^{8,760} Q_{G-T}[h, y]$	ζ _{GHG-Gr} is the emissions factor from the grid; Q _{G-T} is the electricity consumed from the grid over the life of the project

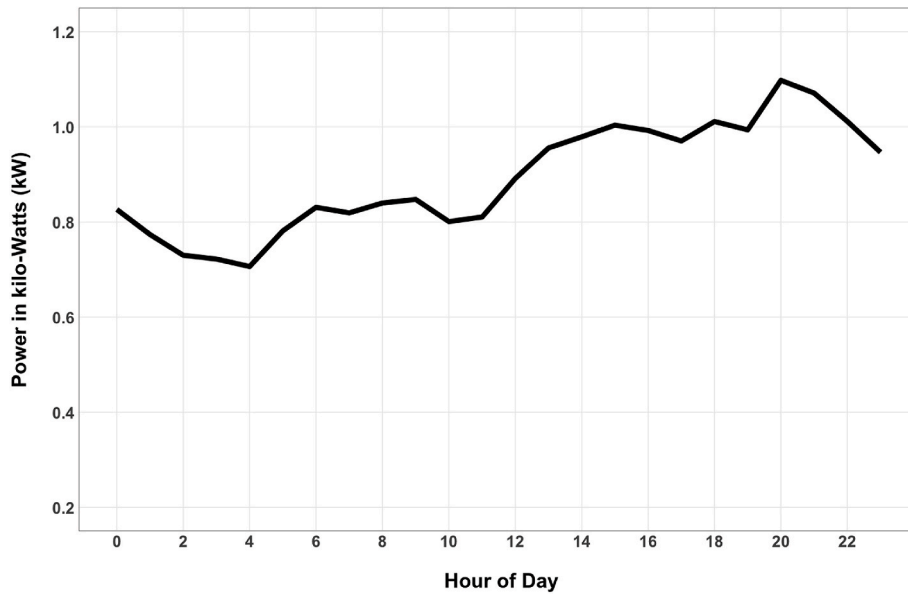


Fig. 3. Hourly average electric load for lagos household ECN (2013).

Table 3
Economic model inputs.

Parameters	Value	Source
Nominal Discount Rate (%)	20	NERC (2017)
Inflation rate (%)	10	National Bureau of Statistics (2018)
Model Horizon (years)	15	Assumption
Diesel Unit cost of Operating & Maintenance, om (N/kW/h)	10.5	Givler and Lilienthal (2005)
Unit cost of Diesel Generator (N/kWh)	121,000	Jumia-NG (2019)
Unit cost of Solar PV (N/kWp)	247,500	Jumia-NG (2019)
Unit cost of Battery (N/cell)	111,000	Jumia-NG (2019)
Unit cost of Inverter/Rectifier (N/kVA)	45,000	Jumia-NG (2019)
Diesel Fuel Cost for Lagos (N/liter)	224	National Bureau of Statistics (2018)

the level 1 preference, the household requires 4 h of reliable services daily. The 4 h with the highest demand are at 6PM, 8PM, 9PM and 10PM. If a grid outage occurs at any of these times, the household’s dispatchable backup systems will be dispatched to meet the load. If a grid outage occurs outside those hours, the household’s dispatchable backup systems will not be available for dispatch as the system is reserved to meet the priority hours in the future. Therefore, the electrical load at non-priority hours could potentially go unmet due to outages. At the other end, in the level 6 preference, the household requires all of their electricity needs met at all hours and would use their backup generators during a grid outage.

2.4.5. Emissions inputs

The criteria air pollutants considered in our study are carbon monoxide (CO), fine particulate matter (PM_{2.5}), Sulphur oxides (SO_x); and

Table 4
Key technical component inputs.

Unit Component	Input Description	Value	Source
Solar PV module	Maximum Power Point Voltage at STC (V _{MPP})	37.8	Jumia-NG (2019)
	Maximum PowerPoint Current at STC (I _{MPP})	5.31	Jumia-NG (2019)
	Open Circuit Voltage at STC (V _{OC})	45.3	Jumia-NG (2019)
	Short Circuit Current (at STC I _{SC})	6.15	Jumia-NG (2019)
	Number of Cells	120	Jumia-NG (2019)
	PV module Lifetime (years)	25	Assumption
	Solar Module Area (m ²)	0.198	Jumia-NG (2019)
Battery	Capacity (AmpH)	200	Jumia-NG (2019)
	Nominal Battery Voltage (V)	12	Jumia-NG (2019)
	Number of batteries connected (in series) in a string	2	Assumption
	Estimated Round Trip Efficiency	89 %	Williams et al. (2018)
	Battery Weight (kg)	45	Jumia-NG (2019)
	Maximum acceptable capacity fade	0.2	Williams et al. (2018)
	Efficiency (%)	0.95	Williams et al. (2018)
Inverter	Inverter Lifetime (years)	12	Assumption
	Bi-directional Inverter Size (kW)	2	Assumption
Backup Generator	No-load consumption parameter (F _{NL}) (liters/hour)	0.0911	Williams et al. (2018)
	Marginal consumption parameter (F _L) (liters/kWh)	0.264	Williams et al. (2018)
	Generator starting lifetime (hours)	7500	Assumption
	Generator Lifetime (hours)	15,000	Williams et al. (2018)
	Generator Size (kW)	1.5 (130 % of peak load in Fig. 3)	Assumption
	Energy Content (MJ/liter)	36.9	Farquharson et al. (2018a)

Table 5
Approved and estimated residential tariffs for Eko Distribution Company (in Naira/kWh).

Year	Tariff
2020	43.01
2021	47.83
2022	46.42
2023	46.25
2024	45.36
2025	45.33
2026	49.9
2027	54.8
2028	60.3
2029	66.4
2030	73
2031	80
2032	88
2033	97
2034	107

nitrogen oxides (NOx). Table 7 summarize the emissions factors for criteria air pollutant from diesel fuel and power generation in Nigeria. For greenhouse gases, we include carbon dioxide (CO₂) and methane emission using the emissions factors reported in the literature. Table 8

Table 7
Emissions factors for diesel fuel and grid.

Pollutant	Emissions factor of diesel (kg/MJ) – ζ _D	Emissions factor of grid (kg/kWh) – ζ _G
Life Cycle GHG Emissions (CO _{2,e})	2.75 ^a	416 × 10 ⁻³ ^b
Carbon Monoxide (CO)	4.084 × 10 ⁻⁴ ^b	0.324 × 10 ⁻³ ^b
Particulate Matter (PM _{2.5})	1.361 × 10 ⁻⁴ ^b	0.007 × 10 ⁻³ ^b
Nitrogen Oxide (NO _x)	1.896 × 10 ⁻³ ^b	0.802 × 10 ⁻³ ^b
Sulphur Oxide (SO _x)	8.598 × 10 ⁻⁵ ^b	2 × 10 ⁻⁶ ^b

^a Venkatesh et al. (2011).

^b (Farquharson et al., 2018b).

shows the GHG emissions factors for the manufacturing of the system components of these systems.

2.5. Sensitivity analysis

We perform a parametric sensitivity analysis on five key inputs in our analysis: 1) grid availability at the start of the simulation period; 2) grid price; 3) diesel fuel prices 4) discount rate; 5) capital costs of solar-battery systems. For each input we used the lower and upper limit values as summarized in Table 9.

Table 6
Tiers of household reliability preference. Grey cells indicate the priority hours in which a household's backup systems must be available to meet the household's load.

Hour of Day	Reliability Preference Level (hours/day)					
	Level 1 (4)	Level 2 (8)	Level 3 (12)	Level 4 (16)	Level 5 (20)	Level 6 (24)
0						
1						
2						
3						
4						
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						
16						
17						
18						
19						
20						
21						
22						
23						

Table 8

Emissions factors for battery and solar PV system components. These emissions factors come from (Ren et al., 2020).

Component	Unit	Lifecycle Emissions factor
Solar	kgCO ₂ -eq/m ²	202
Battery Storage	kgCO ₂ -eq/kg	7.52
Inverters	kgCO ₂ -eq/unit	243

Table 9

Lower and upper bound inputs considered for the sensitivity analysis.

Parameters	Base Value	Lower Bound	Upper Bound
Starting Grid Availability (%)	50	10 ^a	90
Discount Rate (%)	20	10	25
% Change in grid price for Eko Distribution Company (N/kWh)	42	-25 % of Base Value	+25 % of Base Value
Diesel Prices in Lagos (N/liter)	224	-25 % of Base Value	+25 % of Base Value
Up-front cost Solar PV (N/kWp)	247,500	-25 % of Base Value	+25 % of Base Value
Up-front cost of Battery System (N/unit)	110,000	-25 % of Base Value	+25 % of Base Value

^a We did not carry out the sensitivity analysis for the lower bound grid availability for the solar-battery systems without backup generators due to the large sizing requirement that would make the systems uneconomical.

3. Results

We run our analysis for multiple combinations of solar-PV module sizes and battery storage quantities across six reliability preference levels. Due to the computational demands of performing an hourly analysis of multiple size combinations over a model horizon of 15 years, we report our analysis using one single run of the grid schedule simulation. The short durations of the grid-on and grid-off cycles compared to the model horizon of 15 years (131,400 h), lead to a large number of samples that, by the law of large numbers, statistically converges towards the source distribution. We confirmed that random grid schedules do not vary significantly by generating 1,000 sample schedules and assessing the distributions of their statistical properties (further details can be found in the supporting information).

We present the combination of solar-PV (in kW) and battery quantity that yielded the lowest present value of the total costs from Equation (4) because we are analyzing the private benefits of solar-battery systems and assume a rational decision-maker will optimize for the lowest cost option while meeting their minimum reliability requirement. Table 10 shows the combination of solar PV sizes and number of battery units for the base grid availability of 50 %. For full technical, economic and emissions results of the other size combinations see the supporting information.

Table 10

Selected PV and battery size used for comparison with the status quo.

Reliability Preferences Tiers (hours/day)	GD-PB (Grid, Backup Generators, Solar-Battery Systems)			G-PB (Grid, Solar-Battery Systems)		
	PV (kW)	Batt (#)	Inv (kVA)	PV (kW)	Batt (#)	Inv (kVA)
4	0.2	2	2	0.6	4	2
8	1	4	2	0.6	8	3
12	1.6	4	2	2	10	3
16	2	4	2	2	14	3
20	2.4	4	2	2	16	3
24	2.4	4	2	3	18	3

3.1. Technical results

Fig. 4 shows the average annual electricity consumption from all electricity sources for the three system set-ups considered: 1) the status quo option - Grid and Backup Generators (GD), 2) Grid, Backup Generator, and Solar-battery system (GD-PB) and 3) Grid and Solar-battery system (G-PB) under a base grid availability parameter of 50 %. For households installing the solar-battery systems to supplement (but not replace) their backup generators (GD-PB), our results show that the solar battery system would provide an average of 665 kWh/year in Tier 1 (4 h/day) and rise to 4,512 kWh/year in Tier 6 (24 h/day). The contributions from the solar battery systems influence the contributions from the household electricity supply in two ways. First, it lowers contributions from backup generators between 73 % and 87 % depending on the household's reliability preferences. This change translates to a fuel savings of 211–1,360 L per year. Second, due to the additional demands for battery charging, grid consumption increases by 11%–23 %. For households who completely replace their backup generators with solar-battery systems (G-PB), our results show that installing the solar battery system would provide an average of 1,128 kWh/year in Tier 1 (4 h/day) and rises to 5,116 kWh/year in Tier 6 (24 h/day). Similarly, due to the additional demands for battery charging, grid consumption increases by 7%–19 %.

3.2. Economic results

Fig. 5 and Fig. 6 illustrate the economic implications of adding the solar-battery systems in terms of annual household electricity costs and unit cost of backup electricity respectively. As previously discussed, adding the solar-battery systems could significantly lower or eliminate the electricity supply from backup generators while increasing demand from the grid (when available) for battery charging. For households who keep their backup generators, installing the solar-battery systems saves the household between N100 K/year (Level 1) – N699 K/year (Level 6) in fuel costs as Fig. 5 illustrates. Grid expenses rise by N27 K/year (Level 1) to N46 K/year (Level 6). Overall, the solar battery systems save N73 K/year (Level 1) – N653 K/year (Level 6) in operational expenses (grid and backup generator). Despite these savings in operation costs, Fig. 5 shows that the solar-battery system is not an economically viable investment across all reliability preference levels when the capital costs of the systems are considered. For households who only demand 4 h (Level 1) of reliable service daily, the savings from reduced diesel consumption are not enough to justify the investment in the solar-battery systems, while for households with 8 h or greater demand for reliable services, installing the solar-battery systems is economically justifiable. Fig. 6 shows the unit costs of backup electricity is higher with the solar-battery systems in Level 1. It is worth noting that the marginal costs of providing electricity with the solar-battery system decreases for the higher reliability preference levels as the utilization rate of the solar-battery systems increases. Furthermore, higher utilization rates for assets that are similarly sized reduces use of the generator (which also leads to a higher reduction in fuel costs).

Our results show that fully replacing the backup generators with the solar-battery system is the most expensive choice in all reliability preference levels except for households with preferences for full reliability (24 h/day). Even though this system set-up would eliminate all backup generator expenditures, the upfront capital expense is much higher compared to the solar-battery technology option where the backup generator remains operational. Completely replacing the backup generator would require larger PV systems and more batteries than the set-ups in which the existing backup generator supplements the solar-battery system during the more extreme outages, as shown in Table 10. It is worth noting that adding a solar-battery system to the backup generator could be a more cost-effective option to increase the number of hours with reliable power. For example, a household that spends N661k/year to use only a backup generators to ensure 12 h of

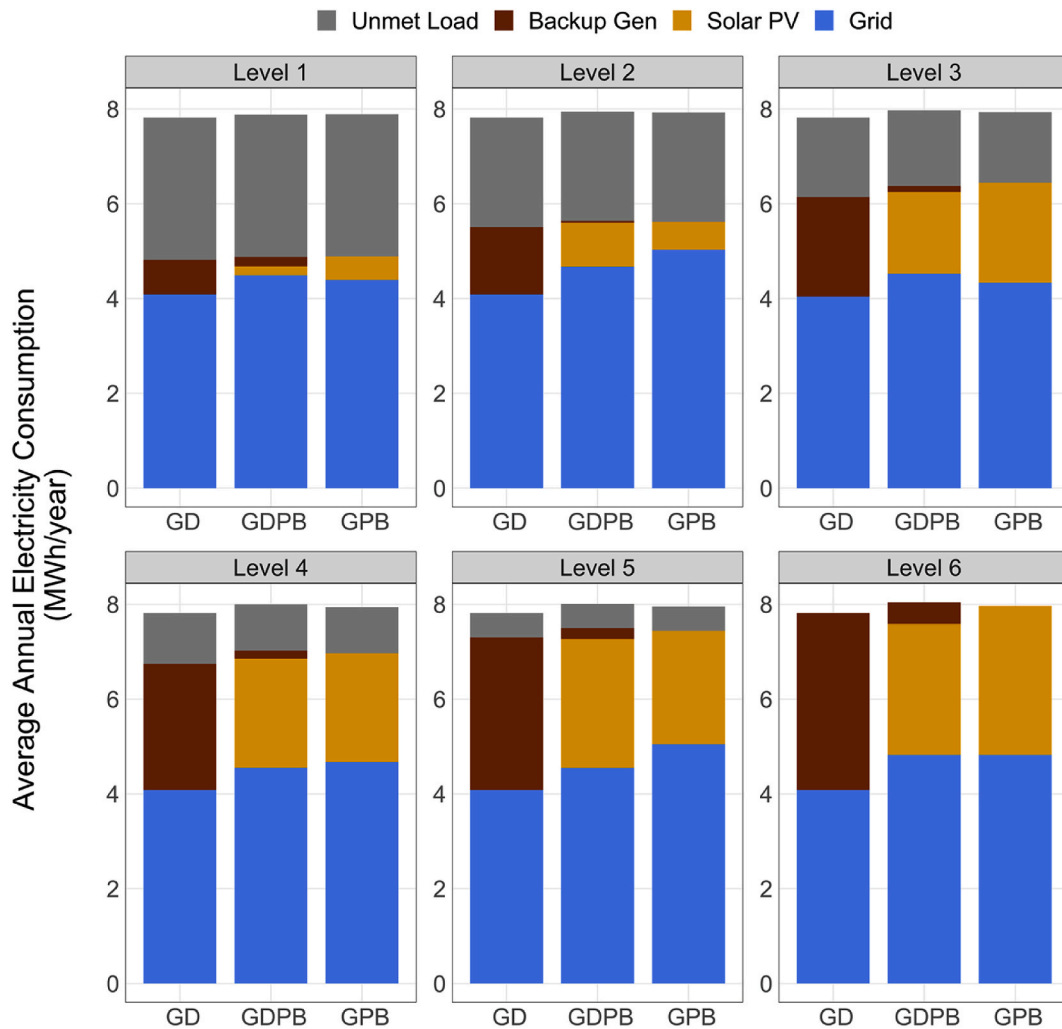


Fig. 4. Average annual electricity consumption from all electricity sources across all reliability preference levels.

electricity daily could ensure 20 h of electricity daily adding solar-battery systems at a lower annual cost of N634 K/year. Figs. 5 and 6 show household could meet all their electricity demand using the GD-PB system at a lower cost than a household using backup-generators alone to ensure 16 h of reliable electricity daily. These results suggest that adding solar-battery systems to complement the existing diesel generators could allow households to have more reliable power at lower cost than they are paying for fewer hours of backup with the generators.

While this paper focuses on an analysis for households that already have a backup generator, the results in Fig. 5 can easily be extended to households that do not currently have backup systems. A new diesel backup generator sold in Nigeria costs N181K (1.5kVA) (Jumia-NG, 2019). Purchasing these generators would thus add roughly N60K to the average annual costs reported in Fig. 5 for the GD setup. Household without an existing backup generator and low reliability preferences would thus have similar or only slightly higher annualized costs if they install a relatively small solar-battery system instead of a backup generator. For households without existing backup generators wishing to install a system to meet high reliability needs (16 h or more), the solar-battery system would be more economic than simply installing a backup generator. However, installing a new backup generator in conjunction with a solar battery system would likely remain the cheapest option for households with higher reliability preferences, even after accounting for the costs of buying the new generator. Further costs reductions in PV panels and batteries are still needed to justify the investments in the larger systems that would be needed to meet the reliability needs without some support from backup generators.

3.3. Emissions results

Fig. 7 and Fig. 8 show the emissions results from each of the system set-up options considered across all the reliability preference levels described in Table 6. Unsurprisingly, our results show that backup generators are the major source of criteria air emissions and greenhouse gas emissions. The solar-battery system with the backup generator option (GD-PB) reduces lifetime criteria air emissions by 15 %–87 % and greenhouse emissions by 12 %–51 % compared to the GD system. Over the model horizon, installing the solar-battery system reduces between 48 and 307 kg of CO, 16–102 kg of PM_{2.5}, 10–65 kg of SO_x, 221–1400 kg of NO_x, and 8000–53,000 kg CO₂eq. The solar-battery systems without backup generator option (G-PB) lowers lifetime criteria air emissions by up to 99 % and greenhouse emissions by 85 %–96 % compared to the GD system. Over the model horizon, the solar-battery system without the backup generators reduces between 66 and 356 kg of CO, 22–119 kg of PM_{2.5}, 13–74 kg of SO_x, 307–1651 kg of NO_x, and 11,360–61,520 kg CO₂eq. The G-PB set-up has lower lifetime air emissions than the GD-PB set-up, but it is also more expensive. An analysis of the social costs associated with such emissions is out of the scope of this paper given the unavailability of air quality models for Lagos and the uncertainty about the social cost of carbon that is appropriate for policy analysis in developing countries. Future work to estimate such social costs could improve the cost-benefit analysis for behind-the-meter energy systems in Nigeria.

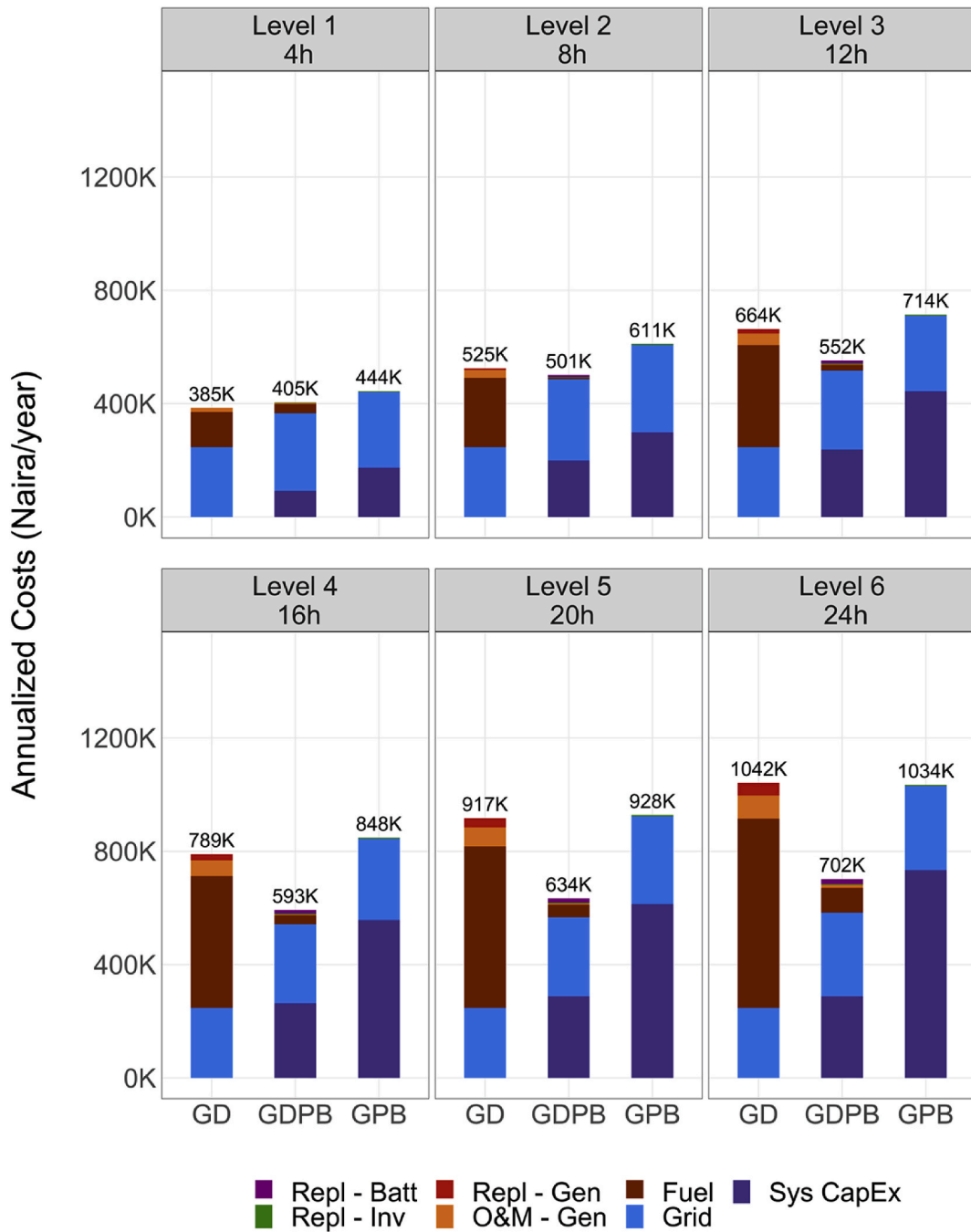


Fig. 5. Annualized household costs across all reliability preference levels.

3.4. Sensitivity analysis

We perform a parametric sensitivity analysis on five key inputs in our analysis: 1) grid availability at the beginning of the simulation period; 2) grid price; 3) diesel fuel prices 4) discount rate; 5) capital costs of the solar-battery systems. We vary each of these inputs separately and report varying outcomes in a tornado plot to study the effects of these inputs across each of the household reliability preference levels. Fig. 9 and Fig. 10 show the results of the net changes in savings because of the changes to the parametric inputs. Note that savings are defined as the difference in annualized costs between the backup system and the PV-Battery systems, and net changes in savings are the difference in savings using the updated parameter and the savings generated using the input's base values. A move to the right indicates that this change in

input resulted in greater savings. The reverse is the case with a move to the left. These results show that across all reliability levels, our economic and emissions results are most sensitive to the grid availability parameter. The supporting information shows similar sensitivity figures for the emissions results. The avoided emissions associated with installing the solar-battery systems are most sensitive to the grid availability parameter.

3.4.1. Effects grid availability

Figs. 9 and 10 highlight the effects of grid availability on the economic attractiveness of solar battery systems with and without backup generators respectively. Lower grid availability results in more frequent outages, and, in households with only backup generators, this implies greater dispatch and increased household costs to meet the same level of

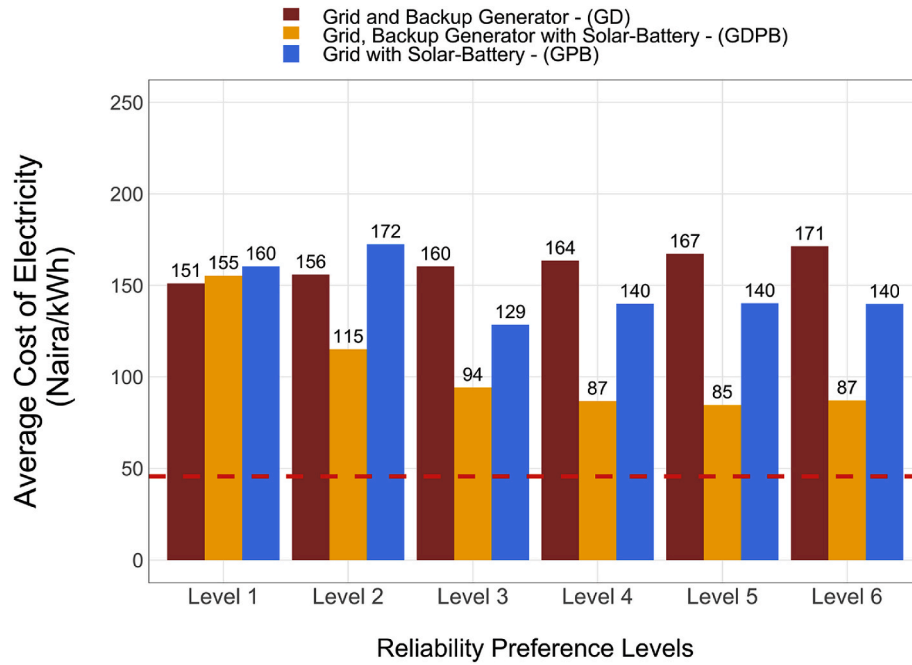


Fig. 6. Average cost of backup electricity across all reliability preference levels. Dashed red line shows the average grid tariff for the utility (Eko Distribution Company).

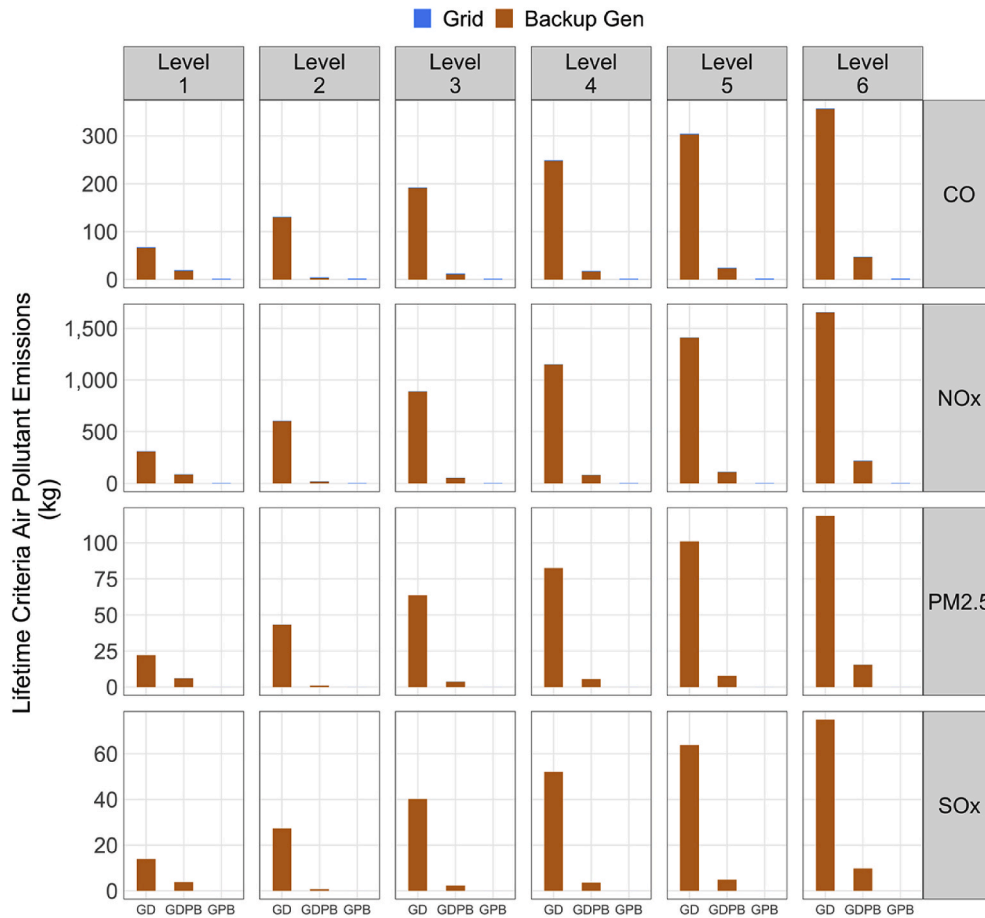


Fig. 7. Lifetime Emissions for Criteria Air Pollutants across all reliability preference levels.

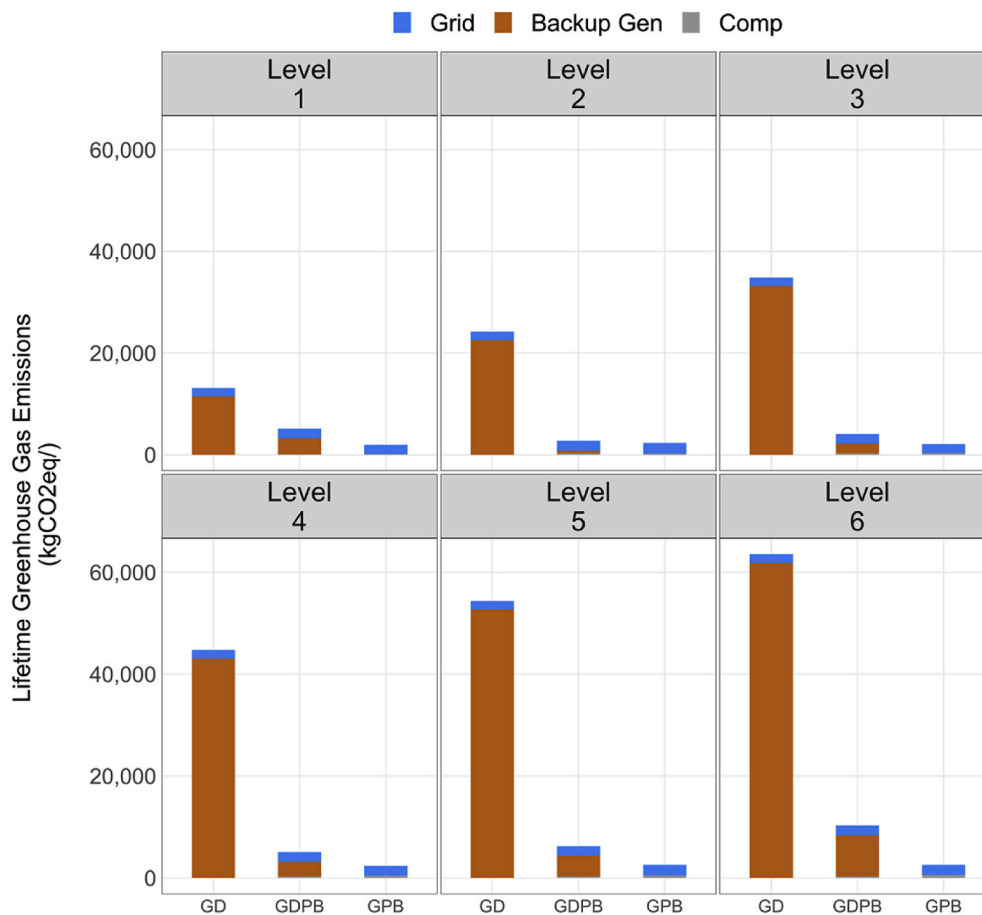


Fig. 8. Lifetime emissions for greenhouse gases across all reliability preference levels.

electricity demand. Households with higher backup generator expenses are attractive targets for solar-battery systems since they can store cheaper sources of electricity (solar and grid, when available) for future consumption, further lowering the need for backup generators.

On the other hand, high grid availability results in less frequent outages, therefore lowering the need for backup generators. Not surprisingly, our sensitivity analysis indicates that households with high grid availability are not attractive for solar-battery systems with or without backup generators available. With high grid availability, the battery systems would be discharged less frequently, and the electricity generated from the solar panels will be used to lower grid demand during the afternoon. Unfortunately, our results show that lowering grid consumption is not as valuable as lowering backup generator reliance since the grid is comparatively cheaper source of electricity than diesel fuel. It is worth noting that the approved electricity tariffs in Nigeria are not cost-reflective (NERC, 2020).

3.4.2. Effects of economic parameters

Figs. 9 and 10 show that the economic attractiveness of the solar-battery systems is most sensitive to discount rates. Discount rates indicate how future costs are discounted relative to the present costs. Lower discount rates compare future costs favorably to present costs and thus favor technology like solar-battery systems, which have higher capital costs and lower operational costs. Lower discount rates make the solar-battery systems with backup generators more attractive by increasing the savings. For solar-battery systems without backup generators (GPB), the lower discount rates result in savings (compared to the status quo set-up - GD) making the systems more attractive across all the reliability preference levels. By providing access to lower cost loans for households, our sensitivity analysis shows that solar-battery systems

become attractive across all reliability preferences (Babajide and Brito, 2021). Access to lower cost loans could make larger systems more economically attractive, which in turn leads to additional emissions reductions.

Fuel prices affect the costs of fueling, which we found to be a significant cost component, particularly in households with higher reliance on backup generators. Lower fuel prices reduce the cost of fueling, which in turn reduces the savings potential of the solar-battery systems, while higher fuel prices increase the overall costs of fueling and increase the value of the saved fueling expenses when using solar-battery systems. Similarly, grid prices influence the cost of grid consumption and with solar-battery systems, affect the additional costs of battery charging. Since grid tariffs are cheaper than fuel, the effects of higher grid prices is not as influential to our results. Since diesel and gasoline are subsidized in Nigeria, these results suggest that reducing such subsidies could serve as a mechanism to incentivize the deployment of residential solar-battery systems.

Finally, our sensitivity analysis shows, predictably, that lower capital costs improve the attractiveness of the solar-battery system, and could make the economically viable for households with lower demands for reliable services. Lower upfront costs of the systems make larger systems more attractive in higher demand households thereby further reducing fuel consumption and the resultant emissions.

4. Conclusions

We find that installing solar-battery systems reduces the reliance on backup generators in Lagos's households with poor grid reliability. In turn, the addition of the solar-batter systems reduces fuel consumption, which is expensive and polluting when burnt. However, the savings

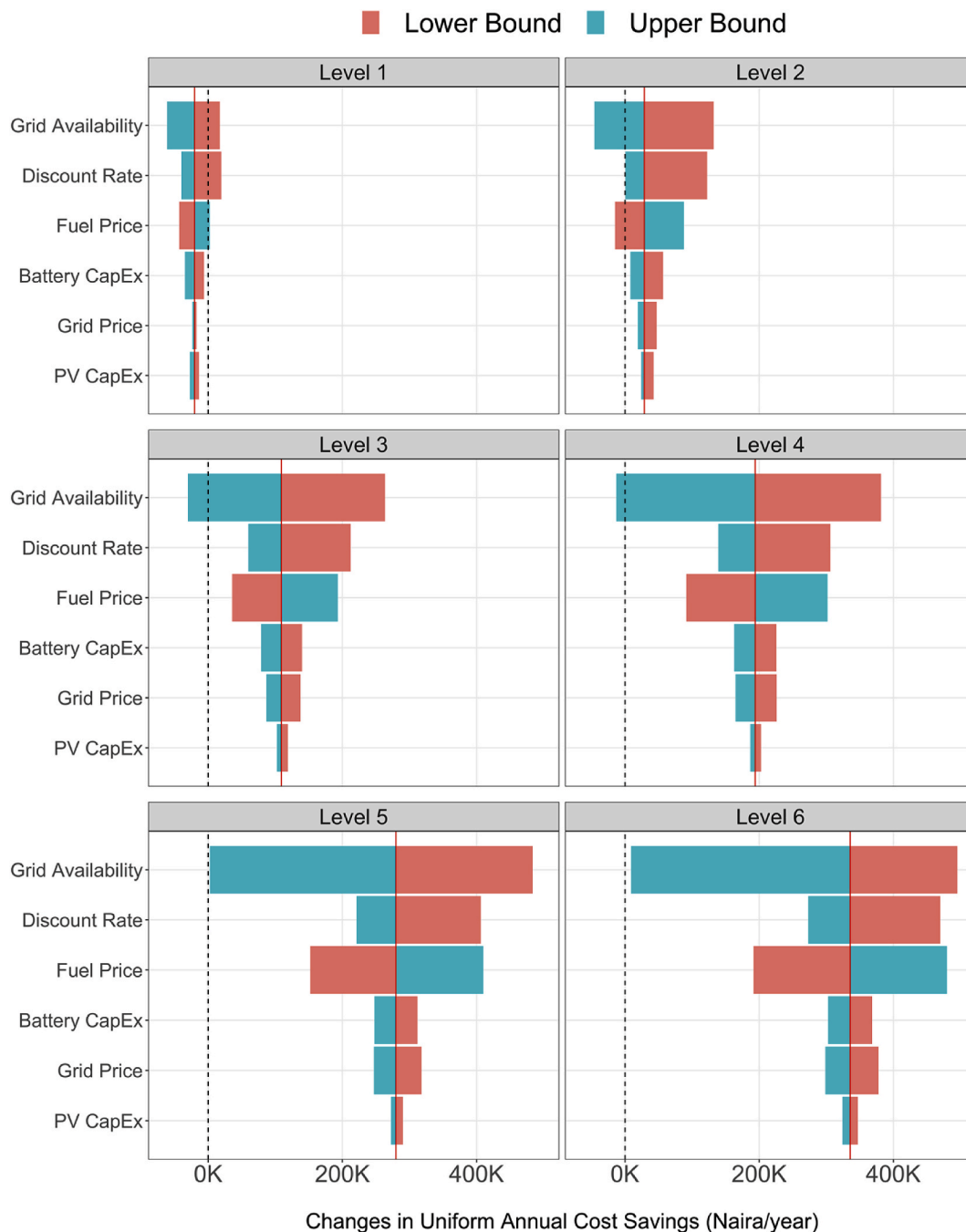


Fig. 9. Economic sensitivity analysis results for solar-battery with backup generators (GD-PB). The x-axis shows the difference in the annual cost of the GD-PB system compared to the GD system.

generated from lower fuel consumption do not translate to lower overall electricity costs for all household as these savings depend on the reliability preferences. For households that require at least 8 h/day of electricity services, installing the solar-battery systems could save them between 5 % and 32 % and could supply longer duration of electricity services more cost effectively than backup generators. However, for households with lower requirements for reliable service (4 h/day), we find that the solar-battery systems increase costs and thus become economically unfavorable. For all households, keeping the backup generator to supplement the solar-battery system is still more economical than installing larger solar-battery systems needed to meet demand during the extreme outage events.

Installing the solar-battery systems in households could also have broader social implications that could interest policymakers. First,

lowering the aggregate household diesel consumption for electricity generation could reduce importation costs since Nigeria imports the majority of the diesel consumed (Nigeria National Bureau of Statistics, 2020). Second, installing the solar-battery systems lowers air emissions that contribute to air pollution and climate change. Finally, behind-the-meter solar-battery systems could be operated to provide power back to the grid, thus contributing to increase capacity of the overall power system. Installing these systems may be less time-consuming than building new centralized power plants (and could potentially be lower cost). Indeed, behind-the-meter residential PV systems are a growing source of electricity in places like California and Germany, highlighting that they can be incorporated as part of the operations of the central grid (Meza, 2021; Mordor Intelligence LLP, 2020). These benefits suggest some justification for interventions like lowering

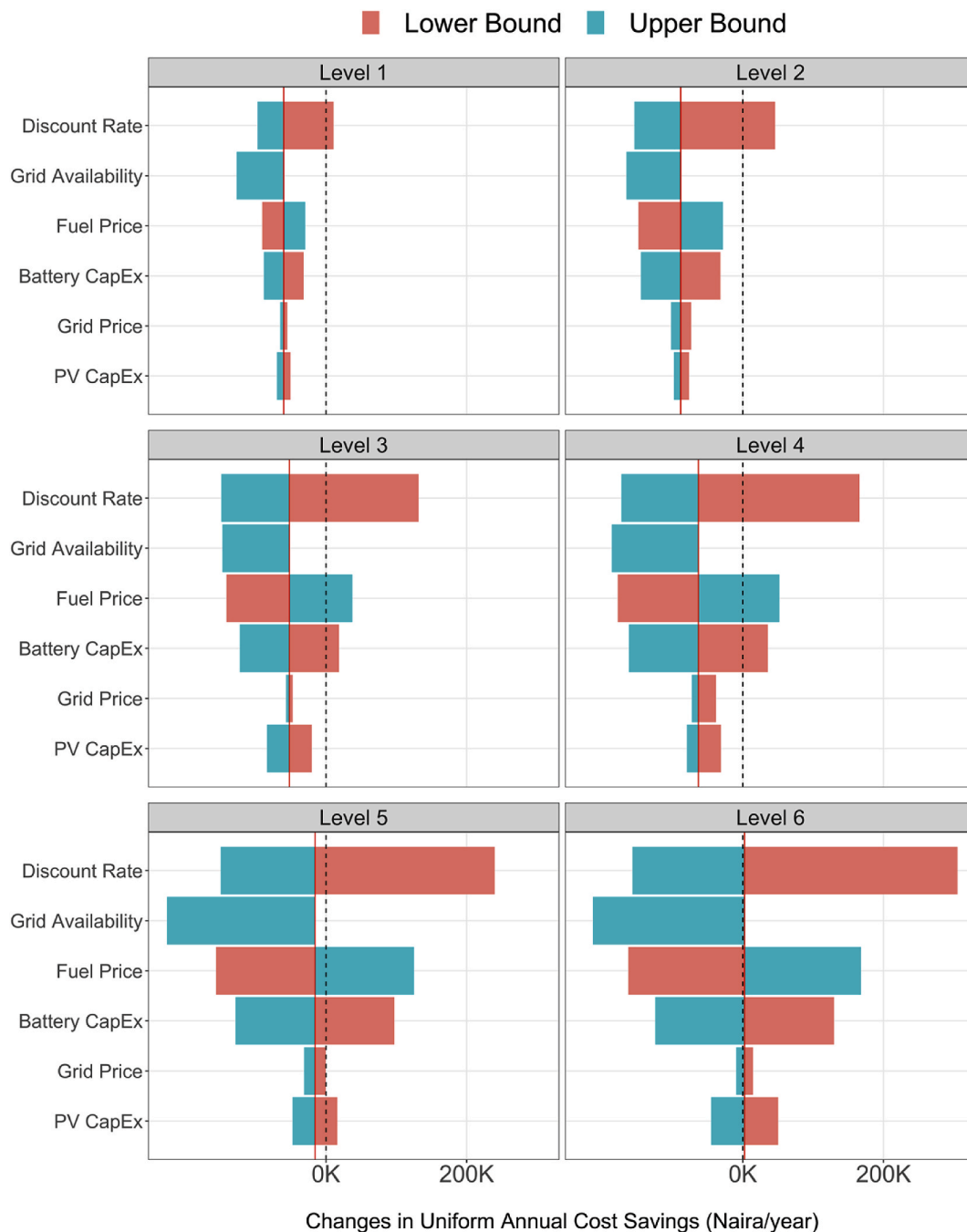


Fig. 10. Economic Sensitivity Analysis Results for solar-battery without backup generators (G-PB). The x-axis shows the difference in the annual cost of the G-PB system compared to the GD system. For this system set-up, we only tested the sensitivity of the results to the starting grid availability parameter of 90 %. The size of the PV-Battery system in the case in which the starting value of the grid availability parameter is 10 % would be prohibitively large. Households with very low grid reliability are better served by using a backup generator in conjunction with a moderately sized PV-Battery system.

the upfront cost of the solar-battery systems in the form of grants and subsidies as carried out in other countries (Hagerman et al., 2016; Tantisattayakul and Kanchanapiya, 2017), or providing access to low interest loans (Tantisattayakul and Kanchanapiya, 2017). Reducing diesel subsidies could also incentivize the deployment of solar-battery systems. Our sensitivity analysis also shows that providing financial support for the solar-battery systems could make larger sized systems more economically attractive, which would further lower reliance or even eliminate the need for backup generators and lead to lower fuel consumption and household emissions. Integrating these behind-the-meter resources into the operations of the central grid would require robust interconnection standard and net-metering policies.

Our analysis is not without limitations. First, we relied on average load profiles data for Lagos and were therefore unable to capture the heterogenous characteristics in terms of varying household load and building type. We were also unable to account for potential temporal correlations between high demand periods on grid outages, as data about such temporal correlation is not publicly available in Nigeria. Furthermore, we did not factor the dynamic response of household electricity demand to outages (where households peak demand may be higher after an outage) or account for annual growth in demand for electricity, as such information is not available. Additionally, we had to rely on parametric assumptions about reliability needs to account for the fact that consumers may not use the backup systems every time there is a

grid outage. Our analysis did not investigate the effects of additional grid demand from the wide adoption of solar-battery systems, which could further stress a constrained grid, making it more unreliable (Murphy et al., 2014). Finally, we did not quantify the human health impacts and associated social costs associated with air emissions that contribute to air pollution and climate change. Analyzing such social costs requires air quality, exposure, and mortality models that are currently unavailable for Nigeria. A deeper understanding about the implications of poor air quality on Lagos residents may strengthen the case for policies that support the deployment of solar-battery systems to provide backup power for households. These limitations notwithstanding, our analysis suggests that there are likely private and social benefits associated with the deployment of distributed “behind-the-meter” solar-battery systems to provide backup power for households in Nigeria.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The Petroleum Development Trust Fund (PTDF) of Nigeria (PTDF/TR/ED/PRESS/OEM/01/01) under the Presidential Special Scholarship for Innovation and Development (NUC/ES/57/VOL.6/416) provided partial funding for this work. The Rockefeller Foundation also provided funding for this project. The results and conclusions in this paper are the sole responsibility of the authors and may not represent the views of the funding agency.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.deveng.2021.100069>.

References

- A2EI, 2019. Putting an End to Nigeria's Generator Crisis: the Path Forward. Access to Energy Institute.
- Adaramola, M.S., Paul, S.S., 2016. Economic analysis and potential feed-in tariff of grid-connected PV systems in Nigeria. *Environ. Prog. Sustain. Energy* 36, 319–323. <https://doi.org/10.1002/ep>.
- Akin, A.O., O, A.D., 2017. Domestic electric power generator usage and residents livability milieu in ogbomosho, Nigeria. *Environ. Manag. Sustain. Dev.* 6, 91. <https://doi.org/10.5296/emsd.v6i11.10941>.
- Akpan, U., 2015. Technology options for increasing electricity access in areas with low electricity access rate in Nigeria. *Socioecon. Plann. Sci.* 51, 1–12. <https://doi.org/10.1016/j.seps.2015.05.001>.
- Amadi, H., 2015. Impact of power outages on developing countries: evidence from rural households in Niger delta, Nigeria hachimenum. *J. Energy Technol. Pol.* 5, 117–131. <https://doi.org/10.1002/biof.1317>.
- Ayodele, T.R., Ogunjuyigbe, A.S.O., 2015. Increasing household solar energy penetration through load partitioning based on quality of life: the case study of Nigeria. *Sustain. Cities Soc.* 18, 21–31. <https://doi.org/10.1016/j.scs.2015.05.005>.
- Babajide, A., Brito, M.C., 2021. Solar PV systems to eliminate or reduce the use of diesel generators at no additional cost: a case study of Lagos, Nigeria. *Renew. Energy* 172, 209–218. <https://doi.org/10.1016/j.renene.2021.02.088>.
- Chidebell-Emordi, C., 2015. The African electricity deficit: computing the minimum energy poverty line using field research in urban Nigeria. *Energy Res. Soc. Sci.* 5, 9–19. <https://doi.org/10.1016/j.erss.2014.12.011>.
- Nwachukwu Clara, 2011. Nigeria maintains lead in generator imports in Africa [WWW Document]. *Vanguard News Niger*. URL8.26.20. <https://www.vanguardngr.com/2011/01/nigeria-maintains-lead-in-generator-imports-in-africa>.
- Coria, G., Penizzotto, F., Pringles, R., 2018. Economic analysis of photovoltaic projects: the Argentinian renewable generation policy for residential sectors. *Renew. Energy*. <https://doi.org/10.1016/j.renene.2018.08.098>.
- Diesel Power Generation, 2014. Diesel Power Gener. <https://doi.org/10.1596/28419>.
- Eboh, M., 2020. Vanguard News - N1.5trn spent on fuel subsidy in 2019— FG [WWW Document]. URL8.17.20. <https://www.vanguardngr.com/2020/04/n1-5trn-spent-on-fuel-subsidy-in-2019-fg/>.
- ECN, 2013. End-use Metering Campaign for Residential Houses in Nigeria.
- Enongene, K.E., Abanda, F.H., Otene, I.J.J., Obi, S.I., Okafor, C., 2019. The potential of solar photovoltaic systems for residential homes in Lagos city of Nigeria. *J. Environ. Manag.* 244, 247–256. <https://doi.org/10.1016/j.jenvman.2019.04.039>.
- Ezeoha, A., Igwe, A., Onyeke, C., Uche, C., 2016. Relevance lost? The Petroleum equalization Fund in Nigeria. *Energy Sustain. Dev.* 31, 152–162. <https://doi.org/10.1016/j.esd.2016.01.004>.
- Farquharson, D.V., Jaramillo, P., Samaras, C., 2018a. Sustainability implications of electricity outages in sub-Saharan Africa. *Nat. Sustain.* 1, 589–597. <https://doi.org/10.1038/s41893-018-0151-8>.
- Farquharson, D.V., Jaramillo, P., Samaras, C., 2018b. Sustainability implications of electricity outages in sub-Saharan Africa. *Nat. Sustain.* 1, 589–597. <https://doi.org/10.1038/s41893-018-0151-8>.
- Givler, T., Lillenthal, P., 2005. Using HOMER® Software , NREL's Micropower Optimization Model, to Explore the Role of Gen-Sets in Small Solar Power Systems Case Study: Sri Lanka. <https://doi.org/10.1016/j.apenergy.2011.11.059>. Contract 1–31.
- Hagerman, S., Jaramillo, P., Morgan, M.G., 2016. Is rooftop solar PV at socket parity without subsidies? *Energy Pol.* 89, 84–94. <https://doi.org/10.1016/j.enpol.2015.11.017>.
- Hittinger, E., Wiley, T., Kluzza, J., Whitacre, J., 2015. Evaluating the value of batteries in microgrid electricity systems using an improved Energy Systems Model. *Energy Convers. Manag.* 89, 458–472. <https://doi.org/10.1016/j.enconman.2014.10.011>.
- IFC, 2019. The Dirty Footprint of the Broken Grid the Impacts of Fossil Fuel Backup Generators in Developing Countries.
- Jumia, N.G., 2019. Jumia online retailers [WWW Document]. URL7.7.19. <https://www.jumia.com.ng/catalog/?q=complete-solar>.
- La Monaca, S., Ryan, L., 2017. Solar PV where the sun doesn't shine: estimating the economic impacts of support schemes for residential PV with detailed net demand profiling. *Energy Pol.* 108, 731–741. <https://doi.org/10.1016/j.enpol.2017.05.052>.
- Ley, K., Gaines, J., Ghatikar, A., 2014. The Nigerian Energy Sector - an Overview with a Special Emphasis on a Special Emphasis on Renewable Energy. Energy Efficiency and Rural Electrification, Internationale Zusammenarbeit (GIZ) GmbH.
- Manwell, J.F., McGowan, J.G., 1993. Lead acid battery storage model for hybrid energy systems. *Sol. Energy* 50, 399–405. [https://doi.org/10.1016/0038-092X\(93\)90060-2](https://doi.org/10.1016/0038-092X(93)90060-2).
- Meza, E., 2021. Germany could see installation of 150,000 residential batteries in 2021 amid solar PV boom | Clean Energy Wire [WWW Document]. URL6.20.21. <https://www.cleanenergywire.org/news/germany-could-see-installation-150000-residential-batteries-2021-amid-solar-pv-boom>.
- Mordor Intelligence LLP, 2020. United States solar energy market - growth, trends, and forecasts (2020 - 2025) [WWW Document]. URL6.20.21. https://www.reportlinker.com/p05954264/United-States-Solar-Energy-Market-Growth-Trends-and-Forecasts.html?utm_source=GNW.
- Murphy, P.M., Twaha, S., Murphy, I.S., 2014. Analysis of the cost of reliable electricity: a new method for analyzing grid connected solar, diesel and hybrid distributed electricity systems considering an unreliable electric grid, with examples in Uganda. *Energy* 66, 523–534. <https://doi.org/10.1016/j.energy.2014.01.020>.
- National Bureau of Statistics, 2018. National Bureau of Statistics [WWW Document]. URL6.26.18. <http://statisticsnigeria.gov.nv/>.
- NERC, 2017. MULTI-YEAR TARIFF ORDER for the DETERMINATION of the COST of ELECTRICITY GENERATION for the PERIOD 1 JUNE 2012 to 31 MAY Nigerian Electricity Regulatory Commission 1 ST JUNE 2012, pp. 1–37.
- NERC, 2020. MULTI-YEAR TARIFF ORDER. FOR EKO DISTRIBUTION COMPANY. Nigerian National Bureau of Statistics, 2020. Petroleum Products Imports and Consumption (Truck Out) Statistics.
- Nwachukwu, M.U., Chike, H., 2011. Fuel subsidy in Nigeria: fact or fallacy. *Energy* 36, 2796–2801. <https://doi.org/10.1016/j.energy.2011.02.020>.
- Okoye, C.O., Taylan, O., Baker, D.K., 2016. Solar energy potentials in strategically located cities in Nigeria: review, resource assessment and PV system design. *Renew. Sustain. Energy Rev.* 55, 550–566. <https://doi.org/10.1016/j.rser.2015.10.154>.
- Oluseyi, P.O., Babatunde, O.M., Babatunde, O.A., 2016. Assessment of energy consumption and carbon footprint from the hotel sector within Lagos, Nigeria. *Energy Build.* 118, 106–113. <https://doi.org/10.1016/j.enbuild.2016.02.046>.
- Oseni, M.O., 2011. An analysis of the power sector performance in Nigeria. *Renew. Sustain. Energy Rev.* 15, 4765–4774. <https://doi.org/10.1016/j.rser.2011.07.075>.
- Oseni, M.O., 2016. Get rid of it: to what extent might improved reliability reduce self-generation in Nigeria? *Energy Pol.* 93, 246–254. <https://doi.org/10.1016/j.enpol.2016.03.013>.
- Oseni, M.O., 2017. Self-generation and households' willingness to pay for reliable electricity service in Nigeria. *Energy J.* 38, 165–194. <https://doi.org/10.5547/01956574.38.4.mose>.
- Oseni, M.O., Pollitt, M.G., 2015. A firm-level analysis of outage loss differentials and self-generation: evidence from African business enterprises. *Energy Econ.* 52, 277–286. <https://doi.org/10.1016/j.eneco.2015.11.008>.
- Ren, M., Mitchell, C.R., Mo, W., 2020. Dynamic life cycle economic and environmental assessment of residential solar photovoltaic systems. *Sci. Total Environ.* 722, 137932. <https://doi.org/10.1016/j.scitotenv.2020.137932>.
- SoDa, 2005. HelioClim-3 archives for free [WWW Document]. URL5.3.19. www.soda-pro.com/web-services/radiation/helioclim-3-archives-for-free.
- Tantisattayakul, T., Kanchanapiya, P., 2017. Financial measures for promoting residential rooftop photovoltaics under a feed-in tariff framework in Thailand. *Energy Pol.* 109, 260–269. <https://doi.org/10.1016/j.enpol.2017.06.061>.
- Williams, N.J., Jaramillo, P., Taneja, J., 2018. An investment risk assessment of microgrid utilities for rural electrification using the stochastic techno-economic microgrid model: a case study in Rwanda. *Energy Sustain. Dev.* 42, 87–96. <https://doi.org/10.1016/j.esd.2017.09.012>.